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Preface

The ideas presented in this book have been brewing in our minds for several years. Before receiving funding from the European Commission under the Seventh Framework Program, we made several attempts at both the national and international levels. One could say that our proposals did not fit the current needs of the users and the market at the time and/or were too innovative. We leave this for our readers to judge.

Certainly, the use of games as incentives for patients to get more involved in their rehabilitation, especially after such serious episodes as strokes has been suggested and tried already and in many different forms, as we have also indicated in this book. Using immersive user interfaces helps patients to exercise their bodies (and minds) while virtual (sometimes also augmented) reality games offer an enjoyable experience allowing users to forget for a moment about their condition. Nevertheless, they can notice significant improvements while having fun. This is the great advantage of the solution that we describe in this book.

Certainly, technologies behind the StrokeBack system are not trivial. We have done extensive applied research on several levels. We advanced the performance, cost, power consumption, and miniaturization of embedded, wearable physiological and activity monitoring sensors. We developed advanced algorithms for body motion capture from diverse types of 3D depth, inertial, EMG, EEG, and other sensors. This allowed us to more reliably detect the accuracy of performing exercises so we can more consistently verify the level of limb manoeuvrability improvement. The great novelty is that the whole process can be prescribed to patients by their leading physicians just like any other prescription using online Personal Health Record (PHR) services. This allowed us to offer the means for physicians to remotely track patients' progress and reconfigure exercises remotely, if needed. On the other hand, this also allowed patients to perform such exercises at home at their leisure.

We have developed several and diverse classes of games, from simple 80s style ones to advanced 3D immersive ones that use the most advanced 3D gaming engines. This allowed us to assess and determine what types of games could be used to best effect with which types of users, respective of age, gender, and level of physical disability. Ultimately, we have produced various prototypes of integrated rehabilitation systems, both a stationary ("Smart Table" like) one and a fully portable one.

At this point, we would like to thank the European Commission for offering funding for conducting this work, as part of its European Union Seventh Framework Program (FP7/2007–2013) under grant agreement no. 288692-StrokeBack, and certainly the reviewers who have positively judged our proposal. We would like also to thank our EU Project Officers for their continuous support and the reviewers who took their time to go through tons of material produced in the project and gave us a lot of valuable suggestions. Our great thanks are also due to the project coordinator, Dr. Steffen Ortmann for his hard work and dedication in pushing us all to reaching the final, successful conclusion of this project.

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Abstract

The proposed book addresses the problem of delivering a cost-effective and efficient means of recovery from strokes, a disease with a very high socio-economic impact. The Public Health Care System spends on average 3 % of their entire healthcare expenditure for dealing with the effects of strokes across different countries in Europe and the USA. This includes inpatient treatment cost, outpatient hospital visits, and long-term rehabilitation and care. Analysis shows that costs of long-term care have increased from 13 to 49 % of overall average costs in recent years. Therefore, devising an effective long-term care and rehabilitation strategy for stroke patients, actively involving patients in the process while minimizing costly human intervention, becomes a matter of urgency.

A new approach enabling people suffering from mild cases of stroke to recover their motor, and to some level also their mental capabilities has been developed in the StrokeBack project, partially funded by the European Commission through its FP7 Research Framework. An automated remote rehabilitation system blending advances in ICT and practical clinical knowledge empowers patients and their immediate care providers and family members to support an effective application of the rehabilitation protocol in their familiar home settings, instead of cold clinical environments.

Such a system combines state-of-the-art monitoring devices, forming a wireless Body Area Network, that enable simultaneous measurement of multiple vital parameters and currently executed movements that are of particular interest from the point of view of effective rehabilitation. The measured parameters are fused using advanced feature extraction and classification algorithms processed on-body, which will denote the accuracy of the executed exercise. The training parameters along with vital data will be stored in a patient health record to which the responsible clinicians and therapists have access so that they can dynamically update the rehabilitation program. By employing manual intervention only when actually necessary, it eliminates costly human intervention and thereby significantly reduces associated costs of the Public Health Care services. The increased rehabilitation speed as well as the fact that the rehabilitation training can be done at home directly improves the quality of life of patients, while gaming technologies increase the effectiveness by combining medical training with entertainment and desire for self-improvement.

The StrokeBack system combines a range of state-of-the-art technologies from augmented/virtual reality gaming environments that join with immersive user interfaces for delivering mixed reality training environments. With advanced embedded microsensor devices, with increased power autonomy, and by exploiting the latest Bluetooth Smart communication interfaces, they are all integrated under the umbrella of the Personal Health Record (PHR) platform, allowing for the delivery of personalized, patient-centric medical services, whether it is at home, in clinic or on the move.

Contents

Chapter 1
Motivation, Market and European Perspective

Emmanouela Vogiatzaki and Artur Krukowski

Abstract Stroke is a disease with very high socio-economic impact. In average, the healthcare expenditure cost for Strokes across different countries in Europe and the USA is 3 % of their entire healthcare expenditure. This includes inpatient treatment cost, outpatient hospital visits and long-term rehabilitation and care. Analysis showed that costs of long-term care have increased from 13 to 49 % of overall costs in average in recent years. Therefore, there is an urgent need for devising an effective long-term care and rehabilitation strategy for Stroke patients, which involves patients actively in the process while minimising costly human intervention.

Later, we describe main motivation behind pursuing research and development work on rehabilitation of stroke patients using an automated remote rehabilitation system by blending advances of ICT and practical clinical knowledge in order to empower the patients and their immediate care takers for effective application of the rehabilitation in home settings. The discussion further describes the state-of-the-art in research and development, signals similar systems already available on the market, concluding with identification of the potential impact of systems like StrokeBack and similar ones in European and worldwide perspectives.

1.1 Motivation Behind This Research Work

Stroke is hitting about two million [1] people per year in Europe. For these people, the effect of stroke is that they lose certain physical and cognitive abilities at least for a certain time period. More than one third of these patients, i.e. more than 670,000 people return to their home with some level of permanent disability, leading to a significant reduction of quality of life which affects not only the patients themselves but also their relatives.

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The ‘Stroke Alliance for Europe’ states in its manifesto:

- *We call on all European Governments to improve the availability of short and long-term rehabilitation to enable all stroke survivors to have access to life changing support* (p. 10)
- *Developing telemedicine systems for management of stroke* (p. 11)
- *We will encourage patients to take part in well-planned and executed controlled randomised trials of stroke prevention, acute care and rehabilitation*

Therefore, there is a strong need to improve ambulant care model, in particular, at the home settings, involving the patients into the care pathway, for achieving maximal outcome in terms of clinical as well as quality of life. In addition to the dramatic effect of stroke for individuals, it has strong impact on our society as well. The total cost of stroke in the EU was calculated to be over 38 billion in 2006. This figure included healthcare costs (about 49 % of total cost), productivity loss due to disability and death (23 % of total cost) and informal care costs (29 % of total cost).

The prevalence of ageing in the European societies is expected to lead to an increased number of people suffering from stroke. For example, [2] predicts that the number of stroke patients in Hessen, Germany; should increase from 20,846 in 2005 to more than 35,000 in 2050 which equals to an increase of nearly 70 % within the next four decades. The German Aerztezeitung predicts an increase of even 2.5 times is predicted leading to an enormous pressure on the healthcare systems in terms of cost. The effect on the healthcare cost might be even more significant since as the current trend suggest the ratio of young and healthy persons to elderly persons also decrease, so that the informal care cost might be shrinking and thereby directly leading to increased direct healthcare cost. This may become a burden for economies.

The StrokeBack project addresses both of the sketched problem areas. The goal of the project is the development of a telemedicine system which supports ambulant rehabilitation at home settings for the stroke patients with minimal human intervention. With StrokeBack the patients can do rehabilitation in their own home where they feel psychologically better than in care centres. In addition, the contact hours with a physiotherapist can be reduced leading to a direct reduction of healthcare cost. By ensuring proper execution of physiotherapy trainings in an automated guided way modulated by appropriate clinical knowledge and in supervised way only when necessary, StrokeBack empowers the patients to exercise much more and at better quality than it is possible today. By that StrokeBack improves rehabilitation speed, and quality of life of the patient. This leads also to the reduction of indirect healthcare cost as well. The StrokeBack concept is complemented by a Patient Health Record (PHR), in which training measurements and vital data of the patients is stored. Thus, the PHR provides all necessary information medical and rehabilitation experts need to evaluate rehabilitation success, e.g. to deduce relations between selected exercises and rehabilitation speed of different patients, as well as to assess the overall healthiness of the patient. In addition, PHR is used to provide the patient with mid-term feedback, e.g. rehabilitation speed compared to average and improvements over last day/weeks, keeping patient motivation high.

1.1.1 Scientific and Technical Objectives

The StrokeBack project aims at increasing the rehabilitation speed of stroke patients while patients are in their own home. The benefit we expect from our approach is twofold. Most patients feel psychologically better in their own environment than in hospital and also rehabilitation speed is improved. In addition, we aim at exploiting the increased motivation of patients when exercising with a tool similar to a gaming console. The ability of doing high-quality exercises without the need of being monitored by a physiotherapist helps to reduce healthcare cost through minimisation of expensive human contact hours. Currently, the quantity of hours performing occupational (ergo-therapeutic) and physiotherapeutic sessions are restricted to payable effort for patient's accommodation, transport or visit of therapists in patient's home. StrokeBack aims at providing new technical means and service structures to enable patients to enhance their healthiness by increasing the number of training sessions.

Very recently gaming consoles have gained a lot of attention when being used in the area of rehabilitation. All publications report on very good results in terms of speed of the rehabilitation process and especially patient motivation. A first evaluation has shown that even though the majority of the publications deal with 'normal' rehabilitation process, e.g. after surgery, that similar results hold true for stroke patients as well [3–8]. But most of the published articles about and envisioned applications for computer-aided rehabilitation of patients have revealed one major drawback. Since these approaches target to train fine motor skills only, they require the patients to already possess, or have recovered up to, a certain level of mobility [3]. By that, these solutions cannot be applied to patients having limited mobility such as spasticity or partial palsy what is the major issue for patients affected by stroke. These patients cannot be asked to hold a sensing device by hand or to exercise by stand. In contrast to that, StrokeBack aims to already assist in early stage of rehabilitation enabling highly affected patients to profit from our proposed monitoring system as well. Our system is designed for ambulant use and targets to be adjustable to the abilities of the patient—a patient-centric approach. For example, it can be used by hemiplegic, paretic patients as well as wheelchair users, too. By that we intend to shorten the full time, stationary rehabilitation and treatment programme and allow patients to be reintegrated into normal life as early as possible.

The StrokeBack concept puts the patient into the centre of the rehabilitation process. It aims at exploiting the fact the patients feel better at home that it has been shown that patients train more if the training is combined with attractive training environments. Figure 1.1 illustrates how we think the vision of such a patient-centric approach can come true. First, the patients learn the physical rehabilitation exercises from a therapist at the care centre or in a therapist's practice (left part of Fig. 1.1). Then, the patients do the exercises at home (middle part of Fig. 1.1) and the StrokeBack system monitors their execution and provide real-time feedback on whether the execution was correct or not. In addition, it records the training results and vital parameters of the patient. These data is then analysed by medical experts (lower right part of Fig. 1.1) for assessment of the patient recovery. The patient also

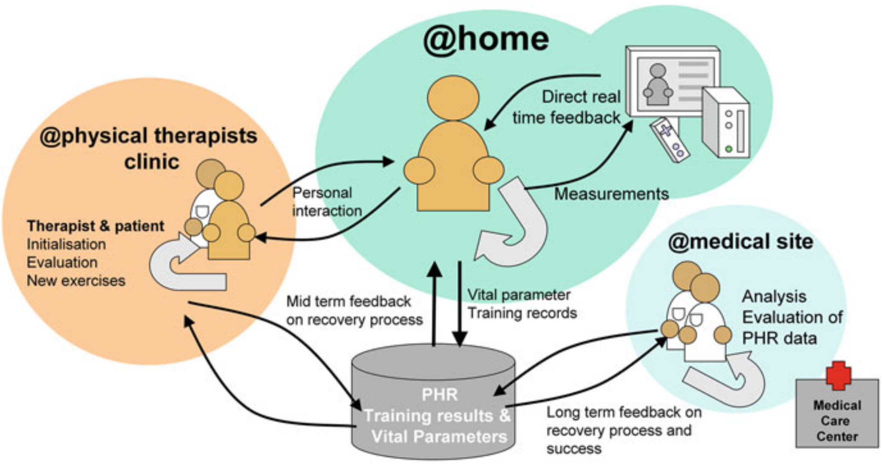

Fig. 1.1 StrokeBack rehabilitation cycle

gets mid-term feedback on his/her personal recovery process. In order to ensure proper guidance of the patient also the therapist gets the information from the PHR to assess the recovery process and decide whether other training sequences should be used, which are then introduced to the patient in the practice again.

The project goal is achieved by investigating the following objectives:

- Telemedicine supervision of rehabilitation exercise
- Continuous monitoring of impact of exercises also in ‘normal’ life situations
- Integration of telemedicine rehabilitation and Personal Health Records for improved long-term evaluation of patient recovery
- Feedback to healthcare professionals on impact of rehabilitation exercises

In order to provide remote rehabilitation exercises at gold standard level, i.e. as good as in a face-to-face training with rehabilitation experts, we plan to exploit the advanced features of today’s body area networks (BAN). A BAN attached to the patient enables permanent monitoring of patients activity and vital parameters. We aim to monitor and record the patients’ activity enabling them to regularly, maybe daily, exercise independently from the guidance of the physical therapist. With a correct instrumentation, we expect to be able to detect also unwanted additional movements. In order to achieve a comparable monitoring by cameras, at least two of them need to be deployed at the patient’s home. This is a costly solution which also bears a privacy risk. Both issues can be solved with our BAN-based solution.

As one possible application, the physical therapist has to look after the patient once a week only to exploit the level of rehabilitation, to analyse the results of last exercises based on recorded data and to take corrective action if necessary. Furthermore, a physical therapist may show new exercises and configure a new exercise schedule. By that, we intend to boost the rehabilitation process at home.

The BAN can be worn by the patients throughout the whole day which enables us to compare actual movements in their daily life with the correct movement pattern define in rehabilitation exercises. To simplify the configuration process of the system, we analyse and evaluate self-learning techniques for exercise recognition, i.e. the StrokeBack system may learn the correct behaviour (patient's movements) when exercises are carried out under instruction of the physical therapist.

We aim to additionally evaluate a feasibility and requirements of using electronic personal health records to store and document recorded data and to remotely track the rehabilitation process, e.g. by the attending doctor. This includes the recordings done during rehabilitation exercises and during daily life. The recorded data is stored and can then be processed by healthcare professionals. The evaluation can be used to deduce detailed information of effects of individual exercises. This feedback can be used to select exercises for other patients, to assess effectiveness of exercises for specific groups of patients, etc. In addition, the vital parameters can be used to assess the healthiness of the patients which might even help to assess the probability of a further stroke. In order for StrokeBack vision to become reality, the following research challenges need to be addressed:

- High speed signal processing inside the BAN
- Security and privacy inside BAN and PHS, including evaluation function
- High confidence decision making on the basis of the pre-processed BAN data

The respective StrokeBack architecture is shown in Fig. 1.2.

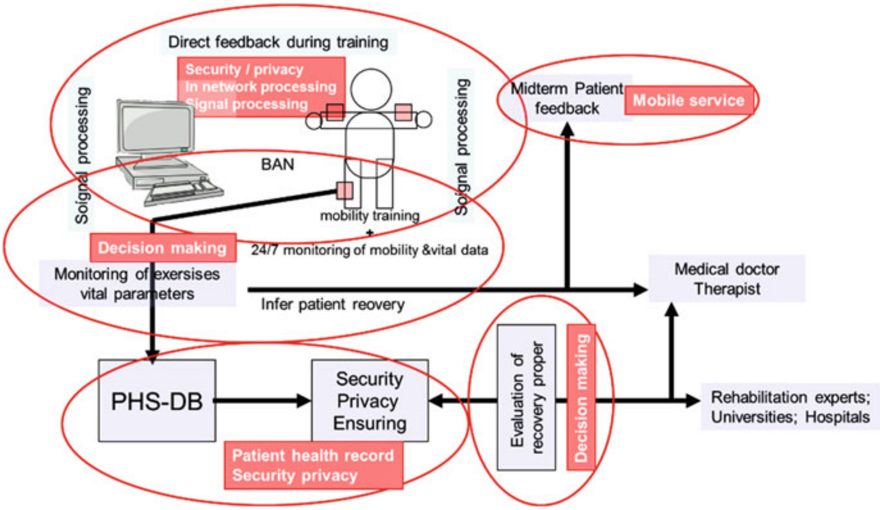

Fig. 1.2 Classification of research issues within the StrokeBack architecture

1.2 Relevance to Research Directions Defined by EU Commission

The European Commission has set research targets in its Research Agenda for European Framework programmes, including the Health domain.

Regarding rehabilitation of stroke and neurological conditions: the Commission seeks *providing patient services at home*, *with tele-supervision by health professionals as and when required*. The StrokeBack project follows this approach and aims at empowering stroke patients in doing physical therapy at home. It goes beyond the tele-assistance by implementing assessment features into the training equipment thus ensuring a correct execution of training sequences. This way it allows the patient to exercise more often than physical therapists are available. In addition, it provides an offline data to medical doctors as well as physical therapists to enable them to monitor their patients' recovery process and evaluating the effect of selected training sequences.

From technology perspective the Commission looks for solutions may build on *robotic and haptic technologies*, *wearable systems*, *implants*, *human–computer interfaces*, *web services or virtual reality environments to facilitate continuity of personalised cognitive and functional rehabilitation*. In this context, the StrokeBack system consists of two major parts. One of them, the BAN tracks patient's movements while a graphical HCI environment offers a virtual reality representation of rehabilitation exercises and the success level of the patient.

The proposed system further offers an a*uto-adaptive*, *self-calibrating and energy-efficient module with multi-sensing*, *advanced on-board processing*, *communication and actuation capabilities*. The BAN can be realised by using resource constraint wireless sensor nodes deployed at the body of the patient. Those nodes are used to gather tracking data for body movements as well as patients vital parameters. The signal processing required to provide direct feedback to the patients on the execution quality of the exercises to be done at the BAN nodes. Such systems are expected to provide *accuracy of measurements as well as remote control and reliable operation of the devices/systems*. High level of accuracy is of movement detection is key for proper assessment of the exercises done by patients. This issue is tackled by using high-quality sensors, specific evaluation and calculation models and algorithms. The reliability of the system is enhanced by using an extra redundancy in the BAN. This is achieved by data replication in the BAN.

From system level the needs are to provide *context-aware*, *multi-parametric monitoring of health parameters*, *activity*, *lifestyle*, *ambient environment and operational parameters of the devices*. Therefore, BAN is used to gather vital parameters as well as movement patterns (by that also activity levels) throughout the whole day. The idea is to detect if and when movement patterns trained during the therapy is adapted during normal life. In addition, clinicians can evaluate the health state of patients on detail data over long-term period.

From sensing point of *view solutions need to implement closed-loop approaches and integrate components into wearable*, *portable or implantable devices coupled* *with appropriate platforms and services*. Such approaches offer *analysis*, *interpretation and use of the multi-parametric data*, *in conjunction with established or newly created medical knowledge*, *for shared patient–doctor decision support systems*. Furthermore, *clinical workflows*, *guidelinesand patient pathways to support remote applications. They also address interoperability issues related to heterogeneous data sources*, *devices and links with electronic health records (EHRs)*; *the use of standards and of any suitable open software platform is recommended*. In order to comply with such needs, the second part of the StrokeBack system implements a custom PHS, allowing for offline/online evaluation of patient data based on web services and by that allow for closed-loop assessment and monitoring when necessary. The online evaluation may be used to provide personal feedback from the therapist to the patient while exercising. The data collected via the StrokeBack system enables medical and therapeutic experts to offline deduce relations between the training done by patients and the improvement of the patients' health status. As result of this evaluation, the therapist might adapt the exercises or try to increase the patient's motivation, i.e. if the requested number of training sessions was not done by the patient. The analysis of collected data offers an additional benefit in revealing interdependencies of specific exercises and rehabilitation success. When designing the StrokeBack system, standardised approaches were used as much as possible in order to ensure its architectural design for interoperability.

The Strokeback system is an advanced system offering *education and motivation of users*. The project idea was partly influenced by the observation that patients who have been using gaming consoles as the WII were more motivated and exercised more than other patients. Hence, the project embedded the physical therapy training sequences into serious gaming applications. Furthermore, recording the number of executed exercises as well as the level of correctness allowed more accurate tracking of progress that the patients made. This has contributed to improving patients' motivation, i.e. they can see that their effort has visible impact and this fact teaches patients indirectly since it shows them that proper exercising helps while laziness may lead to degradation of already achieved improvement.

An important aspect of the project was careful attention to *user acceptance*, *patient compliance*, *patient data security and confidentiality*. StrokeBack has investigated security/privacy issues in order to ensure confidentiality and data integrity in all parts of the system and in all stages of processing. This means strong, but energy-efficient crypto-operations implemented for ensuring confidentiality of patients data while transmitting it wirelessly in the BAN. Privacy protection was also investigated for protecting patients' privacy when their data is analysed by medical experts, who are not directly their leading physicians or physical therapists. In order to ensure user acceptance, patients who had indicated their consent to take part in the project were involved from the very beginning in the design process.

An important aspect of any development project is certainly the evaluation of its results in clinical environment in order *to demonstrate the proof of concept*, *efficiency gains and*, *if possible*, *cost-effectiveness of the proposed solution. Validation should include comparison versus currently accepted gold standards and include quantitative indicators of the added value and potential impact of the proposed* *solutions*. The StrokeBack solutions has therefore been extensively evaluated throughout the whole project duration by clinicians and physical therapists with their patients. This way we were able to assess the quality of rehabilitation and patient acceptance early enough and use this feedback to improve the overall solutions.

1.3 Progress Beyond the State-of-the-Art

The StrokeBack project pursued advanced applied development in several key research and technological areas: Personal Health Record (PHR), Tracing Body Movement, Wireless Body Area Networks (W-BAN), Protection of Privacy and Private Data, Knowledge Representation and Reasoning (KRR) and Immersive Gaming Environments for Stroke Rehabilitation. Progress beyond the state-of-the-art in each of those areas is detailed in the following subsections.

1.3.1 Personal Health Record

The main objective of this activity was to develop an European online PHR database system as an alternative to the already existing US-based ones from Google (Google Health) and Microsoft (MS Health Vault) with advanced functionalities and fully compliant with European standards. Such a system complying with the latest HL7 standard would allow seamless integration with hospital and private medical assistance service systems. Having WSDL web services as the main programming interface, it simplifies and enables the development of secure third party systems, services and applications built upon the core PHR database. A significant innovation is the API programming layer and similar scripting device integration interface allowing to avoid pre-installation of the device support for each medical devices within the device layer of the core system before users can use the device to upload measurement data to their PHR account. Furthermore, the PHR therapy definition has been extended to include physical training/exercises prescribed by the physician in the same way that other medicines are prescribed. The added advantage of such an approach is to provide data to physicians for assessing the effectiveness of the exercises against the changing patient's condition. In order to do this reliably, the correctness of performing such exercises needs to be carefully monitored against predefined templates (temporal and spatial record of body movements and their frequency/retentiveness, treated each as a different therapy type).

State-of-the-Art: EHR platforms have been developed through various European activities, ranging from LinkCare platform promoted by the LinkCare Alliance [9] or the intLIFE PHR platform [10] from Intracom, developed alongside the ICT-PSP-NEXES project [11]. The popularity of EHR/PHR systems has given rise to the development of open-source platform too [12–14]. Their capabilities and features can closely compete with commercial and proprietary implementation, except when it comes to interoperability and flexibility in developing add-on services and applications.

Beyond State-of-the-Art: The base PHR platform has been further enhanced with fully HL7 complaint web service programming interfaces, the PHR database has been supplemented with extra medical information as required by the NHS and/or necessary for supporting the specific project needs. Furthermore, an open-source approach enables an easier integration with existing applications and services contributed by project partners and easier integration with third party systems.

1.3.2 Tracing Body Movement

In order to enable the tracking, the correctness of performed exercises automatically without the constant assistance of the physicians, an automated means of tracking and comparing patient's body movement against correct ones (templates) has been developed. Although many methods are in existence, most of them employ elaborate sets of wearable sensors and/or costly visual observations. In our project, we adopted initially visual-light scanning methods allowing computationally effective and cheap dynamic 3D object (in our case patient's body) tracing. The idea was similar to laser scanning employed in the Kinect game interfaces for Xbox (now also available for Windows operating systems on PCs), but using specially designed images projected on the person. The part of the R&D work was to determine if shifting to light wavelengths just beyond visible spectrum (infrared and ultraviolet) would allow achieving necessary accuracy and performance. Considering extremely small sizes of such sensors (less than 5×5 mm each) a development of lightweight wireless energy-autonomous (employing energy harvesting technologies) were possible, leading to the target sensor node form factor of a small sticker. Considering a vast amount of products appearing in the recent years, the Strokeback project has also taken advantage of such products, among them the Leap Motion IR sensor [15], Emotiv EPOCH EEG sensor [16], Myo EMG sensor [17], etc.

State-of-the-Art: The need to monitor movement and activity both within and outside the laboratory has been the focus of considerable research over the last decade. Body-worn sensors such as goniometers [18], pressure tubes [19], gyroscopes [20] and accelerometers [21–24] have been used in a range of activities and clinical conditions [22, 24–29] and for control of Functional Electrical Stimulation (FES) in walking and upper limb movement [29–31] and in standing with spinal cord injured patients [32–34]. However, body-worn sensors are often bulky and require associated instrumentation and accurate placement of the sensor elements. Nevertheless, such studies have already demonstrated the feasibility and potential benefits of long-term monitoring of movement [35, 36] and what is needed now is a shift in approach to make this feasible and usable in clinical practice and particularly in the home environment for rehabilitation. Such an approach has already been embraced by the textile industry. The so-called smart textiles have been developed to measure vital signs, such as the Electrocardiogram (ECG), and have even been commercialised in, for example, the ProArmBand from SenseWear™ [37] or various systems from Vionetics [38]. Predictions are that wearable systems become a part of routine clinical investigations [39]. Movement and muscle activity are, however, more challenging than vital signs and, in addition, processing, storing, transmitting and using the data poses an even greater challenge. The SMART project (funded by the UK Engineering and Physical Sciences Research Council through the EQUAL initiative) has explored how technology can be used in the home to support rehabilitation following stroke. Devices have been developed that are attached to the wrist and upper arm using clothing resembling sportswear to give a measure of movements made by the patient in activities prescribed by the therapist. Data are recorded and displayed on a computer or TV screen. Joint angles have also been measured using conductive fibres integrated into fabric which change their resistance due to bending as the joint angle varies [32] and by covering the fabric with an electrically conductive elastomer with piezo-resistive properties so that when deformed acts as a strain sensor able to detect movement [40].

Muscle activity poses problems for measurement since it has been well known for many years [41] that the EMG reflects effort rather than output and so becomes an unreliable indicator of muscle force as the muscle becomes fatigued. Consequently measurement of force, in addition to the EMG activity, would be a considerable step forward in assessing the effectiveness of rehabilitation strategies and could not only indicate that fatigue is occurring, but also whether the mechanism is central or peripheral in origin [42]. Similarly, conventional surface EMG measurement requires accurate placement of the sensor over the target muscle, which would be inappropriate for a sensor system integrated within a garment for home use. Electrode arrays are, however, now being developed for EMG measurement and signal processing is used to optimise the signal obtained.

Some of the building blocks for a body sensor network of the form proposed are therefore already in place. Existing commercial systems provide basic information about activity such as speed and direction of movement and postures. Providing precise information about performance, for example, relating movement to muscle activity in a given task and detecting deviations from normal, expected patterns or subtle changes associated with recovery, requires a much higher level of sophistication of data acquisition and processing and interpretation. The challenge is therefore to design and develop an integrated multimodal system along with high-level signal processing techniques and optimisation of the data extracted. The Kinect sensor has potential for use in haptic interfacing [43] and software support has already been offered, while by Open Kinect Community [44] and the official Kinect SDK programming support offered by Microsoft [45].

Beyond State-of-the-Art: The existing techniques for taking measurements on the human body are generally considered to be adequate for the purpose but are often bulky in nature and cumbersome to mount, e.g. electro-goniometers, and they can also be expensive to implement, e.g. Vicon camera system [46]. Their ability to be used in a home environment is therefore very limited. This proposal addresses these deficiencies by extending the state-of-the-art in the following areas:

- *Extending the application of existing sensor technology into new areas*. For example, we aim to use commercially available MEMS accelerometers with integrated wireless modules to measure joint angles on the upper and lower limbs to allow wire-free, low-cost sensor nodes that are optimised in terms of their information content and spatial location.
- *A study of novel-sensing methodologies to reduce the number of sensor nodes on the human body*, while maintaining good information quality. For example, many homes now have at least one games console (e.g. Xbox, Nintendo Wii) as part of a typical family home entertainment system. With the advent of the Xbox Kinect system, the position and movement of a human can be monitored using a low-cost camera mounted below the television.
- *Easy installation and calibration of the system by non-experts* for use in a non-clinical environment offering solution suitable for first-time home users.
- *Fully transparent verification* whether the patient has done his/her exercises and if he/she has done them correctly. Based on data recorded by the BAN, correlation of prescribed therapies with medical condition allows determining their effectiveness on patient's condition, either positive or negative.

1.3.3 Wireless Body Area Networks

The central aspect of the BAN is the data processing and handling. This is realised by the processing logic that is physically represented by the distributed system of nodes interconnected by (wireless) network means. All the features of this underlying system, like data handling middleware, compression, data aggregation or fusion, networking protocols and hardware architecture, help reaching the goals set by the primary aspect on different layers. Due to the small size of the network there is not really a need for sophisticated routing mechanisms. Thus, the MAC protocol becomes the central part of the networking.

State-of-the-Art: The wireless medium can be multiplexed in code (CDMA), space (SDMA), time (TDMA) and frequency (FDMA). Time multiplexing is best suited to be used for coordination of the communication between nodes in a single BAN. The main MAC protocols for BANs use TDMA and the access is random [47], contention-based [48–51] and or scheduled [52–67]. The schedule of the access can also be created as a result of a contention phase. The main advantages of schedule-based protocols is that they provide more predictable communication latency important for Quality of Service (QoS) and allow duty-cycling, i.e. saving energy by switching the radio off while there is no communication planned for a particular node.

Beyond State-of-the-Art: We intend to investigate a cross layer approach to ensure real-time behaviour of the protocol stack. Here, design and implementation is focused on adaptable TDMA-based data flow control to provide QoS for real-time evaluation of the movements tracked by the sensors attached to BAN nodes.

1.3.3.1 Proactive Data Storage Middleware

State-of-the-Art: There are several approaches that offer the data storage and management functionality in the field of sensor networks [68–74]. More specific approaches, i.e. [75–78] have been developed to ease the data handling in the application layer. They provide a middleware layer that abstracts the direct data and message exchange and simplifies the development of the processing logic module. TeenyLime [75] provides a possibility to share the data using a common set of tuples, available to the nodes in the network, i.e. every node can insert and remove a tuple to and from the shared set. The nodes can also be notified if a specific tuple is inserted into the set. In TinyDB [77], the network topology is a tree rooted at the central node that can order data from the sensor nodes on an on-demand or periodic basis, and the data is delivered down the tree. MacroLab [76] provides mechanisms to programme the network of nodes as a vector of data items. Such a global programme is then optimised for a chosen deployment platform and broken into individual programmes for the nodes. The tinyDSM [78] middleware provides a shared memory abstraction realised as a shared set of variables that can be defined as array with one item per node or as singletons. The former is similar to the vector in MacroLab, and the latter is similar to the tuple concept provided by TeenyLime. The tinyDSM is configurable to support the needs of the application and be optimal at the same time. It provides an event mechanism that notifies the application running on top of it in case a specified condition described using a logical equation with the shared variables as terms is fulfilled. It can be also extended to support security and privacy.

Beyond State-of-the-Art: The data collected by the sensors shall be stored and evaluated directly in the BAN. Such a pre-evaluation as an additional step in the data path helps to detect abnormal situations as fast as possible. In the StrokeBack project, we want to evolve the data storage middleware tinyDSM to support the distributed architecture of the StrokeBack BAN. The middleware shall provide a consistent view of the data stored together with mechanisms to evaluate the data to detect abnormal events of a predefined character. This might be deviations from expected movements but also deviations of the vital parameters. The efforts are mainly put in the data consistency research and in the migration of the pure software approach to a combined SW/HW one. The physical realisation includes microcontroller enhancements providing the DSM (Distributed Shared Memory) functionality to the Wireless Sensor Networks (WSN).

1.3.3.2 Signal Processing in BAN

State-of-the-Art: Medical data captured at the sensors require sophisticated signal processing for signal de-noising, artefact removal, signal classification and feature extraction. Wavelet Transform (WT), Kalman filtering and Short Time Fourier Transform (STFT) are widely used for these purposes [71, 79–82]. Approaches like Blind Source Separation (BSS), in particular Independent Component Analysis

(ICA), has been used for accurately separating out the target signal from its artefacts and in its feature extraction [83, 84]. However, all the methods (traditional and advanced) mentioned above, although accurate to clinical standards, are extremely demanding in terms of computation. Thus, in a traditional patient monitoring system owing to the lack of energy (in terms of battery power) at the sensor nodes, these processes are carried out on a more powerful computation platform like a central server or using an on-board microprocessor. Therefore under the continuous monitoring scenario, the sensors are used as data collectors only and the unconditioned data are continuously transmitted to the central station for further processing. This puts a huge burden on the wireless network owing to the plethora of data to be transmitted continuously. In addition, the continuous data transmission over long distance puts high energy demand on the analogue front-end of the embedded radio structure leading to fast draining of the battery.

In addition to the regular signal processing tasks, in order to reduce the amount of data to be transmitted and; in the PREACTION system; to increase the on-sensor storage time-efficient data compression algorithm needs to be developed. Some data compression techniques provide an alternative to merely reducing the sampling frequency. These techniques can be characterised as either ‘lossy’ or ‘loss-less’. When data is compressed using a ‘loss-less’ method, it is possible to reconstruct the original waveform without losing information. Such non-distorting compression modes are exemplified by the Huffman coding method and the Lempel-Ziv method [85, 86]. Loss-less compression modes are computationally expensive, resulting in a more complex circuit design, increased power consumption, and a longer data processing time. Moreover, the compression rate that is achieved depends on the content of the physiological signals. The content may vary depending on the physiological condition being monitored. As a result, the amount of memory needed to store the compressed data cannot be determined in advance. As an alternative to the use of a loss-less compression process, a lossy technique may be employed. Lossy techniques (SAPA or ‘fan’ method [87], Wavelets [88, 89], Lifting Scheme WT or its combination with distributed source coding [90]) may require less processing power to implement. The resulting system may therefore be both smaller and more energy efficient. However, when data is compressed using a lossy method, some information is lost when the compressed data is later used to reconstruct the original waveform. However, owing to the required reliability in medical application it may not be always recommendable to use lossy compression.

Beyond State-of-the-Art: In contrast to the classical architecture of remote monitoring in our architecture, sophisticated signal processing is carried out within the BAN with an emphasis on medically trustworthy parameter extraction in order to reduce the burden on the network and transmission energy. Separate optimisation of signal processing algorithms and architecture cannot be applied here since this approach does not guarantee overall energy optimisation. Thus, a cooperative and holistic approach needs to be taken for increasing energy efficiency. Following this route in this part of the present proposal, we have developed novel energy optimal algorithms and architectures leading to an ultra-low-energy ASIC realisation for on-board signal de-noising, artefact removal and accurate feature extraction and classification. Especially, the latter allows measuring in real time how accurately the patient carries out the prescribed exercise from the data acquired by sensor nodes using low-complexity computer arithmetic.

In our approach, the sensors send their captured raw signals over the BAN to the ASIC (which also is a part of the BAN) for data processing, and therefore continuous data (required when the patient is doing exercise) need to be transmitted only within the BAN leading to energy efficiency from the communication perspective as well in addition to that resulted from the proposed algorithm-architecture joint optimisation. In order to retain the best properties of lossy and lossless data compression techniques, an event-driven data compression technique has been developed in this research programme. Based on the information content of the physiological signal, the compression ratio is dynamically adjusted upon encountering a potentially abnormal event and thereby achieving high compression ratios under normal circumstances whereas preserving all the relevant clinical detail under potentially dangerous scenarios. A low-power VLSI architecture for such an event-driven data compression algorithm has been developed which is integrated with the on-sensor signal pre-processing architectures to devise a complete tailor-made ultra-low-power signal processing unit.

1.3.4 Protection of Privacy and Private Data

State-of-the-Art: Whereas many privacy and data protection means aim at a declarative approach only, there are limited approaches for technical protection. To the best of our knowledge, there are only two approaches [91, 92] that try to make sensitive data available to a third party while ensuring secrecy of that data. The authors of [92] propose an architecture that ensures secure data processing by exploiting the Java sandbox model as an execution environment for data processing code and by limiting the feedback from the data processing code to the outside world. For correct interpretation of data processing results and the development of appropriate algorithms, a part of the data has to be publicly accessible. In addition, sensitive data are always kept at its owner's site. The prerequisites of this concept render it impractical for implementation of location based or context-sensitive services, although it is well suited for privacy preserving data mining. The approach presented in [91] and in [93] tries to make user data inaccessible outside a specially secured execution environment. User data are enclosed in an agent and securely transferred into an isolated, closed-door, one-way platform provided by a trusted third party. The service agents proceed analogous with their own data. These entire agents interoperate within the trusted environment and agree on a certain result. The result is forwarded by each involved agent to the closed-door platform, which posts the result to the agents' origins if the forwarded results are equal. This ensures that no private data is transmitted to the opposite party unless requested by the agent. All agents, together with their enclosed data, are deleted after service completion in order to ensure the privacy of the user and to protect service data.

In [94] a publication of the IHP, a partner of the StrokeBack Consortium, the authors described a Privacy Guaranteeing Execution Container (PGEC) that does not rely on a trusted third party that provides processing capabilities, such as a server plus a specific agent platform. By design this container provides encapsulation of sensitive data and its deletion after service completion. Basically, the concept is that the application obtains access to the user data in a specially protected and certified environment, the PGEC. PGECs enable applications to access private user data and guarantee that the user data are deleted as soon as the service is quit. In a few words, they guarantee a 'one-time use' of the provided private data. The PGEC also restricts the communication between the application and the service provider to what is explicitly allowed by the service user.

Beyond State-of-the-Art: In StrokeBack, we consider to port the PGEC to a low-power portable device that could act as a data sink for a body area sensor network. That way we would enable a pre-processing of the arising data and a relevancy decision before sending it over a wide area network. In addition, we plan to extend its data access control means with a self-adaptive feature so that the data access can be adapted to the current medical conditions of the patient, i.e. in urgent medical conditions such as emergencies, treating medical staff might access gathered data that were usually privacy protected. In addition, we want to integrate it in the medical work flow so that anonymous studies and comparisons between various patients and treatment methods could be achieved within a network of containers.

1.3.5 Knowledge Representation and Reasoning

State-of-the-Art: Answer Set Programming (ASP) [95] owes its increasing popularity as a tool for KRR [96] to its attractive combination of a rich yet simple modelling language with high-performance solving capacities. ASP allows for solving all search problems in a uniform way [97], offering more succinct problem representations than available in SAT [98]. ASP has been used in many application areas, among them, planning [99], product configuration [100], decision support [101], reasoning tools in systems biology [102, 103], and many more. The success story of ASP has its roots in the early availability of ASP solvers. The ASP solver Clasp [104], developed in the KRR group of UP, demonstrates its performance and versatility by winning first places at international competitions like ASP'09, PB'09 and SAT'09. More related to the StrokeBack, a reactive reasoning engine based on ASP has already been developed by UP, a partner of the StrokeBack Consortium [105].

The BAN consists of many sensor nodes. In order to represent and reason on the data coming from sensors of BAN, one should fuse sensor data. Most commonly used methods for sensor fusion are quantitative approaches like Kalman and Particle Filters [106–108]. The main limitations of these methods are identifying good cost function to merge heterogeneous sensor data and dealing with situations like addition of new sensor devices or the presence of misbehaving devices. In [109] a publication of the UP, the authors used ASP for knowledge-intensive sensor fusion in the domain of localisation.

Beyond State-of-the-Art: In StrokeBack, we plan to integrate a knowledge-intensive representation scheme of rehabilitation exercises. The causal knowledge related to exercise movements and the complex relationship between parts of body are represented in an ASP paradigm. Knowledge-intensive representation compared to traditional quantitative methods is more transparent and elaboration tolerant. We plan to use these advantages for shortening the time required to represent exercises and more importantly, for making the whole representation more tolerant to changes and variations. The reactive reasoning engine performs decision based on live data originating from BAN and check whether the current movement is the expected one in the plan if the desired exercise. Additionally, since nodes in a BAN are limited devices in terms of computational power and energy, we want to design a modular representation so that the reasoning process and tools can be distributed into nodes.

1.3.6 Immersive Environments for Stroke Rehabilitation

The use of virtual, augmented and immersive environments for training and rehabilitation of post-stroke patients opens an attractive avenue in improving various negative effects occurring as a result of the brain trauma. Those include helping in recovering the motor skills, limb–eye coordination, orientation in space, everyday tasks, etc. Training may range from simple goal-directed limb movements, achieving a given goal (e.g. putting a coffee cup on a table), improving lost motor skills (e.g. virtual driving) and others. In order to increase the efficiency of the exercises advanced haptic interfaces, allowing direct body stimulation, are being developed to supplement visual stimulation.

State-of-the-Art: Immersive environments have quickly been found attractive for remote home-based rehabilitation giving raise to both individual and monitored by therapists remotely. Depending on the type of a physical interface, different types of exercises are possible. Interfaces like CyberGlove [110] or Rutgers RMII Master [111] allow the transfer of patient's limb movement into the virtual gaming environment. They employ a set of pressure-sensing servos, one per finger, combined with motion sensing. This allows therapists to perform, e.g. range of motion, speed, fractionation (e.g. moving individual fingers) and strength (via pressure sensing) tasks. Games include two categories: physical exercises (e.g. Digi Key, Power Putty) and functional rehabilitation (e.g. Peg Board or Ball Game) ones. They use computer monitors for visual feedback. CyberGlove has been used by Rehabilitation Institute of Chicago, also for assessing the pattern of finger movements during grasp and movement space determination for diverse stroke conditions. Virtual environments are increasingly used for functional training and simulation of natural environments, e.g. home, work, outdoor. Exercises may range from simple goal-directed movements [112] to learning/training the execution of everyday tasks.

Beyond State-of-the-Art: Current generation of post-stroke rehabilitation systems, although exploiting latest immersive technologies, tend to proprietary approaches concentrating on a closed range of exercise types, lacking thoroughly addressing the complete set of disabilities and offering a comprehensive set of rehabilitation scenarios. The use of technologies is also very selective and varies from one system to another. Although there are cases of using avatars for more intuitive feedback to the patient, the use of complicated wearable devices makes it tiresome and decreases the effectiveness of the exercise. In our proposal, we intend to explore novel technologies for body tracing that exploit the rich information gathered by combining wearable sensors, and visual feedback systems that are already commercially available (e.g. MS Kinect, Nintendo WII) We intend developing more advanced and potentially less expensive ones (e.g. visual-light 3D scanning). The immersive environment supports full 3D physical and visual feedback through Augmented Reality technologies placing the user inside of the training environment. Considering that detecting muscle activity cannot be done without wearable device support, we intend to develop a customisable lightweight embedded sensor device allowing short-range wireless transmission of most common parameters including apart from EMG, also other critical medical signs like ECG, Blood Pressure, heart rate, etc. Training exercises offer a more intuitive approach by using exercise templates with feedback showing correctness of performed exercises. Therapists are now able to prescribe a set of the rehabilitation exercises as treatment through the EHR/PHR thus offering means of correlating them with changes of patient's condition, thus showing their effectiveness in patients' recovery process.

1.4 Potential Impact in Europe and Worldwide

The StrokeBack system offers an opportunity for reducing the hospitalisation rate and improving disease management, treatment or rehabilitation at the point of need, through more precise assessment of health status.

The StrokeBack system empowers patients to do physical rehabilitation training without the need of being supervised by a physical therapist. Even though this is mainly thought to support the rehabilitation process when patients are back at home, the StrokeBack system can be used in hospitals and rehabilitation centres as well. Since the StrokeBack system allows the patient to exercise more often than with systems used by now, patients recover faster than today and can be released from hospital or rehabilitation centre earlier than today. The fact that the StrokeBack training exercises are embedded into a kind gaming application has a significant positive impact on the motivation of patients to do the training sequences, which also contributes to improve rehabilitation speed. In addition, the StrokeBack system records the patients' vital data. By analysing all collected data, i.e. training effort and vital parameters, actual health status of patients can be assessed and the recovery speed can be determined and compared to standard recovery speed for example.

Strengthened evidence base on medical outcomes, economic benefits and effectiveness of the use of Personal Health Systems in evolved care models are the strengths of the StrokeBack approach. Physical therapists report that the vast majority of patients (up to 80 %) does not do the exercises shown to them when they are at home and that the number of patients doing the exercises correctly is even lower. Here, the StrokeBack system provides significant improvements. Its body-sensing features combined and integrated with EHR/PHR to enable therapists to easily monitor the effectiveness of exercises (number and correctness of executed training sessions) in recovering from traumas caused by strokes by correlating the types of exercises prescribed and their execution with changes in psychokinetic performance and body coordination.

1.4.1 Reinforced Medical Knowledge Versus *Efficient Disease Management*

StrokeBack-supported rehabilitation exercises are recorded in the EHR and/or PHR databases similarly to other therapies and medicines. Therapists and patients' physicians are able to record various performance parameters and patients improvement ratings in the EHR/PHR. As a result they are able to reliably (considering that a large number of cases are cross-checked statistically) arrive at establishing medically acceptable procedures for applying certain types of therapies to certain types of exhibited stroke-induced mental and motor-coordination disabilities.

The proposed StrokeBack approach contributes to a more sustainable European healthcare system through provision of high quality, personalised care, with better use of the available healthcare resources. StrokeBack helps to improve knowledge on the impact of rehabilitation effort as sketched above. By that it allows better planning on how available resources could/should be used. This could be for example additional support for patients who really put effort in their rehabilitation in order to improve their health status as fast as possible to a level in which they do no longer need help. Another option could be to reduce effort for those patients who recover due to the StrokeBack system very well and put freed resources to support patients who are recovering more slowly. A general decision how freed resource should be used is out of the scope of this proposal and it might be needed to decide individually. In addition, it is well known that patients feel better at home, so reducing the time in hospital improves quality of life for patients. StrokeBack contributes to this as well. In addition, it allows physical therapists and medical doctors to evaluate the impact of training sequences on the patients' recovery process. By that these specialists are empowered to personalise training sequences to helping individual patients.

Reinforced leadership and innovation capability of the industry in the area of Personal Health Systems, medical devices and services through introduction of new business models, creation of spin-offs and better exploitation of intellectual property contributing to products, standards and regulation.

To the best of our knowledge, StrokeBack is the first system that aims at remote rehabilitation of stroke patients which does not require a physical therapist to monitor the execution of training sequences. Even more it is the first system that clearly addresses patients in early recovery stages, i.e. long before they are able to stand and hold remote controls in their hands, which is the point at which many already cited initiatives start. By that we see a solid chance to develop an unprecedented technology which can be used to gain international leadership in this market segment, and which can be commercialised by the project partners directly or by a common spin off company. Two of the partners (IHP; MEYTEC) have already started discussions to assess the potential of a joint venture in the telemedical area. Here, StrokeBack could be a concrete starting point. Accelerated establishment of interoperability standards and of secure, seamless communication of health data between all involved partners, including patients is ensured.

The StrokeBack project aims at designing and testing a PHS which allows interaction between medical doctors, physical therapists and patients. The issue of proper security features as well as proper privacy protection are addressed in the StrokeBack system. Relevant standards have been taken into account in order to allow for compatibility from the very beginning. In addition, the StrokeBack architectural design follows a modular approach so that specific module, e.g. cryptographic operations can be exchanged transparently. Moreover, relying on web services for remote operations decouples the services almost fully from the underlying technologies. Also, one of the StrokeBack partners involved in a national project, called MATRIX [113], which researches telemedical systems in compliance to the HL7/VITAL (ISO/IEEE 11073) [114] standard while aiming to contribute to new standardisation processes as well. We exploited this cooperation for securing interoperability. Links and interaction between patients and doctors facilitates a more active participation of patients in care processes.

StrokeBack allows to record patients vital data 24 h 7 days a week as well as to record his/her training effort and success. By that doctors and physical therapists can adapt the treatment exactly to the patient needs and can respond to variations in the recovery processes. Since all parties can have access to the data via networks, the need for physical meetings is reduced and thus faster and more often feedback between the parties is feasible. One of the major benefits of StrokeBack is the direct patient feedback. This can be used twofold. First, patients get direct feedback concerning training exercises they carry out, i.e. the patients see whether or not they do the training correctly and by that can improve the training execution. Second, patients can get personalised feedback on how fast they recover from the data recorded when exercising. This feature can be enriched with the vital parameters which are recorded as well. By this personalised long-term feedback to patients significantly increased patient motivation leading to additional training effort and by far better understanding of the recovery process by patients.

Participation of essential stakeholders in the production of end-to-end solutions for personalised care has been of paramount importance when developing the StrokeBack solution. Partners participating in the project reinforced national or regional commitment in deployment of innovative services following participation in R&D projects. Two partners of the StrokeBack consortium have strong expertise in the realisation of end-to-end solutions in the telemedical area. The partner MEYTEC has several years of expertise in building telemedical systems for treatment of acute stroke patients, and their systems are deployed in hospital and managed by MEYTEC since several years. MEYTEC also hosts WEB service-based medical services. ICOM expertise lies in the development of leading edge telecommunication products and solutions, delivering end-to-end integrated solutions, implementing large-scale turnkey projects, providing a wide range of engineering, consulting and outsourcing professional services in thematic areas of mobile, wired and wireless communication, e-Health and Tele-Assistance solutions, Smart Energy and Audio-Visual systems. Dedication to R&D and commitment to technology innovation are fundamental components of the company's business strategy with a long record in research in networked systems and active product lines, actively participating in shaping up the future.

1.4.2 European Contribution

The StrokeBack has pursued ambitious objectives, offering complementary technological expertise from various fields. The StrokeBack consortium covered all the required expertise ranging from the medical and physical therapy requirements over efficient wireless communication and signal processing to secure and dependable network and service architecture including personal health services and the management of remote health services. In order to ensure significant impact of the technology developed in the StrokeBack project, it has developed an open architecture, taking into account existing standards and ensuring interoperability and easy adaptability by design. A consortium reflecting all parts of the value chain stimulated better user acceptance of the system and reflected a diversity of the European community. In other words, the consortium needs to be a European one to get the support of relevant Europe-wide stakeholders and not only from national stakeholders. In addition, the required expertise is hardly found in a single country.

1.4.3 National and International Research Activities

In Germany, the BMBF is funding a project called MATRIX that intends to provide highly flexible middleware aiming at supporting tele-assistance services. IHP is participating in that project and ensures close collaboration wherever possible and necessary. Since the major focus of MATRIX was on service composition, the overlap was very limited, nevertheless the collaboration helped to widen the impact of StrokeBack, since renowned medical sites, i.e. the Charité, were also partners in MATRIX, similarly to StrokeBack partner MEYTEC. Furthermore, several technologies have been integrated from projects of other partners in the Strokeback consortium. Those included, e.g. ICT-PSP-NEXES [11], PAMAP-AAL-2008-1-162 [115], Artemis-CHIRON-2009-1-100228 [116], FP7-ICT-ARMOR [117], GR-IL-3215–MOMIRAS [118] and many other ones.

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Chapter 2
Requirements and Conceptual Architecture

Artur Krukowski, Emmanouela Vogiatzaki, and Steffen Ortmann

Abstract This chapter describes an overview of research into the design principles for the system envisioned for the rehabilitation of stroke patients. The report identifies the design principles from two perspectives. From one side, it describes the system user needs/clinical specification—this describes the system requirements from a user/therapist perspective in order to provide the service and ensure effective usability of the system. On the other hand, it shows the system from a technical perspective—detailing the operational system to be used for pilot testing, proof-of-concept experiments and demonstration purposes. This offers the development of system requirements from both perspectives for a functional and operational system. These requirements can be implemented into forthcoming work packages to achieve both technical objectives and to satisfy user needs. A review of the literature and the findings of our National Institute of Health Research (NIHR) Programme 'Assistive Technologies in Rehabilitation of the Arm following Stroke' (ATRAS REF: RP-PG-0707-10012) has informed the proposed design from the user needs perspective. The chapter then follows up with the system specification and the description of the conceptual architecture.

2.1 User Needs for Post-stroke Home-Based Rehabilitation System

There is a paucity of literature published on user perspectives of home-based rehabilitation technology; however, some key work from the 'SMART' consortium research project may be useful to aid the development of the StrokeBack system. The SMART project, funded by the Engineering and Physical Sciences Research Council (UK), was a joint project with partners from Sheffield Hallam University,

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University of Bath, University of Essex, University of Ulster and the Stroke Association. The project started in November 2003 and completed in December 2006. The aim of the project was to explore how technology might be used to facilitate active in-home rehabilitation for people following stroke [1, 2]. The main issues to consider when developing a rehabilitation system for post-stroke patients are:

- How home-based rehabilitation for stroke can be promoted
- How to develop and test a home-based stroke rehabilitation system
- The use of a computer interface and wearable sensor technologies
- The practicalities of home-based rehabilitation technologies

The SMART system was developed to offer home-based upper limb rehabilitation to stroke patients. It utilised accelerometer technology with a goal to collect 3D data at preferred locations on the patients' limbs. Patients interacted with the interface of the system via their personal computer. Their computer also served as a base station to receive movement data collected by their body area network. The monitoring system was web based and consisted of a central server which managed all data from patients and health professionals. System has two levels of access, one for health care professionals and one for patients. In order to identify the necessary components of the SMART system, the research group has published a number of papers which detail the user needs of a home-based rehabilitation system [1–7].

The initial design requirements, sensor attachments and usability of the system were identified by interviews and focus groups with a total of 16 therapists, 39 patients, and 13 carers. The interviews were carried out with new participants and some expert patients (who became familiar with the system and could comment on new developments). A first prototype of the system was tested with 5 therapists and 4 stroke patients who could use the system in a 2-week trial. The clinical specification of the system was developed from 28 therapist responses to a postal survey. The second prototype was tested on 8 patients. The findings of this research were that the home-based rehabilitation should be:

- An aid to therapy—patients did not want a standalone therapy
- Not to be specific to one 'model of therapy'
- Flexible to individual needs as no two stroke survivors are the same
- Simple and compact to use, adaptable to individual needs in their home
- Take into account difficulties with memory, perception, language, information processing, and attention impairments associated with stroke
- Give feedback on rehabilitation performance, even when progress is slow

2.1.1 Sensor Attachments and Fastening

During testing of the initial prototype, stroke patients tried to don sensors that had been designed with a clip to accommodate left- and right-sided stroke patients. Each sensor therefore had two clips; patients found this too confusing and were unable to don the sensors easily. Clothing garments were also found to be initially difficult to don. Patients found the chest strap too confusing and those who were able to use it found they became fatigued quickly after attempting to don the chest strap sensors. This led to patients who wore the chest straps doing less rehabilitation exercises due to their fatigue levels. Sensor attachments which had Velcro fastening were difficult for patients to attach due to the high level of friction. A fastening with a ridged strap was found to be simple to don but not comfortable to wear for extended periods of time. The patients felt the optimal sensor attachment was a simple wristband that can be adjusted with one hand.

2.1.2 Physical System Design

The prototype testing revealed that many stroke patients have problems with computers and using a standard mouse. One fundamental finding is that the system is easily incorporated into patients living environments, without the need to store large amounts of equipment in the home or the need to set it up daily. The majority of patients were very unfamiliar with standard computers and preferred an interface with a touch screen and audio instructions of how to use the system.

2.1.3 Computer Interface Design

With regard to the rehabilitation exercises patients found a 'tree style' navigation confusing, (e.g. they had to click on an image of a whole body, then click on an image of an upper limb, then click on an image of an elbow before they could view elbow exercises they had done). The researchers replaced the tree style navigation with a 'calendar function'. This allowed patients to select and review exercises based on the time and date they were carried out. Patients found having visual icons for each movement helpful. For example:

 Reaching movement

 Grasping movement

Therapists and patients found a text area for therapists' comments useful, as therapists could provide further tailored feedback and encouragement to patients. Finally, the later prototypes of the SMART system were developed with a minimum number of buttons and options. Buttons had to be large, easy to view and colour coded with themes.

2.1.4 Exercise Prescription

Patients and therapists felt that a home-based system could create a danger of allowing patients to have too much exercise, which can be demotivating and stop them from using it. There has to be a balance between protecting the stroke patient and not progressing their rehabilitation and giving too much exercise that is directly unsupervised.

2.1.5 Feedback on Progress (and Interface Design of Feedback)

The majority of patients described this as one of the most important factors in adhering to the exercises. The first prototype of the system used graphs as feedback. Patients did not find this helpful and required a simpler visual feedback system. Patients opted to see a 'target movement' next to their own movement. This allowed them to see how close their upper limb exercises were compared to an ideal movement. The smart system used a 3D graphic of a target movement, which was generally well received. One prototype of the system allowed patients to view the target movement and their own movement from three angles; however, patients found this unnecessary and overly complex. Patients agreed that they wanted an objective score of their movements and rehabilitation progress in addition to a display of their previous attempts over time. Finally, some patients reported that they would like the option to record their own notes. In the event of a fall at home or illness, they wanted a method to see if adverse conditions meant their rehabilitation was more difficult than usual.

2.1.6 Outcome Measures and Compliance

Patients and therapists felt that all outcomes must be relevant to restoring upper limb function and activities of daily living as opposed to directly addressing impairments. The researchers found that displaying visual prompts to remind the patient to don the sensors was helpful to increase adherence. Patients also found providing a list of FAQs and a user manual with images and instructions of how to use the system helpful to aid their memory. Giving patients an example of the sensor output on the screen helped them to know if the system was working, and that they had donned the sensors in the correct position and on the correct limbs. In addition, colour coding the sensors for donning on the left and right arms helped to increase adherence to wearing the body sensors. Both patients and therapists felt engagement of family and/or carers in the development of any home-based rehabilitation system was vital, as they will often assist patient to do rehabilitation.

2.2 Clinical Specification of the System

The StrokeBack system will consist of two parts:

1. 'Expert clinical system' that in principle is hosted in a hospital, though it could be also portable, which requires expert user to set up for detailed studies and clinical knowledge for the assessment of a patient.
2. 'Home-based system' that is much simpler and easy to use, allowing it to be set up by non-experts, e.g. family members or caretakers.

The StrokeBack system is specific to upper limb rehabilitation and has been developed and tested during the performance of a subset of the 'Wolf Motor Function Test' (WMFT). The activities will encompass a wide range of levels of ability and functional tasks. The system generates extra impairment level data including: spasticity/stiffness, motor control, speed, smoothness, repeatability, fatigue and endurance, as well as effort put in.

The fundamental principle of the expert system is to become a diagnostic tool for the identification of key impairments, identified by analysis of data generated during the performance of standardised tasks. It offers a method of activity prescription. It consists of a BAN of external sensors, e.g. cameras with an aim to collect large amounts of rich highly informative data for real-time data analysis. Both real-time feedback and power consumption were not critical in this case.

The fundamental principles of the home-based system were the usability as a key to user adherence to prescriptions. The system was expected to be minimalistic and utilise a subset of the sensors allowing patients to easily interact with workstation activities. In this case, power consumption is critical, as well as the real-time data analysis and presentation.

2.2.1 WMFT Tests

The WMFT was chosen to test patient's ability to perform everyday tasks using household items—being suitable for patients to perform in their homes as well as in clinic. Such tests are sensitive to a wide range of abilities; they are standardised, validated and widely used.

They enable characterisation of functional movement—i.e. not simply joint ranges and permit correlation with test-score as validation of sensor data while score can be used to prescribe rehabilitation and give feedback.

The WMFT scoring scale selected by therapists with each individual task or exercise was given a numerical value defined from:

- 0 = when patient does not or is unable to attempt with the involved arm
- 1 = when the involved arm does not participate functionally and the task is not achieved; however, an attempt is made to use the arm
- 2 = when arm does participate and the task is achieved, but movement is influenced to some degree by compensatory movements and/or abnormal movement patterns or performed slowly and/or with effort
- 3 = when arm does participate and the task is achieved in one attempt; movement is close to normal but slightly slower; may lack precision, fine coordination or fluidity
- 4 = when arm does participate; movement appears to be normal, timely (pay attention to expected normal times) and controlled

2.2.2 Sensors, Data and Metrics

Sensors were selected to measure movement (accelerometers, rate gyros, magnetometers), electromyogram (EMG) and possibly include also heart rate and respiration as measures of physical activity and effort. Sensor data were to be used for determining conventional metrics such as joint ranges, velocity and acceleration. More meaningful metrics related to normal movement patterns will also be determined, e.g. trunk movement during reaching, symmetry, accuracy of performance and smoothness as well as the correlation of WMFT data with the clinical score—'assessor-free' measure of function.

2.2.3 Design Overview from Clinical and User Perspectives

A decision-making system presents suggestions to the patient about activities to practice that are appropriately challenging, address-specific impairments, goals and interests. These suggestions were classified as exercises and ADL.

Basic principles were for patients to choose activities that they want to practice from an appropriate targeted range and then allowing patients to sets their own targets for each day or for the longer term. Patients become more motivated because they have chosen their activities and feel more in control and responsible. In conclusions of clinical, the system specification included:

- Self-management as key to patients—locus of control [8]
- Motivation and fun as key to ensure adherence and achieving benefit
- Designed to achieve realistic goals
- Intensity of exercises targeted to individuals based on results assessment
- Reaching ability level near normal operation is likely to be maintained
- Offering an intelligent progression of tasks and activities

2.3 Ethical and Privacy Protection Regulations and Directives

One of the most controversial issues for PHRs is how the technology could threaten the privacy of patient information [9]. Network computer break-ins are becoming more common, thus storing medical information online can cause fear of the exposure of health information to unauthorised individuals. In addition to height, weight, blood pressure and other quantitative information about a patient's physical body, medical records can reveal very sensitive information, including fertility, surgical procedures, emotional and psychological disorders, diseases, etc. Various threats exist to patient information confidentiality, example of are:

- Accidental disclosure: during multiple electronic transfers of data to various entities, medical personnel can make innocent mistakes in its disclosure.

- Internal leaks: medical personnel may misuse their access to patient information out of curiosity, or leak out personal medical information for profit, revenge or other purposes.
- Uncontrolled secondary usage: those who are granted access to patient information solely for the purpose of supporting primary care can exploit that permission for reasons not listed in the contract, such as research.
- External intrusion: Former employees, network intruders, hackers or others may access information, damage systems or disrupt operations.

Unlike paper-based records that require manual control, digital health records are secured by technological tools. Rindfleisch [6] identifies three general classes of technological interventions that can improve security:

- Deterrents—These depend on the ethical behaviour of people and include controls such as alerts, reminders and education of users. Useful form of deterrents is Audit Trails, recording identity, times and circumstances of users accessing information. Users aware of such a record keeping system are discouraged from taking ethically inappropriate actions.
- Technological obstacles—These directly control the ability of a user to access information and ensure that users only access information they need to know according to their job requirements. Examples of technological obstacles include authorisation, authentication, encryption, firewalls and more.
- System management precautions—This involves proactively examining the information system to ensure that known sources of vulnerability are eliminated. An example of this would be installing antivirus software in a system.

The extent of information security concerns surrounding PHRs extends beyond technological issues. Each transfer of information in treatment process must be authorised by patients even if it is for their benefit. No clearly defined architectural requirements and information use policies are yet available. While the trends and developments of ICT in healthcare have given rise to many positive developments, concerns about the use of ICT in user services mainly concentrate on the difficulty of respecting privacy and confidentiality when third parties may have a strong interest in getting access to personal health data electronically recorded and stored and difficulty in ensuring the security of shared personal data [10].

Therefore, the project is dedicated to respecting and protecting the personal data, considered as extremely sensitive since they refer to the identity and private life of the individual. It recognises the intent to create a potential for the circulation of personal data across local, national and professional borders, giving such data an enhanced European dimension, while respecting the principles of the European Convention of Human Rights, the rules of the Convention of the Council of Europe for the protection of individuals with regard to automatic processing of personal data and especially the European Directive 95/46/EC, for the protection of personal data will be strictly followed when addressing ethical issues.

2.3.1 Involving Adult Healthy Volunteers

Potential ethical issues that are addressed in this research will involve end-user interviews, questionnaires and trialling of prototype systems during the development and testing. The right to privacy and data protection is a fundamental right, and therefore volunteers have the right to remain anonymous and all research will comply with Data Protection legislation as to ICT research data related to volunteers.

During our research, only participants who have sufficient cognitive and physical ability to be able to safely participate and clearly give informed consent are asked to participate. Potential ethical issues arise from the fact that participants, especially those who may tire easily or become distressed. Ethical issues may also arise when the system is used to give participant location or well-being information to third parties. Here, release of this information is subject to informed consent of participants, and subject to the ethical frameworks to restrict knowledge of this information to only those given consent.

All participants in the research are volunteers enrolled from the end-user groups connected with this research, and all ethical criteria are supervised by ethicists. At all times, participants are ensured privacy and technical platform managing private user data is fully geared to enforce ethics.

2.3.2 Tracking the Location of People

Tracking the location of people is tightly linked with services delivered at the location of the user. This requires new look at the new socio-legal issues they raise. In the developed system, we only consider laws applicable to protecting privacy of the general population and NOT the laws and regulation specific for the case of the employee tracking and localisation.

The European legislation has adopted specific rules requiring that the consent of users or subscribers be obtained before location data are processed, and that the users or subscribers be informed about the terms of such processing. The rule is that the applicable law is that of the Member State where the 'controller' is established; and not that of the Member State of which the data subject is a national. 'If the controller is not established in a Member State, and in that case data protection laws of the third country should be found adequate by the EU-Commission' [11].

Location data collection will be in accordance with some basic principles: finality, transparency, legitimacy, accuracy, proportionality, security and awareness. Access to location data must be restricted to persons who in the course of exercising their duties may legitimately consult them in light of their purpose. The relevant laws include:

- Directive 95/46/EC: Protection of individuals with regard to processing of personal data and free movement of such data [12]

- Directive 2002/58/EC: Processing of personal data and protection of privacy in electronic communications [11]
- Directive 58/2002/EC of the European Parliament and of the Council of 12th July 2002 [13]

Processing of personal data and the protection of privacy in electronic telecommunications sector is governed by:

- Directive 97/66/EC: Data Protection in the Telecommunications Sector [14]
- Directive 99/5/EC: Radio equipment and telecommunications terminal equipment and the mutual recognition of their conformity [15]
- Art. 29—Data Protection Working Party: Working Document on Privacy on the Internet [16]

2.3.3 Specific Approaches Adopted

The consent of users or subscribers shall be obtained before location data needed for supplying a value-added service are processed. Users or subscribers will be informed about the terms of such use. Access to location data must be restricted to persons who in the course of exercising their duties may legitimately consult them in the light of their purpose. All required user profile data are stored upon his/her mobile device and be securely protected.

Relevant preferences relate to his/her diet, physical activities, dietary or transport/tourism-related preferences, and, in general, simple everyday task preferences will not be stored locally. The user will have the capacity to view/hear, change or delete, as he/she wishes, all stored data by the system (including his/her profile data), with the help of a very simple and multimodal interaction (touch, buttons and voice input supported).

Types of data to be retained under categories identified in Article 4 of Directive 95/58 of 12th July, 2002. Specific safeguards—issues considered by the Article 29 working parties to be addressed with regard to the retention of data processed in connection with the provision of public electronic communication services (21st October 2005 opinion on the same subject directive proposal issued by the EU Commission on 21st September 2005).

2.4 Authentication and Authorisation

Authentication and authorisation are two main means for allowing access for the user to a resource. Authentication involves such issues like identifying the user by means of either a simple login/password check to elaborate biometric analysis involving fingerprints, retina scans and voice and/or face recognition. Authorisation then performs checks whether a given user may be granted access to a given resource or not.

Such processes have been part of any secure system from the beginning of computing systems. Their complication has increased recently with the rapid growth of the amount of information resources and number of user accounts in each system, platform and/or network. This increases network administrators' work on properly securing their network and databases against unauthorised access at the same time providing users' with uninterrupted access to resources that they should be authorised to access.

However, currently employed methods for performing authentication and authorisation, in most cases, require user authentication every time he moves between resources stored on differently protected sites causing annoyance and loss of time. On the other hand, approach to authorising users based on user-resource association requires tedious administrators' job to properly secure access to different resources and gives rise to frequent faults when users are either authorised to access resources that they should not have access to or not being able to access those that they should be able to.

This problem has been identified and addressed in almost all the systems since long time [17]. Administrators are offered means for specifying access rights per-user group, policy definition mechanisms and macros allowing them to simplify management of access right to both existing and new users. Despite the fact that these tools are used, the problems of authentication and authorisation still contain loop holes attributed mostly to human errors than to machine security as such. Our proposed seamless authentication and authorisation is aimed to simplify further the process of securing access to multiple-interconnected systems as well as making authorisation less prompt to faults.

Authentication is the process of authenticating a user across multiple account protected resources and platforms, i.e. agreeing between different authentication authorities means of establishing trust relationships and dependability for transferring users authentication status, i.e. checking that a user is who they claim to be. The process will include customisation of means of authentication whereby users will not be required to perform authentication while transferring from one trusted party to another using single authentication.

In the case of moving from a party with lower authentication requirements to one requiring higher level of authentication, user will only be required to perform extra security checks while accessing differently protected resources instead of performing the whole authentication process from the beginning. Approaches like this have been already proposed, most known being Windows Passport or Live Account [18], where user may move between sites that support this technology. However, such methods do not take into account differences between authentication means required by different sites. This limits applicability of technologies to social websites aiming to keep a record of users accessing their services.

Authorisation in computer terms refers to granting access to a resource to a given user. In most computer systems, granting access is related to belonging to a specific user group meant to allowing administrators defining single access rights rules for a group of users. However, this makes it very difficult when it comes to more per-user access granting, especially in systems with large number of user accounts. What we propose is to unify and simplify means of granting user access to given resources.

The process will define sets of resource authorisation dependencies whereby access to one resource may be implicitly granted upon prior-assigned access rights to another resource. This will allow removing the need for the security administrator to provide access rights to every user to every resource, instead concentrating on defining security interdependencies between resources and defining user access right only to key global resources. Note that this will not remove a possibility to explicitly grant or block access to a given resource to a given user, if required.

2.5 Concept Platform Architecture

The PHR platform developed internally by Intracom S. A. Telecom Solutions, name intLIFE, has been enhanced and geared to diverse health application through a number of FP7-funded research projects, such as Artemis-CHIRON [19], ICT-PSP-NEXES [20], AAL-PAMAP [21], FP7-StrokeBack [22] and FP7-ARMOR [23]. Special adaptations have been geared to allow safe sharing of patients' clinical data with appropriate measures, as described earlier, for the protection of private data, ensuring controlled access to it while ensuring that any data distributed cannot be traced back to the person from whom data has been taken from. This way a medical system based on PHR system could be safely applied for the purpose of deriving clinical models build from large amount of data for subsequently allowing more reliable feature-based clinical diagnosis on other patients and detection of conditions not possible earlier. In order to provide necessary privacy and security safeguards EHR/PHR, Vital Signs Monitoring and Management subsystems are all connected via secure and encrypted interfaces controlled via authentication, authorisation, and anonymising modules.

A conceptual system architecture of the StrokeBack system is presented in Fig. 2.1. It contains a Patient System deployed at home supporting physiological remote monitoring of patient well-being, runs the rehabilitation games and offers full integration with online Personal health Record (PHR) used as a data repository for sharing information between the patient and his/her physician(s).

It offers full support to immersive user interfaces like Kinect [24], Leap Motion [25], Emotiv EEG [26] and other ones, combined with a range of virtual and augmentation systems in order to enable fully immersive gaming experience. As shown in Fig. 2.2, we support 3D Smart TVs, AR/VR visors and 3D projectors.

The system is geared to offer also fully support usage also on mobile devices like smartphones, tablets, etc. We have developed an affordable integrated gaming solution for both near field and full-body exercises, which we call the 'Smart Table' (Fig. 2.3). The clinician part of the system provides access to back-office PHR data repository for constant monitoring of patients' condition. The current design contains two Kinect sensors: one at table level for supporting use of physical objects and one at the top for upper body exercising. Two displays are embedded, one flat

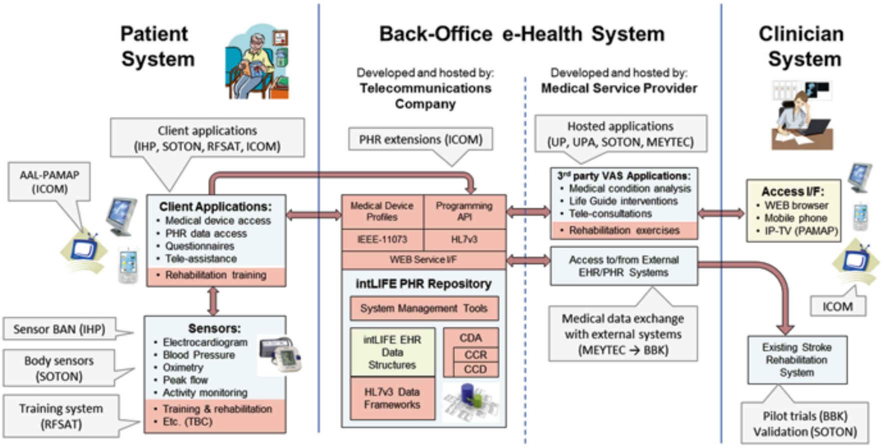

Fig. 2.1 Concept architecture of the overall rehabilitation system

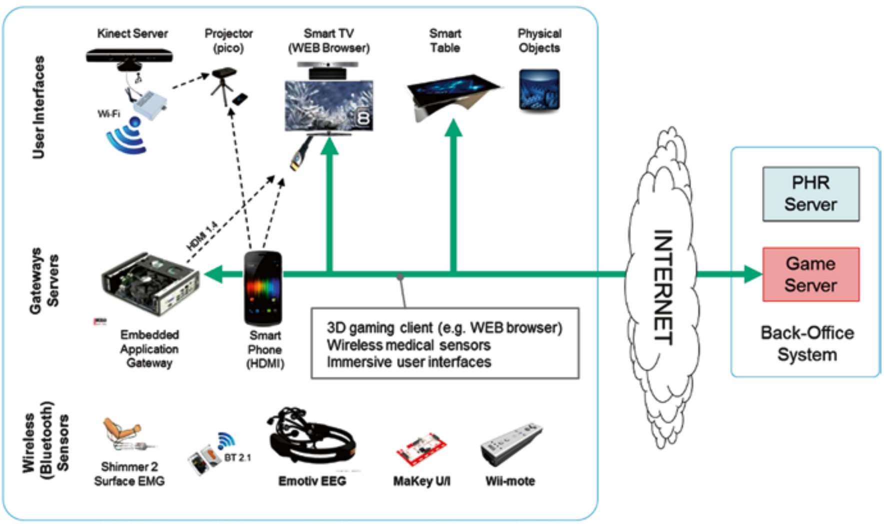

Fig. 2.2 Physical architecture of a gaming subsystem

for physical objects while the top one for displaying more classical board games controlled either with Kinect or other user interfaces. The progress of their rehabilitation and other relevant physiological data including audio–visual connection are also provided, if needed. The back-office services are currently based on open-source solutions like Open EMR [27] platforms.

Ultimately, they will be migrated to the intLIFE core PHR service platform. The overall gaming system has been designed using client–server approach allowing us to store the game repository and game provision of the PHR server, thus maximally

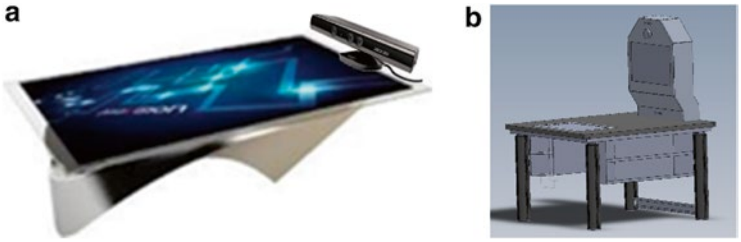

Fig. 2.3 Concept (**a**) and actual (**b**) 'Virtual Table'

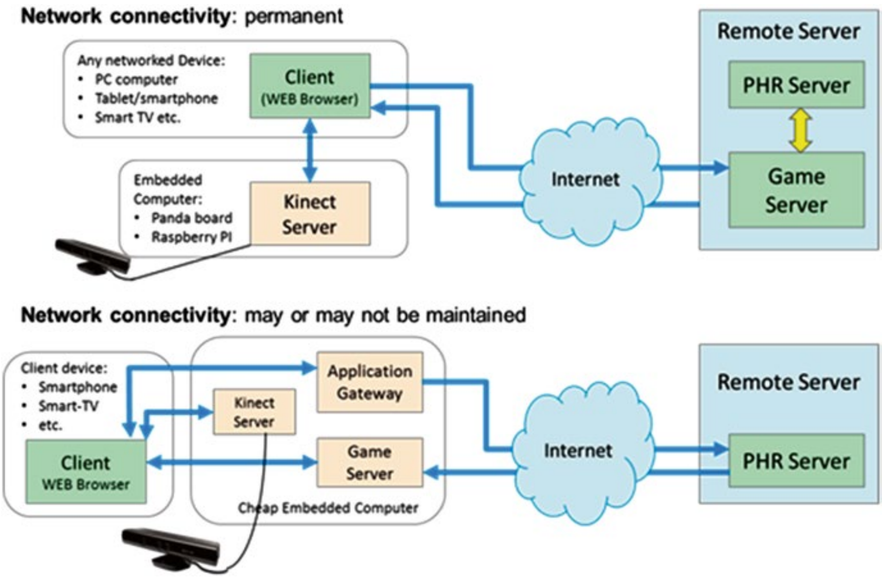

Fig. 2.4 Online and off-line 'game' management

lowering the load on the client devices. This allowed us from one side to run games on such devices as Smart TVs or Smartphones, while offering us flexibility of maintaining the latest versions of the games without the need of updating the clients. However, since any network-based system needs to anticipate that connectivity may not be always maintained, we have built into our system two scenarios: when network is constantly available and when it is not (Fig. 2.4).

In the former case, game server is executed remotely, while in the latter one it can be executed locally and use games downloaded earlier. Similarly, physiological data and game progress info can be either uploaded on the fly or pre-stored and uploaded when network link is re-established.

2.6 BAN System Overview

It is not appropriate or possible to provide a technical specification for the BAN system this early since this is an area that will continue to evolve over the duration of the research programme. Nevertheless, it is possible to present an overview of the BAN system in terms of its intended use. Basically, there will be two types of BAN system: an expert system and a home-based system. The former is intended for use within the clinic and will host a number of different types of sensor producing ‘rich’, high quality data. It will be the more complex of the two systems and therefore by necessity will require the assistance of skilled operators to set it up and fit it to a patient. By comparison, the home-based version will contain a minimal set of sensors and a data logging capability. Its design will be driven by the requirements for simplicity of use, ease of donning/doffing and operational lifetime. The quality of data expected from this system will not be as high as that for the expert system, though still of sufficient value to produce a qualitative indicator of rehabilitation progress.

2.6.1 Sensor Specification

Prior to and while the BAN sensors are being developed, initial investigations will use commercially available wireless sensors with measurements being performed both on able-bodied subjects and on stroke patients with varying degrees of upper limb impairment. These investigations will allow us to develop and evaluate various data compression techniques and feature extraction methodologies, as well as establishing sensor type, number and placement to optimise reconstruction of limb movement. Methods for securely attaching sensors to the body will also be investigated with particular emphasis on the ease with which these items can be put on and taken off.

A review of the available literature indicates that accelerometers are widely used in kinematic studies of various clinical pathologies and in studies monitoring a range of different human movements [28]. The magnitude of accelerations generated during human movement varies across the body and depending on the activity being performed generally increase in size from cranial toward caudal body parts. Bouten et al. concluded that waist level body-worn accelerometers must be able to measure accelerations up to ±6 g with frequencies up to 20 Hz in order to assess daily physical activities [29]. Magnetometers are often used in conjunction with accelerometers to provide spatial coordinate information using the Earth’s magnetic field as a reference allowing more accurate tracking of body parts [30, 31]. Errors can however occur when a body part is rotated since such a motion would be recorded by an accelerometer as a decrease in acceleration (due to a change in the magnitude of the gravitational component of the measured signal). To overcome this problem, rate gyroscopes can be used to detect when body part rotation occurs and correct the accelerometer signal [32].

Table 2.1 Shimmer 9DoF sensor module parameters

Parameter	Accelerometer	Magnetometer	Rate gyroscope
Range	±1.5 g, ±6 g switchable	±4 G	±500°/s
Sensitivity	800 mV/g	7 mG	2 mV/°/s
	206 mV/g		
Linearity	±1.0 % FS	±0.1 % FS	<1.0 % FS
Cross-axis sensitivity	±5.0 %	±0.2 % FS/G	±1.0 %
Frequency response	300 Hz	–	140 Hz

An ideal sensor system for the accurate kinematic measurement of human body parts should therefore comprise accelerometers, magnetometers and gyroscopes. A commercial sensor system that meets this requirement has been identified: the Shimmer platform (www.shimmer-research.com). This system is based upon a body-worn node that contains as standard a 3-axis accelerometer, a 2 Gbyte detachable memory card for on-board data storage and a low power 2.4 GHz 802.15.4 radio communication link for live data transmission. A range of other modules can be directly attached to the base module each of which provides additional functionality (e.g. magnetometers, rate gyroscopes, EMG and ECG). The wireless capability of this system permits untethered connection of the sensor modules to the body, thus reducing movement restrictions associated with cabling and allowing unhindered, natural movement.

Of particular interest in the Shimmer system is the 9-degrees of freedom (DoF) sensor module which includes a 3-axis accelerometer, a 3-axis angular rate gyroscope and a 3-axis magnetometer. Relevant parameters for this sensor module are listed in Table 2.1. Having three different types of sensor housed together in a single unit means that each type of sensor can be simultaneously subjected to exactly the same movements and forces during evaluation. This will allow direct comparisons to be made between sensor types and between specific kinematic parameters derived from the data produced by single types of sensor or by combinations of sensor types.

A PC-based motion capture system will also form part of the measurement system. This can be trained to recognise the upper limb of a patient and track its motion during exercises and tasks, producing near real-time values for joint angle, upper and lower arm segment velocities, etc. Depending on how accurately this can be achieved, data from the motion capture system could be considered as a 'gold' standard. It may also prove possible to train the system to recognise the locations of sensors on the BAN and recalibrate them if they are observed to be out of position, in an incorrect orientation or misaligned.

Two different motion capture systems will be assessed: the Microsoft Kinect and the ASUS Xtion Pro Live. Both have two vision systems: RGB and infrared. The former simply responds to visible light and as such cannot provide depth information but will be used to provide real-time recordings of patient movement. The infrared camera system works by using time-domain reflectometry (TDR), where the time difference between a pulse of infrared light emitted from the system and its subsequent detection when reflected from an object is used to calculate the distance

Table 2.2 Comparison of motion capture system specifications

Parameter	Xtion Pro Live	Kinect
Range (m)	0.8–3.5	1.2–3.5
Horizontal field of view	58°	57°
Vertical field of view	45°	43°
Data streams		
320 × 240 16-bit colour (frames/s)	60	30
640 × 480 32-bit colour (frames/s)	30	30

to the reflecting surface. Thus, the infrared camera system is capable of measuring depth. It might be possible to use the infrared system to calibrate the Shimmer sensors. In this respect, the camera system will be trained to recognise a Shimmer sensor and its orientation and then used to record its movement during predefined calibration exercises.

Data produced by the Shimmer sensors can then be directly compared with the data generated by the camera system and any differences in derived spatial positions can be used to generate calibration coefficients. Relevant technical specifications for the two motion capture systems are directly compared in Table 2.2. Microsoft have recently released the Kinect version 2 system which is reported to have a near field range down to 0.4 m, though no other technical data is available from their website. A number of different sensors and assessment techniques will be used to monitor patient rehabilitation both in the home environment (the home-based system) and also in the clinic (the expert system). The types of sensor and how they will be deployed will depend on the assessment technique used.

2.6.2 Expert System Use Case

The expert system is designed to be employed in a controlled environment under the supervision of a physiotherapist, or other appropriately qualified clinician, trained in its use. This will generally take place at the clinic although it could possibly be used within the home environment as well if suitable personnel are present.

The expert system will consist of a number of body-worn wireless sensors (the expert BAN) and a PC-based motion capture system (Kinect or ASUS [33]). The choice of sensors used will be kinematic sensor modules (comprise tri-axial accelerometers, tri-axial rate gyroscopes and tri-axial magnetometers, which when combined give 9 degrees of freedom in measurement), EMG sensors to monitor muscle activity in the biceps and triceps and an ECG sensor to monitor heart rhythm. The kinematic sensor modules will be positioned on the forearm just above the wrist, on the upper arm just above the elbow and on the sternum, though exact positioning will be determined through early stage investigations. The motion capture system will be used to film the patient as they perform specific tasks and exercises, and the temporal film record will be used as a qualitative measure of patient rehabilitation progress.

Appropriate methods to provide secure and repeatable attachment of the sensors to the body will be investigated early in the research programme as well as the effects of sensor orientation and misalignment.

Assessment with the expert system will initially commence with a face-to-face dialogue between the patient and clinician. From this, the clinician will be able to establish the patient's level of impairment and the patient will be able to inform the clinician as to what their personal objectives from rehabilitation are. This will enable the clinician to decide which of a range of upper limb functional tasks and exercises are most appropriate for the patient. Following on from this dialogue, the measurement phase commences with the patient encouraged to perform a subset of exercises and functional tasks from the WMFT collection, which will have been specifically selected by the clinician to suit the patient's objectives and perceived capabilities.

The motion capture system will record the patient's movements during the exercises. Through suitable signal processing, the motion capture system will produce temporal and spatial kinematic information including: limb segment position in space, limb segment velocity and acceleration, joint angles, and total time for individual task completion. Accordingly, the motion capture system can be considered as a 'standard' against which data derived from other sensor sources can be compared.

During the exercises, data from the body-worn wireless sensors will also be directly transmitted to the host PC in real time and processed in two different ways. Firstly, transformation algorithms will convert the raw sensor data to three-dimensional spatial information which will be directly compared with the data generated from the motion capture system. This will serve as a simple check on the accuracy and robustness of the transformation algorithms. The second data processing strategy will involve searching for patterns within the sensor data that exhibit high correlation with specific movements of the upper limb or specific functional tasks being performed. These data patterns will be used by the home-based system as templates to determine whether such movements are being performed by the patient during normal activities of daily living. Other features of the data recorded (such features to be determined) will also be used as metrics to assess rehabilitation progress. For example, this might include calculating energy expenditure from EMG data or estimating metabolic rate from ECG data.

The clinician will also assess the patient while they perform the prescribed exercises and use their professional judgement to rate the patient in accordance with the WMFT scoring system. This score will be entered into the PHR. All of the raw data collected from the body-worn wireless sensors and motion capture system as well as processed data will also be stored in the PHR.

Subsequent scheduled or ad hoc visits to the clinic will involve re-rating the patient's performance of their specific and prescribed subset of tasks from the WMFT, allowing a longitudinal measure of rehabilitation progress to be determined with clinical credibility.

2.6.3 Home-Based System

Because the home-based system is required to be used with non-professional intervention, it is less complex than the expert system and will involve fewer sensors. Specifically, EMG and ECG sensors will not be incorporated within the home-based BAN. Simplicity of use and ease of donning will, however, be of prime importance since the system is intended to be operated either solely by the patient or with the assistance of a carer or family member. Two different use cases are proposed for the home-based system, representing a short controlled assessment phase and a longer uncontrolled assessment phase.

2.6.3.1 Use Case 1

In this first use case, the home-based BAN will be used in conjunction with a PC motion capture system within a controlled 'measurement zone' (e.g. at a work table with a customised interaction platform). Initially, the patient will be instructed to perform a number of simple tasks that effectively move the sensors through a number of predefined orientations while being filmed by the motion capture system. At the same time, the sensors will be transmitting their data to the host PC. By comparing the sensor data with that from the motion capture system, it will be possible to re-calibrate the sensors, accounting for any positional inaccuracies in sensor placement.

After this calibration phase, the patient will be asked to perform repetitions of the specific WMFT exercises identified as being appropriate to them during initial assessment at the clinic. To keep the patient engaged with these motor function tests, motivational software games will be developed that will require the patient to move the upper limb in a manner that mimics the movement requirements of the specific exercises assigned to them. Data from the body-worn sensors will be transmitted in real time to the PC through a wireless communication link and converted directly into time-stamped spatial coordinates that will be used as the input controls to the PC games. As well as making the exercises more enjoyable, this will also present the patient with real-time visual feedback on their performance.

Other relevant kinematic information will be derived from the spatial coordinate data including body segment acceleration, body segment velocity, body segment angle, body segment tremor, etc., and these will all be stored on the PC for post-exercise analysis to yield quantitative measures of performance. Such performance indicators will be presented to the patient in a suitable format at the end of the exercise session (e.g. graphs, road maps). In this manner, the patient will feel a greater sense of involvement in their own rehabilitation.

Although not (yet) clinically endorsed by health professionals, the performance indicators produced from the kinematic data as well as the raw data can still be used as symptomatic measures of patients' rehabilitative progress. As an example, con-

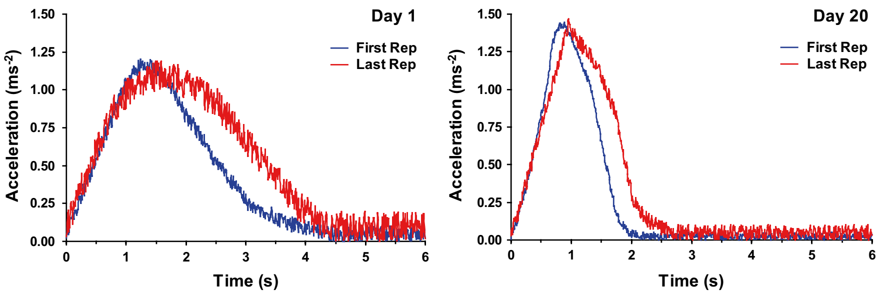

Fig. 2.5 Example of accelerometer data collected during a task

sider Fig. 2.5 which shows a pattern of data which might be collected from a single accelerometer located on the forearm. This is not real data, but has been generated simply to illustrate the point. Consider further that the data has been collected during repetitions of a specific task (e.g. reach and grasp). On the first day (left side of figure), the data shows a high degree of noise indicating a jerky movement of the forearm. It also shows that the level of noise and the time taken to complete the task have both increased by the final repetition, indicating fatigue. By comparison, the data collected for the same task some weeks later (right side of figure) shows less noise suggesting a much smoother movement of the forearm. Greater acceleration levels are also achieved, and the task is completed in a quicker time. There is also less variation between the first and final repetition indicating a lower degree of fatigue. Such comparisons of data patterns over time can therefore be used as a qualitative indicator of rehabilitation progress.

Data patterns like those shown in Fig. 2.5 are examples of classified data: in this example, the data has been classified as being representative of the reach and grasp task. Data collected during the game playing phase of rehabilitation will be examined to identify whether such characteristic patterns exist that can be associated with particular arm movements or tasks. The fact that the game playing involves repetitions of discrete arm movements is beneficial to this objective, allowing correlation scores to be calculated across data sets for nominally the same task, effectively ranking the patterns with a score indicating how representative they are of that particular task. Furthermore, since the game playing phase is repeated on a daily basis, any such data patterns found can be routinely updated to compensate for the patient's improvement in task performance. These patterns will be used to determine whether their associated arm movements are being performed by the patient during activities of daily living (see next section).

Raw sensor data, processed sensor kinematic data, motion capture kinematic data and processed sensor classifying data will all be stored in the PHR through an Internet connection to the patient's home PC, which can be accessed on demand (remotely) by clinicians to assess rehabilitation progress.

2.6.3.2 Use Case 2

In this second use case, the home-based BAN will be used to surreptitiously gather data from the patient during activities of daily living (ADLs). This removes the bias often encountered due to patients trying harder during exercises when they know that they are being assessed and therefore provides a more accurate measure of patient effort and progress. It is therefore of vital importance that the method by which the sensors are attached is both comfortable and non-intrusive to the patient and does not restrict normal activities or movements. Ideally, the BAN garments might take the form of a simple wrist strap, upper arm strap and chest band.

The home-based BAN will also contain a processing hub with data storage facility and a wireless receiver. The BAN sensors will at this stage have been reprogrammed by the PC software to operate at a lower acquisition rate to prolong battery life. The hub will process the sensor data in real time and perform data compression to reduce data storage requirements (thus helping to extend the BAN operational lifetime).

Data will be gathered by the BAN over a fixed period (battery life dependent), and at the end of a session this data will be downloaded from the hub to a PC through some form of docking station. The data will then be analysed to look for the classifying, characteristic patterns that are associated with particular movements or operations (as defined in the clinical assessment phase and daily PC gaming phase). Other patient activities not previously defined by data patterns may also be inferred, such as inactivity, lying down, sit-to-stand, stand-to-sit and so on. Once these activities have been identified within the BAN data, they will be presented to the patient in a meaningful format and also stored on the PHR for later analysis by clinicians. Presentation formats might for example simply convey information such as the patient performed 20 reach-and-grasp tasks during the monitoring period which revealed that the time to complete this task increased over the course of the day by 15 % or the patient was inactive for 3 h and 20 min during the monitoring period.

2.6.4 Summary of the System Design

Figure 2.6 presents a simplified comparison of the three different use case scenarios for the expert and home-based system: at the clinic, gaming at home and ADL at home. The figure graphically compares three metrics: the estimated number of sensors required for each use case, the estimated time taken to complete each use case and the clinical relevance of each use case. The latter is a subjective score with maximum value of 10. It is based on the perceived quality of the data collected and its ability to generate a reliable and quantifiable score indicative of rehabilitation progress. For this metric, the scores assigned to both use cases of the home-based system are low in comparison to the clinical use case. This may prove to be rather conservative if it can be demonstrated that the home-based system can produce quantifiable data that indicates the state of rehabilitation and if it can be accepted (believed) by clinicians.

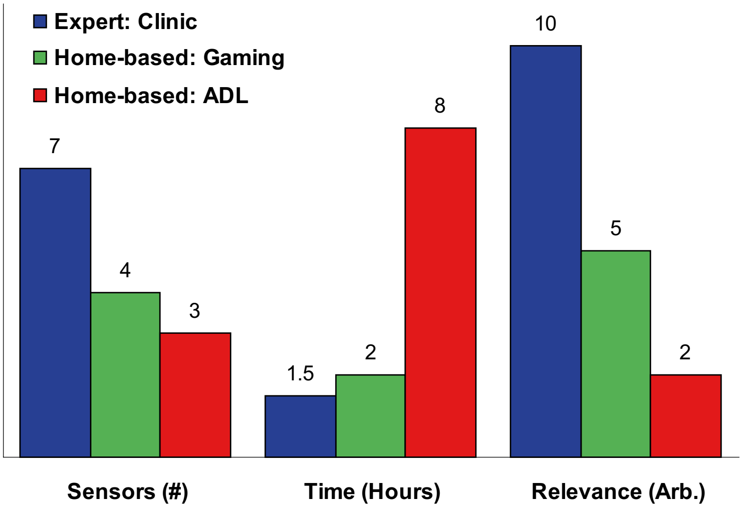

Fig. 2.6 Comparison of systems

2.7 Validation and Preliminary Evaluations with Users

Both technical system validation tests and preliminary evaluations by other project partners have been performed. Regarding the evaluations of the home rehabilitation system, we have used the following regime:

- Patient switches on the rehabilitation gaming device.
- Patient starts the 'Tele-rehabilitation'-session by using the interaction-board (Kinect-based 'touch table').
- Patient selects the 'autonomous training', i.e. without real-time connection to the therapist, or 'with supervision'. In case of no supervised training is scheduled or there is no connection to Internet, an 'auto training' mode is selected automatically.
- Patient selects an exercise game and runs it. She/he may consider former trainings scores and adjust the difficulty level. Some exercises may be accompanied by music and the patient may be asked for the desired music title. Actions follow a set of permissions configured earlier by the therapist.
- Patient executes the exercise in the autonomous modus. The PHR monitors and analyses the execution of tasks and exercises and generates respective feedback. Finally, training results and acquired scores are uploaded to PHR.
- Patient executes the exercise with live-supervision of the therapist. She/he is observed by the therapist may see the therapist on the screen via bidirectional video communication and may receive training guidance in real time.
- Patient can see the final evaluation and score of an exercise after finishing it.

As expected Kinect has proven unreliable for near-field upper limb tracking requiring frequent re-calibration, while Leap Motion offered sufficient precision for fingers and palm tracking.

2.8 Summary and Observations

The introduction of EHR/PHR systems is the response to the inherent problem of the medical community in dealing with growing amount of papers and printed type of medical records. This becomes also a matter of costs as much time and money is wasted on copying, faxing, and retrieving paper files. Move to electronically stored and managed patient records is both a simplification of the past problems, while adding new ones.

Hence, governments demand increasingly secure and standard-compliant health records [34, 35]. In today's world, it takes more than a simple document to meet national record keeping guidelines. Electronic Health Records are an obvious solution to all emerging problems in the medical care, offering simplification of growing patient records, stimulates easier exchange of data among medical professionals, and contributes to cutting costs of medical care as a whole. Records are accessible by multiple health providers. Subject to providing sufficient safeguards at every level, a complete security of data may be achieved. Through data encryption, password protection, the electronic health record offers a peace of mind that data is kept away from unauthorised eyes. Nevertheless, although the future of e-health has never looked so bright, there are still several concerns that need careful attention.

Growth of e-health systems inherently implies that any patient's data may be stored not in one place, but on several diverse systems implying increased risk of leaking information to unauthorised third parties. Cyber security procedures are also not consistent across various systems, implying that some may be easier to break into and increasing vulnerability of data stored there.

What adds to the problem is lack of seamless interoperability among e-health systems based on electronic records [36]. Since early stages of development of HL7 standard [37], now one of the base reference standards for e-health, it was considered only as a set of guidelines and not a factual standard to follow. This has resulted in systems being built and deployed that had implemented only a part of the HL7 specification [38] suited to particular needs of a given service provider. Interoperability among such restricted systems is a tiresome process, resulting in exchanging incomplete information. This deficiency has been recently recognised as critical for future e-health and the HL7 is being evolved to define the base set of interoperability criteria for ensuring smooth collaboration among different health systems. However, this process is still ongoing and requires much more research work, including interoperability at the device level and especially for mobile physiological monitoring.

In conclusion, we can observe a dramatic change in the e-health domain with the introduction of electronic health records, boosting the efficiency of medical services at a lower cost, at the same time offering still a vast range of research challenges that we may expect to be pursued and hopefully resolved in the near future.

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Chapter 3
Data Flow-Driven BAN: Architecture and Algorithms

Steffen Ortmann and Peter Langendörfer

Abstract This chapter reflects the objectives and the design of the StrokeBack Body Area Network (BAN) with respect to the requirements given by the application scenarios of clinical assessment and recognition of daily activities, as well as the user feedback from patients and therapists. The StrokeBack sensor platform, called GHOST, is designed to provide smaller size, more efficient power consumption, stronger security means and much better usability than the currently available state-of-the-art sensing devices. The GHOST platform is a tiny sensor platform with inertial sensors, Qi compliant wireless power transfer and an embedded Bluetooth Low-Energy (Bluetooth 4.0) front end. In a full package, the complete GHOST sensor platform is of matchbox size only, including a Lithium cell battery pack and a receiver coil for wireless power transfer. Two versions of the StrokeBack sensor nodes have been assembled. The first sensor node design uses the shelf components while the second variant of the sensor nodes incorporates a customised crypto-microcontroller providing enhanced security options. This platform is used for detection of Activities of Daily Living (ADL) within the StrokeBack project, where the patient wears the platform at the affected limb. The daily data flow principle is described in detail. The platform collects movement data from accelerometer, gyroscope and magnetometer throughout the day, which are uploaded and analysed during the night when the sensor resides in the wireless charging station.

3.1 Motivation and Objectives for the Use of Body-Worn Sensors

The StrokeBack project pursues providing two novel training and assessment means for patients in the post-stroke rehabilitation at home. The first approach develops a fixed training place that allows supervised rehabilitation training at home. It is a

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fully equipped workstation with sensors, cameras and other components necessary to support autonomous training sessions according to a pre-defined schedule.

To complement the training system, the second approach facilitates the use of body-worn sensors, called Body Area Network (BAN), to monitor and assess the patient's activities during daily life, especially during the time when the patient does not perform any other rehabilitation training. In other words, the data gathered by the BAN allows for delivering more detailed insights of what usually remains hidden for the therapist in the ambulant rehabilitation phase, i.e. how the rehabilitation training influences daily life of the patient.

The BAN captures motion data of upper extremities during daily life of a patient. It is used to document transfer of motion abilities regained in training sessions. It logs sensor data and transmits it to a local base station in regular intervals, where these data are analysed before results are stored in the Personal Health Record (PHR). In this way, the therapists will be provided with objective data about patient activities for assessing individual rehabilitation progress and health status of the patient.

This approach provides several advantages in contrast to other ones such as video monitoring. Sensor nodes are relatively cheap, minimal invasive only, not bound to certain area or fixed power supply and hence, they can be used nearly everywhere and at any time. In addition, sensors can be easily adapted to other or refined tasks, e.g. by reprogramming or new extension modules (yet including actuators) to overcome problems and needs that may occur during development or use. Last but not least, the number of nodes per patients and task can be adapted quite efficiently due to their autonomous and cooperative nature.

3.2 Goals of BAN Use

There are three main tasks the StrokeBack sensor nodes will be used for, which will be sketched in the following three paragraphs.

3.2.1 Clinical Assessment

The clinical assessment will be done by letting a patient execute a streamlined version of the Wolf Motor Function Test (WMFT). Sensor nodes attached to the affected side of the patient's upper limbs will thereby objectively measure speed and movement accuracy of executed exercises. Regular WMFT sessions with same patients will enable to compare gathered data for single exercises directly to assess rehabilitation progress.

3.2.2 Investigated Activities of Daily Life

Besides the training exercises, daily activities are to be monitored by the BAN throughout the day. Therefore, all collected raw data will be evaluated each day to gather statistics about activities and activity pattern. It is quite obvious that it is almost unfeasible to find out about all kind of activities the patient does during the day by just analysing sensor data, in particular with a minimum set of sensor attached. In principle, the StrokeBack team will try to automatically detect the following subset of ADL:

1. Reach and retrieve object
2. Lift object (e.g. a cup) to mouth and return to table
3. Swing arm in horizontal plane through 90° and return
4. Rotate wrist through 90° and return

These actions of course consist of consecutive or parallel sequences of smaller movements the BAN needs to classify. Given this data the BAN should help to get insights into the following things during the absence of the therapist:

Activity of the patient in general: This includes any information about what the patient does during the day, regardless whether the information is more general, e.g. percentage of time where the patient was sitting around, or whether it is related to particular movements such as ‘Reach and grasp an object’.

Walking: The number of steps taken or the walking distances reached per day are a pretty good measure for clinicians and therapists to assess the patient’s state of rehabilitation. Therefore, we’ll investigate an individualised step counter that can estimate the walking activity. Due to the very individual walking pattern of stroke patients, that differs between patients and usually differs from walking pattern of healthy subjects, we see a need to research novel algorithms for that.

Comparison between affected/unaffected body parts: One of the most important outcome measures of rehabilitation is the comparison of the usage of affected body parts in contrast to the unaffected parts. In ideal case, the algorithms to be developed will allow for direct comparison what kind of movements has been carried out with which part of the body at which time.

3.2.3 Instrumented Objects

For training of fine-grained hand motor skills, the StrokeBack sensor node may be integrated into objects for Arm Ability Training (AAT). Therefore, integration of a sensor node into a cube was investigated. The node gathers and reports the orientation of the cube in real time while being used in therapy, e.g. which side of the cube is currently on top. Using cubes or similar objects for simple tasks is common in occupational therapy. Here, the goal is to implement evidence-based occupational therapy means for effective home use.

3.3 Related Work

Monitoring movement and activity both inside and outside the laboratory has been the focus of considerable research over the last years. Body-worn sensors such as goniometers [1], pressure tubes [2], gyroscopes [3] and accelerometers [4–7] have been used in a range of activities and clinical conditions [5, 7–11] and for control of Functional Electrical Stimulation (FES) in walking and upper limb movement [12–15] and in standing with spinal cord injured patients [16, 17]. However, body-worn sensors are often bulky, require associated instrumentation and accurate placement of the sensor elements. Nevertheless, such studies have already demonstrated the feasibility and potential benefits of long-term monitoring of movement [18, 19] and what is needed now is a shift in approach to make this feasible and usable in clinical practice and particularly in the home environment for rehabilitation.

A potential approach has already been embraced by the textile industry. The so-called smart textiles have been developed to measure vital signs, such as the electrocardiogram (ECG) and have even been commercialised in, for example, the SenseWear™ [20], Samsung GearFit™ [21] and the FitnessSHIRT™ [22]. Predictions clearly indicate that wearable systems will become part of routine clinical investigations [23]. Movement and activity are, however, more challenging than vital signs and additional processing, storing, transmitting and using the data poses an even greater challenge. The SMART [24] project has explored how technology can be used in the home to support rehabilitation following stroke. Devices have been developed that are attached to the wrist and upper arm using clothing resembling sportswear to give a measure of movements made by the patient in activities prescribed by the therapist. Data are recorded and displayed on a computer or TV screen. Joint angles have also been measured using conductive fibres integrated into fabric which change their resistance due to bending as the joint angle varies [16] and by covering the fabric with an electrically conductive elastomer with piezo-resistive properties so that when deformed acts as a strain sensor able to detect movement [25]. Nevertheless, smart textiles have yet not made it for ambulant home use by single persons, in particular due to the fact that these are hard or unfeasible to be dressed by partly impaired people. Similar objections have been raised by our therapists from the very beginning of our work as mentioned.

Meanwhile several motion sensing systems, the so-called Inertial Measurement Units (IMU), are freely available on the market. These usually combine gyroscopes, accelerometers and magnetometers (inertial sensors) with low power processing and short-range communication features. IMUs have been proven functional for body motion capture [26–28], gait analysis [29] as well as monitoring of rehabilitation exercises for arm [30] and hand training [31]. For our very first experiments with both healthy and stroke subjects [32, 33], we have used the Shimmer platform [34] that already fulfils the requirements in terms of processing and storage capabilities. However, we have not been fully satisfied with link errors in the Bluetooth connectivity resulting in unreliable data transfers, available security means and the overall power consumption. We have also investigated the use of XSENS platform

[35], but with initial costs of more than ten thousand euro for the first full set of sensors it was in our view way too expensive for our needs. In summary, both platforms still do not fulfil our needs regarding ease of use (no plugs and cables) and to some extent have been even too bulky for smooth usage in daily life, e.g. our subjects under investigation have felt that the Shimmer devices are too large in size.

The existing techniques for taking measurements on the human body are generally considered to be adequate for the purpose but are often bulky in nature and cumbersome to mount. That especially holds true when it comes to individual use by a single person, in particular for stroke patients suffering from physical impairments or palsy. Moreover, published motion sensing systems in the rehabilitation area require usage of several devices—sometimes up to ten or more sensors [28]—in parallel. The abilities to use mentioned sensing devices in a home environment is therefore very limited. Last but not least, existing platforms merely come along with standard encryption features based on low-power Advanced Encryption Standard (AES) as well as unreliable and power hungry standard Bluetooth links.

Our work addresses these deficiencies by extending the state-of-the-art approaches with up-to-date Bluetooth Low-Energy communication, enhanced usability and extended security features. The latter issue is incorporated by embedded means for low-power privacy protection and data security built upon our crypto-microprocessor with hardware for Elliptic Curve Cryptography (ECC). In addition, we have investigated some more technical features such as wireless power transfer to enhance the user-friendliness and thereby increase the acceptance of such system when used in daily life.

3.4 Objectives of BAN

As the sensing platform is to be used in applications outside of well-controlled laboratory environments, i.e. the daily life of patients, the physicians and therapists have specified a couple of requirements that should be met by the platform. Despite clinical/therapeutical advances and opportunities, usability is by far the most crucial acceptance factor! That means a comfortable and easy way to use the sensor nodes is the key to success in the real world beyond any research trials. Thus, body-worn sensors should work nearly ‘invisible’ and must not hinder the patient in his/her daily life activities. The sensors should be small and lightweight and allow for monitoring the patient for several hours or the whole day, respectively. The latter is certainly a trade-off between power consumption and an appropriate battery supply, which grow in size and weight with the amount of energy that is needed. All mentioned features are obvious of course. Considering them altogether in the right way allows for creating a proper *sensor node* that:

- *Provides acceleration and orientation sensor data* of the sensor node itself for measuring relative speed and direction of motion. Merging data of several nodes at different points of the body will allow for analysing relative motion activities of the person's body part wearing the sensor node. That way, insights into the accuracy and speed of rehabilitation training sequences and Activities of Daily Living (ADL) will be investigated and assessed automatically.

- *Works autonomously* in a way that a single sensor node does not need any infrastructure or wired link to gather and process sensor data. Therefore, the sensor node must be equipped with adequate rechargeable power supply as well as processing power and storage means.
- *Fulfils all privacy and security obligations* that are considered mandatory for any kind of use due to the fact that the sensor node gathers personal and private data, respectively. That especially holds true if sensor nodes are used in medical/clinical context, in particular due to the fact that gathered data is transmitted wirelessly to the base station at night (in theory freely accessible), from where it is uploaded into the PHR. Therefore, the sensor nodes should make use of standard encryption/decryption means to protect from non-authorised access to data. It may further provide flexible authentication and digital signature capabilities to ensure proper access control and data integrity.
- *Can collaborate with other sensors and/or a base station by wireless means* to form a network for executing common tasks. In addition to the autonomous nature of single sensor nodes, these must be capable of communicating configuration and calibration data amongst each other, e.g. to synchronise data taken from different nodes at the same time, to cope with clock drifts or to update routing and link information. Sensor nodes further deliver gathered data to a central network sink, i.e. the base station. In the StrokeBack system, the patient's home station takes the part of the base station. It will process and analyse recorded raw sensor data and update the PHR.
- *Provides plug and play feeling* for a comfortable patient experience. Usage of the sensors must be easy and intuitive. Despite being as small and lightweight as possible, the sensor nodes need to get by with a minimum or better no configuration by the patient and must be freely wearable during the day. Therefore, means of automatic calibration, wireless communication and wireless charging have been investigated and used whenever possible in the StrokeBack BAN. Especially integrated wireless charging capabilities allows to get rid of cables and plug connectors that are usually hard to use by stroke affected patients due to missing precision of motor hand control.
- *Facilitates a compact and very flat design* that does not further reduce already limited mobility of a patient. In addition, resistance against water—at least against splash water and dust—is demanded.
- Ideally supports the envisioned monitoring scenario with *one sensor node per patient* only. This has been proven to work with only one sensor worn at the wrist of the affected limb, but however strongly depends on the quantitative measures to be realised. If detailed data about movement rates, velocity and movement angles of the limb are needed, several sensor nodes have to be used in parallel of course.
- *Expandability* of the sensing platform should be foreseen to provide the opportunity to integrate further modules or other sensing features later.

3.5 Selection of Key Technical Features

To enable straightforward and convenient use of the GHOST sensor nodes in common therapy practice, the following selections of technical key features have been made to fulfil the prerequisites:

1. Wireless charging was integrated to make sure the sensor nodes do not need to use any cables or wired connections. This enables yet another useful feature to completely close the sensor housing as this might then become resistant to water. This wireless charging protocol further needs to be compatible to the Qi standard and hence, allows for using off the shelf charging stations, e.g. available for smartphones.
2. Due to physical impairments of patients using the platform in daily life, the sensor cannot be integrated into gloves or sleeves. In fact, most patients cannot put on sleeves or gloves on their own.
3. The platform should be of ultra-low-power consumption to enable usage over several hours each day with battery powered sensor nodes.
4. According to power limitations and to the clinical needs to have ADL statistics on daily basis only, streaming data directly to a base station in real time is unfeasible. Also, direct streaming would not allow using the sensors everywhere and anytime during the day, where no base station might be in place. Hence, the activity data is collected and stored on the sensors during the day and uploaded at night, when sensor are recharging near the base station.
5. To apply with legal rules regarding the security and privacy protection requirements, strong security means are integrated. Therefore, the final StrokeBack BAN will be empowered by the crypto-microcontroller of IHP that enables such strong security means even in low-power modes by using the integrated AES and ECC crypto hardware modules.

3.6 Data Flow Concept and Design Requirements

This section introduces the data flow concept that will be implemented in the StrokeBack system followed by the sensor node requirements with respect to the sensor data and other issues to fulfil the BAN objectives.

3.6.1 General Data Flow During Rehabilitation Process

A complete rehabilitation process can only be effective if regular outcome measures and assessment means for the needs of the patient are in place that can efficiently influence the future rehabilitation schedule. Therefore, the StrokeBack data flow concept follows a cycle like approach, see Fig. 3.1.

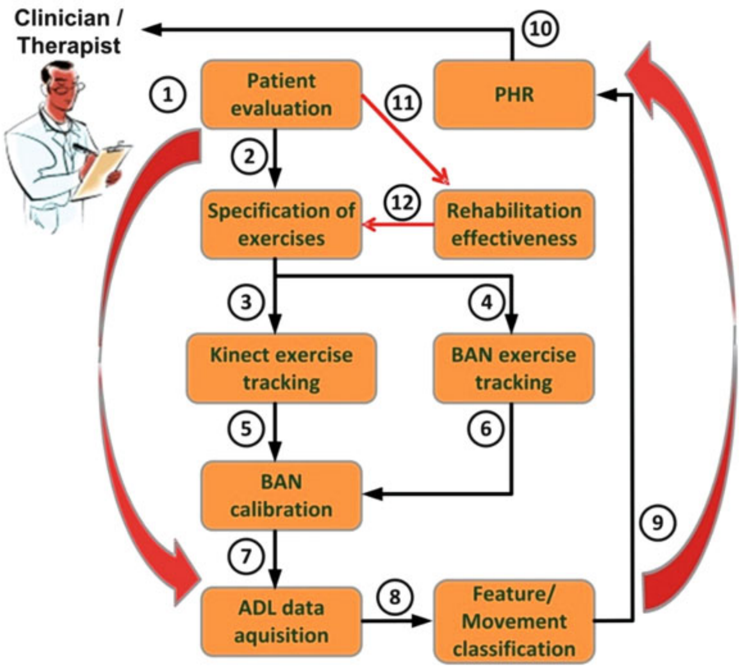

Fig. 3.1 StrokeBack data flow cycle for complete rehabilitation process

It allows analysing the state of the patient in regular intervals and then applying respective feedback and/or corrective measures to the rehabilitation process. With reference to Fig. 3.1, the numbered arrows specify the following data flows:

1. Initially, the clinician or therapist, respectively, analyses the current state of rehabilitation and the patient's rehabilitation needs.
2. According to the patient's needs, individual exercises and a rehabilitation schedule should be specified.
3. Defined exercises are to be executed at the patient's training place at home, which is equipped with Kinect capabilities for movement tracking and training supervision.
4. As all movement data is recorded throughout the day, the BAN in parallel gathers motion data during the training sessions too.
5. Results and effectiveness of training sessions are stored at the patient's home station.
6. Since the patient's home station is the base station for the BAN at the same time, exercises data and recorded BAN data can be compared. We will investigate whether it is possible to use both recorded data sets for autonomous BAN calibration means. This calibration may be necessary due to changed orientation and location of the sensor nodes that may occur due to daily attachment by the patient.

7. Right after attachment of the sensor nodes to the body, each sensor node will record raw motion data throughout the day. Needless to say that recorded raw data will of course be much more precise or better analysable, respectively, after the calibration phase.
8. When the sensor nodes are removed from the patient's body, they'll transfer all recorded raw data to the base station, where these data are processed with different algorithms to analyse ADL.
9. Daily ADL statistics are stored into the patient's PHR.
10. Daily ADL statistics can be seen by the clinicians or therapists at any time and from anywhere via remote access. This in principle closes the cycle of StrokeBack BAN data flow.
11. Access to gathered ADL statistics and training results enables to again analyse and assess the patient's rehabilitation progress.
12. Re-definition or respectively adaptation of the training schedule can be done with respect to ADL statistics or training results.

3.6.2 Daily BAN Data Cycle

The BAN will store all data gathered throughout the day, i.e. when the patient wears it, on the sensor nodes and will submit all data to the base station while recharging during the night. There is no need to establish permanent online connectivity from the sensor nodes to a base station (or gateway). From therapeutical point of view, it is merely required to gather statistics about ADL on daily basis, i.e. the patient's ADL need to be available on the following day in the PHR. In addition, permanent wireless communication would unnecessarily and rapidly drain energy resources from the technical and usability point of view. Last but not least, it would require having a base station in reach of the BAN all day long. For example, the Bluetooth Low-Energy (BT-LE) communication module provides a solicited communication range of up to 10 m within a home environment only.

According to this, the daily BAN data cycle is very simple as well as without the necessity to be triggered by the patient. In principle, the operational mode of the sensor nodes is divided into two phases only, i.e. recording data during the day, when the BAN is worn by the patient, and uploading data to the base station during night, when the sensor nodes reside in recharging position. Each sensor node automatically starts recording and storing data locally right after being removed from the power supply, respectively, the charging device. The sensor node keeps on recording data throughout the day as long as it is unplugged from the recharging station or the battery charge condition undergoes the minimum level required for proper functioning. If any communication between different sensors or between sensors and the base station is necessary, e.g. for synchronisation of time data or calibration issues, this is done automatically without patient intervention.

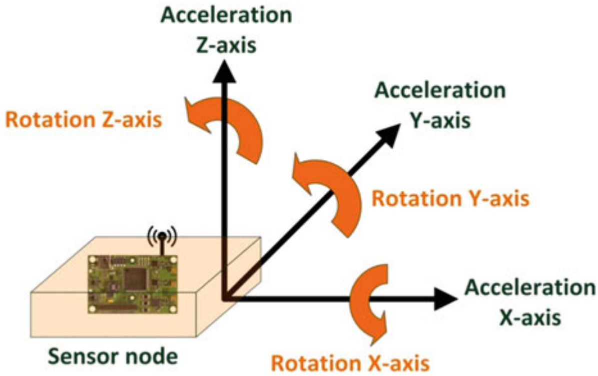

Fig. 3.2 Schematic of rotation and acceleration data measured in relation to the sensor node

3.6.3 Sensor Data Requirements

The sensor node gathers raw sensor data of three-dimensional relational orientation and acceleration. Therefore, the sensor platform includes an accelerometer and a gyroscope sensor that calculates acceleration and rotation data for the *x*-, *y*- and *z*-axes, as schematically drafted in Fig. 3.2.

In addition, the StrokeBack sensor platform includes a magnetometer and sensors measuring vibration. Both sensory options may allow even more improved sensing skills to be investigated later on. Data from the accelerometer and the gyroscope are gathered in a frequency of 50 Hz in the basic setting, which equals to 50 samples per second or one sample every 20 ms, respectively. This is currently driven by parallel investigations using state-of-the-art sensor nodes, which do not support changing the sensing frequency with the given driver implementation. However, usage of lower sampling rates will in future be investigated to save memory and power consumption during operation.

According to that, the expected data recorded throughout the day volume per sensor node and day sums up to a maximum of 50 MB. The accelerometer and the gyroscope sensor each provide three channels (*x*, *y*, *z* axes). Hence, the sensor node records 6 sensor values of 16 bit at every 20 ms. Together with a 64 bit timestamp, the sensor node will store a minimum of 6×16 bit (sensor values) + 64 bit (timestamp) at every 20 ms as raw sensor data. This is equal to 18 bytes (1 byte = 8 bit) at every 20 ms, which sums up to 900 bytes per second and node. In total, we assume to store approximately 1 Kbyte per second on the node. By recording approximately 1 Kbyte per second, one sensor node will record 3600 Kbyte per hour and therefore 43.2 MB pure sensor data during 12 h.

3.7 Other Technical Requirements

3.7.1 Security/Privacy

All data gathered by the BAN are personal/private data of the patient that need to be protected from non-authorised access for the complete data lifetime, as already mentioned. Therefore, data transmitted from sensor nodes to the base station (and to the PHR later on) need to be protected against eavesdropping and malicious damages or changes. The StrokeBack system makes use of the AES protocol, which provides a symmetric cipher for encryption of data streams. Since it is symmetric, both the sender and the receiver need to know the secret encryption key to be able to access encrypted data. In the simplest setting, this secret key has to be selected during the configuration phase of the sensor nodes and cannot be changed during usage of the system. This approach may be suitable for controlled trials, but will become more or less unsecure when the StrokeBack system would be used in its envisioned application for daily rehabilitation monitoring, since the key can then not be changed during operation. Thus, anybody who possesses the configured AES key can then in principle access all data gathered by the system, regardless whether this access is permitted.

To overcome these problems, the final BAN nodes are empowered by the IHP crypto-microcontroller that provides hardware for AES too, but additionally provides energy-efficient integrated hardware accelerators for the asymmetric cipher protocol ECC and the standardised Secure Hash Algorithm 1 (SHA-1) for generation of digital signatures and hashes. The latter can be used to detect unwanted or malicious changes of data, e.g. during wireless transmission. The hardware support for ECC (software variants for microcontrollers exist, but are much too heavy to be used on sensor nodes as side application) enables to implement a public–private key infrastructure in parallel even on the sensor nodes. This is used to implement access control directly on the sensor nodes and to enable secure exchange of new AES encryption keys at any time if needed. On the other hand, this ensures that no sender or receiver other than the authorised base station can communicate to the sensor nodes to exchange information or patient's data.

3.7.2 Synchronisation Protocols

Due to the non-precise and cheap clocks on the sensor nodes, these suffer from different clock drifts over time. That means, even if the clock of all sensor nodes is synchronised at the beginning of the day, e.g. during attachment, it may occur that the sensor data is not recorded exactly at the same time in parallel on all sensor nodes. Since sensor data is recorded at all nodes in intervals of 20 ms, the clock drift during the day must not exceed 10 ms in total to avoid incorrect correlation of motion data taken at different nodes. Communication facilities on the sensor nodes are to be used to synchronise all nodes and timestamps while recording data throughout the day.

3.7.3 Communication

For all communication issues between the sensor nodes and the base station mentioned before, each sensor node is equipped with a wireless communication module. According to previous estimations, it is assumed to transfer about 50 MB of data in total for each sensor node in use per day, including overhead data required for instance for packet headers, checksums, MAC (Medium Access Control) and routing data. Provided that a patient wears three sensor nodes in parallel for the maximum setting (wrist, upper arm, chest), about 150 MB of data have to be transferred to the base station during the recharging phase (at night). Taking the minimum time slot of 5 h for charging and transmission of all nodes into account, the BAN needs to transfer about 30 MB per hour. This equals to 500 Kbyte per minute or about 8.3 Kbyte per second, respectively. To summarise, to comply with the requirements set above, the communication module of each sensor node should provide a minimum transfer rate of 10 Kbyte per second (80 Kbit/s).

For wireless communication, the widely used Bluetooth (BT) standard has been investigated while focusing on using the more advanced BT-LE. Both would provide more than sufficient data rates to fulfil estimated transfer rates. The BT-LE allows data rates up to 1000 Kbit per second (1 Mbit/s). The BT standard even provides data rates of up to 2.1 Mbit/s (Enhanced Data Rate (EDR) mode), but usually consumes much more energy. Unfortunately, a dual BT front end that is compatible to both BT standards in parallel (called 'BT Smart Ready') was not available at the time of the design phase of the sensor nodes. Hence, a single BT-LE module was integrated.

3.7.4 Memory

Estimated raw sensor data of course need to be stored at the node throughout the day. Flash is the currently most widely used technology of non-volatile memory for small devices. In principle, two options of flash memory are available for our application, i.e. tiny flash modules directly assembled on the sensor board or flash memory cards that can be exchanged. Both options are relatively cheap, but feature different advantages and drawback.

Flash memory cards, or micro-SD cards in our case, are very cheap and available as mass product with capacities ranging from several hundred megabytes up to 64 Gigabyte. Further advantages are that they in principle are compatible to other devices and can be replaced easily and hence provide more flexibility. Their drawback is the required size for the SD-card slot on the board and their power consumption. Very small card slots still require a board area of about 12×12 mm, which is already half of the envisioned board size (refer to Sect. 3.9.1). The power supply for micro-SD cards requires around 3.0–3.3 V.

Flash modules for on-board assembly are slightly more expensive than SD-cards and provide less memory capacities. Nevertheless, such modules feature much smaller dimensions than a micro-SD slot and more important: the power consumption is significantly lower. Both features are of utmost importance for the StrokeBack sensor nodes. Hence, we decided to assemble a flash module with 128 MB storing capacity.

3.7.5 Power Supply

Energy efficiency is one of the key aspects when it comes to design of sensor nodes. The more energy the sensor nodes consumes during operation, the more energy need to be available and stored on the nodes to reach a certain minimum operation time. The minimum operation time for each node is assumed 12 h, as introduced before. However, not only the amount of energy consumed by the node itself need to be minimised of course. Obviously, using larger battery packs would solve most of energy supply problems, but there are several aspects that need to be considered as well, in particular from the usability point of view. Larger battery packs might not fit into very small and lightweight sensor cases and will unnecessarily increase weight of the sensor node.

Therefore, the StrokeBack BAN is supplied by very small rechargeable Lithium-Polymer batteries providing several hundred milliamps per hour (mAh). The sensors can commonly be charged via a standard micro-USB adapter. In addition, the StrokeBack sensor nodes integrate wireless power supply based on the Qi wireless power standard [36] for automatically recharging batteries when the sensor node is in charging position. This will enable getting rid of cables and cable plugs and therefore significantly improve patient's experiences and acceptance.

3.7.6 Application Specific Integrated Circuits

The introduced monitoring cycle does not need to facilitate on-BAN movement classification by default. However, the ultimate research challenge of monitoring with body-worn sensors is enabling the BAN to classify and analyse motion data directly on the sensor nodes, without the need to use a base station for post-processing of sensed raw data. Therefore, the StrokeBack team investigated integration of a novel hardware module, called Application Specific Integrated Circuit (ASIC), for accelerating on-BAN movement classification while reducing the amount of recorded data at the same time. This would provide a novel and unique application.

3.7.7 Patient's Safety

Safety in this context means the BAN may not put the patients' health at risk. The StrokeBack BAN is used for monitoring issues only and hence, it does not provide any actuators. Two more features may be considered, i.e. wireless communication and power supply. The exposure of wireless transmission should be kept minimal by reducing the communication frequency and transmission power. This can be neglected for the StrokeBack application scenario, since usage of radio transmission is almost reduced to recharging time when the patient does not wear the BAN. The power supply on the node is very low and the amount of energy stored is small. This should not be a risk for the patient. Furthermore, the charging module on the board includes autonomous temperature control and shuts down the sensor node in case of difficulty while charging and overheating problems.

3.8 StrokeBack BAN Architecture

This section introduces the design and performance of the GHOST platform, which is a tiny sensor platform with inertial sensors, Qi compliant wireless power transfer and an embedded BT-LE (Bluetooth 4.0) front end. In a full package, the complete GHOST sensor platform is of matchbox size only, including a Lithium cell battery pack and a receiver coil for wireless power transfer. This platform is used for detection of ADL within the StrokeBack project, where the platform is worn by patient at the affected limb. It can collect movement data from accelerometer, gyroscope and magnetometer throughout the day, which is uploaded and analysed during the night when the sensor resides in the wireless charging station.

Due to the investigation and implementation of a pre-processing ASIC for the crypto-microcontroller, two variants of the GHOST platform have been designed. In principle, both provide equal functionality as required for the project and trials. The first version is equipped with a state-of-the-art microcontroller of the MSP430x family from Texas Instruments (TI). In the following, this sensor platform is referred to as GHOSTv1. This platform has been rapidly prototyped for testing and necessary CE signing procedure and tests in a third party laboratory.

The second and final version of the StrokeBack sensor node GHOSTv2 is empowered by an individualised crypto-microcontroller manufactured by IHP. This microcontroller is code-compatible to the MSP430x family from TI. The rest of the sensor node components mainly remain the same despite very small changes.

3.8.1 Sensor Node Components

A full list of chosen main components can be found in Table 3.1. Most of these components have been used on both platforms. However, differences in the set of integrated components between both platforms are marked.

Table 3.1 Components of StrokeBack sensor nodes GHOSTv1 and GHOSTv2 according to application requirements at a glance

Component	Specification
Micro Processing Unit (MPU) (GHOSTv1 only)	MSP430F5528
	2× UART/SPI/IrDA
	2× I2C/SPI
	8× ADC
	47× GPIO
	RTC, USB
	128 KB Flash, 8 + 2 KB RAM
	2.32 mA (active, 8 MHz, 3 V)
	1.9 µA (standby, LPM3)
	0.18 µA (LPM 4.5)
	9.8 × 9.8 × 1.0 mm, QFN-64
Micro Processing Unit (MPU) (GHOSTv2 only)	IHP crypto MPU
	2× UART
	2× SPI
	4× ADC
	24× GPIO
	AES, SHA1, ECC
	64 KB Flash, 16 KB RAM
	2× Timer (16-bit, 32-bit)
	Package: 9 × 9 × 2 mm, PQFN-64
Communication module	TI CC2541, BlueTooth
	UART, SPI0 @ 4 MHz
	Low Energy
	18.2/17.9 mA (tx, rx)
	270/1/0.5 µA (LPM)
	6.8 × 6.8 × 1 mm QFN-40
Flash data memory	Micron N25Q00AA
	128 MB
	SPI0,3 @ 54 MHz
	64 byte OTP, unID
	20/6 mA (write, read)
	200 µA (standby)
	6 × 8 × 1.2, T-BGA-24
Battery pack	EEMB LP502030
	Single cell Lithium-Polymer (LiPo)
	3,7 V, 250 mAh, 0.9 Wh
	31 × 20.5 × 5.3 mm
IR remote control (GHOSTv1 only)	Vishay TSOP 75236
	RC-5, 36 kHz
	450 µA (active)
	6.8 × 3.4 × 3.2 mm

(continued)

Table 3.1 (continued)

Component	Specification
IrDA (GHOSTv1 only)	Vishay TFBS 4652
	9.6–115.2 kb/s (SIR)
	30 cm
	2 mA (transmission)
	75/0.1 µA (LPM)
	6.8 × 2.5 × 2.8 mm
LED	Small SMD (not further specified)
	2× System
	2× User
Buttons	C&K KMT 2
1× Reset	150000 cycles
1× User	3.6 × 2.6 × 0.65 mm
Extension	Hirose DF40
	50 Positions
	Max. 300 mA
	12.8 × 3.83 × 1.5 (/2–4) mm
SPI to I2C bridge (GHOSTv2 only)	Silicon Labs CP2120
	3.8 mA (@25 MHz)
	4.2 × 4.2 × 1 mm, QFN-20
Binary decoder	TI SN74HC139 PW
	2 zu 4 (2×)
	Max. 500 µA
	3.1 × 4.1 × 1.0 mm, BGA-20
USB bridge	Micro-USB Receptacle
	SMP U004-0112-01X0-Z
	5 Positions
	9.8 × 6.15 × 3 mm
Wireless power (Qi)	Texas Instruments BQ51050B
	2 × 3.2 × 0.5 mm, BGA-28
Accelerometer	FreeScale MMA8451Q
	3 axes, digital, I2C, 14 bit
	Max. 2/4/8 g
	1024/2048/4096 counts/g
	2.5 V, 44 µA (active, 100 Hz)
	1.8 µA (standby)
	3 × 3 × 1 mm, QFN-16

(continued)

Table 3.1 (continued)

Component	Specification
Gyroscope	ST micro L3G4200D
	3 axes digital
	Max. 250/500/2000°/s
	I2C, SPI3 @ 10 MHz
	16 bit data, 8 bit Temp.
	14, 57, 114 counts/(°/s)
	3.0 V, 6.1 mA (active)
	1.5 mA (sleep)
	5 μA (off)
	4×4×1.1 mm, LGA-16
Magnetometer	FreeScale MAG3110
	3 axes, digital, I2C
	16 bit signed
	10 counts/μT
	138 μA @ 10 Hz (active)
	2 μA (standby)
	2×2.4×0.85 mm, DFN-10
Vibration sensor	SignalQuest SQ-SEN 200
	Omnidirectional vibration
	50 nA
	7.2×3.3×3.3 mm

3.9 StrokeBack Platform GHOSTv1

To cope with the introduced prerequisites, technical requirements and suitable flexibility, the GHOSTv1 sensor platform has been composed of a baseboard providing processing and communication parts as well as a separate sensor board. Both are connected to each other by a small bridgeboard (refer to Fig. 3.3).

This design decision is because the baseboard might also be exploited separately as development platform for usage with other sensors or for different application scenarios. In addition, some components or even selected sensor modules might be exchanged later if proven unusable or not providing expected accuracy.

3.9.1 GHOSTv1 Baseboard

The GHOSTv1 baseboard is made to provide the basic features of each sensor node in a tiny and smart way including the power supply management, sensor control, data processing, data storage and communication facilities. Therefore, the following components have been implemented:

- Microcontroller: The GHOSTv1 is empowered by the MSP430F5528 microcontroller of the MSP430 family from Texas Instruments (TI). It combines conve-

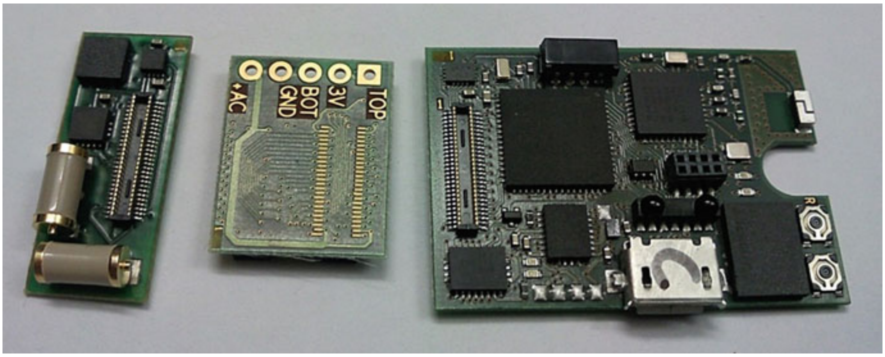

Fig. 3.3 Components of the StrokeBack GHOSTv1 sensing platform with sensor board, bridge-board and baseboard (from left to right)

nient memory resources with low-power processing features and widely used interfaces such as SPI, UART and IIC.
- Communication: Even though the BT-LE standard was brand new at the beginning of the StrokeBack project, we have implemented the CC2451 Bluetooth 4.0 front end from TI in combination with an ultra-small ceramic on-board antenna. The CC2541 front end is connected to the microcontroller via SPI interface.
- Data memory: The board contains a 1 GBit (or 128 MB, respectively) non-volatile Flash memory that should primarily be used as data storage. The data memory is also connected via SPI.
- Infrared communication: As a second communication interface, an IrDA receiver and a respective infrared transponder are included. This infrared communication interface enables to remotely control the sensor node or to allow small data rate communication, e.g. for troubleshooting purposes.
- Wireless power supply: This enables to wirelessly power the sensor node and provide wireless charging by using the BQ51013 chip from TI. The protocol used is fully compliant to the Qi wireless power transfer standard as it is used for smartphones for example. This allows using commercially available mobile phone tools as charging station for the GHOST platform. A key compliant receiver coil needs to be connected to the platform.
- Battery: The platform provides charging and power management for single lithium polymer cells via the BQ24030 chip from TI.
- Other power supply: In addition to the power supply options mentioned, the platform can be connected to a standard micro-USB adapter or other external sources for power supply. The latter option, also defined as AC-in feature later, allows connecting to any linear power source providing voltages from 4.5 up to 16 V, e.g. solar cells.
- Extension header: This header provides SPI, UART and IIC interfaces as well as a couple of GPIO pins for extension of basic features, e.g. by sensors. This header further provides the programming interface for the BT-LE front end using the CC-Debugger from TI.

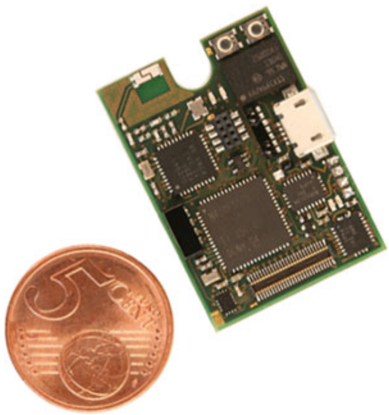

Fig. 3.4 Size of the GHOSTv1 baseboard in comparison to a 5 Euro cent coin

- Buttons: The platform provides two buttons. The first one allows to manually resetting the sensor node. The second one can be enabled for user-defined purposes.
- LED: The platform provides four LEDs, from which two signal the power good status bits from USB and Qi-wireless power inputs, whereas the other two LEDs can be used by the programmer.
- Programming: The platform can be programmed via a micro-JTAG adapter.

The overall dimensions of the GHOSTv1 baseboard are only 45 mm in length, 24 mm in width and merely 4 mm in height, see also Fig. 3.4 presenting the GHOSTv1 baseboard in comparison to a 5 Euro cent coin.

3.9.2 Sensor Board

The small sensor board can be connected to the extension header of the baseboard via the bridging module. The size of the sensor board is about 11 mm in length and 24 mm in width. The sensor board contains the following digital sensors, which are connected to the platform via the IIC interface:

- 3-axis 14-bit digital accelerometer of Freescale Semiconductors MMA8451Q
- 3-axis 16-bit digital gyroscope L3G4200D of ST Microelectronics
- 3-axis 16-bit digital magnetometer MAG3110 of Freescale Semiconductors
- Two vibration and tilt sensors for low power sensing of movements

3.9.3 Bridgeboard

The bridgeboard connects both the baseboard and the sensor board. It further provides extra connectors for power supply and testing purposes. The fully composed GHOSTv1 platform as used in the StrokeBack project is depicted in Fig. 3.5.

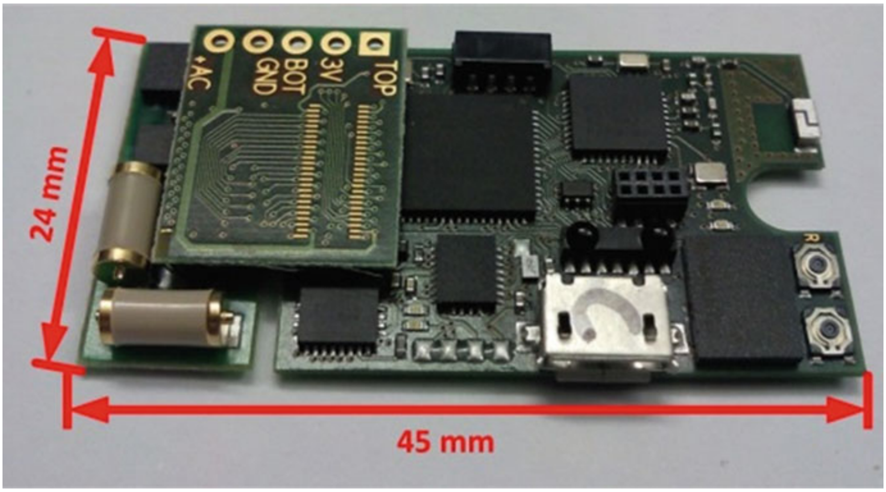

Fig. 3.5 Composed GHOSTv1 sensor node as used for the StrokeBack application

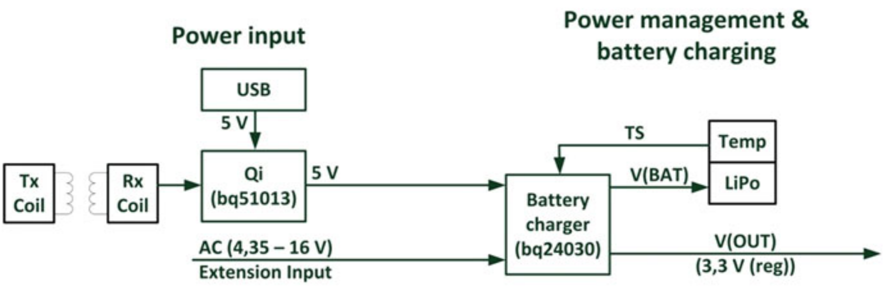

Fig. 3.6 Power supply scheme of the GHOST sensor platform

3.9.4 Power Supply Scheme

As mentioned before, the GHOST platform can be supplied by four different power sources, which are managed autonomously by the platform itself. Figure 3.6 overviews the applied power scheme. To generate the 3.3 regulated voltage output (V_{out}) for the platform, the battery charging circuit BQ24030 regulates charging and power supply from a single lithium-polymer (LiPo) cell. This battery charging circuit can either be supplied by a linear 5 V source or secondly by an input source delivering power in between 4.35 and 16 V. In addition, the battery charging circuit implements autonomous power path management, i.e. it empowers the device and charges the lithium cell when power is available, but automatically taps the battery support when no other power source is available.

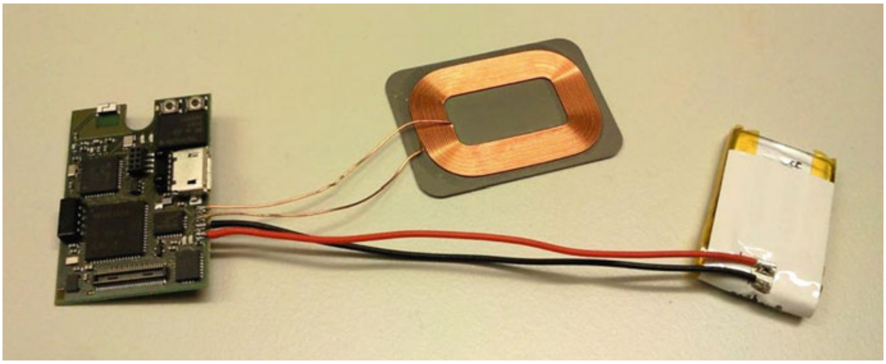

Fig. 3.7 GHOSTv1 board with LiPo battery (*right*) and Qi wireless power coil (*centre*)

The 5-V supply for the charging circuit can be powered by two more supply options, which are the 5-V support from the USB connector (up to 500 mA according to the USB specification) and the Qi compliant wireless power transfer on the other hand. The Qi compliant circuit BQ51013 then regulates input coming from the receiver (Rx) coil, defined to deliver a maximum of 1 A at 5 V. Figure 3.7 shows a GHOSTv1 board with a small LiPo cell and Qi receiver coil.

3.9.5 Sensor Housing

Following the design pre-requirements set by the therapists, the main goal was to achieve a very small and in particular very flat and lightweight design of the final sensor node housing to improve pleasant usage in daily life. It must further fully integrate the LiPo cell and the receiver coil too. Moreover, patients have repeatedly pointed out that the state-of-the-art sensor nodes are too large in height for comfortable and unperceived use, in particular when the sensor is placed at the wrist. The finally selected sensor case, purchased from OKW [37] is depicted in Fig. 3.8. This case is made of plastic fibre (well suited in terms of wireless communication and wireless power transfer) and further is permeable to infrared light (useful for remote control application using IrDA). Finally, this case could optionally be glued to achieve a proper level of water resistance.

The chosen case features the size of a matchbox. It is of 15 mm in height only, while the length is 52 mm and the width is 32 mm. Given sizes are the outer dimensions of the sensor case. The inner dimensions are certainly much more limited. The size of the sensor board itself is limited to a maximum of 35×24 mm. To make matters worse, the inner height of the complete sensor node assembly including the battery pack is limited to a maximum of 8 mm only in the centre and about 6 mm at the outer edges! For the StrokeBack trials, the GHOST platform has been put into this sensor case together with a LiPo cell of 250 mA h and a Qi compliant receiver

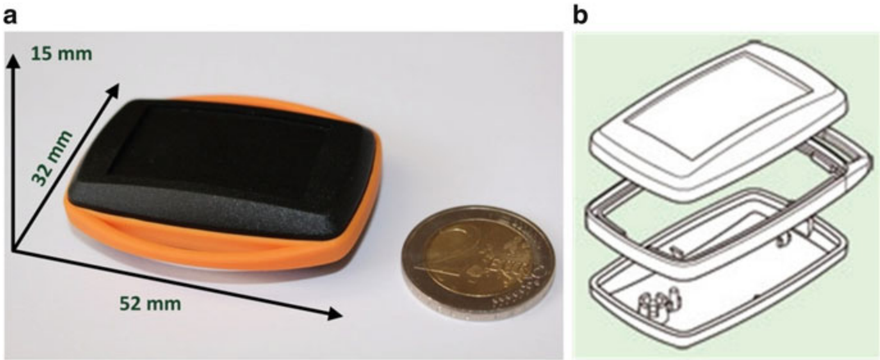

Fig. 3.8 Pluggable housing of matchbox size for complete sensor node in comparison to a 2-Euro coin (**a**) and a schematic view of the case (**b**) from OKW

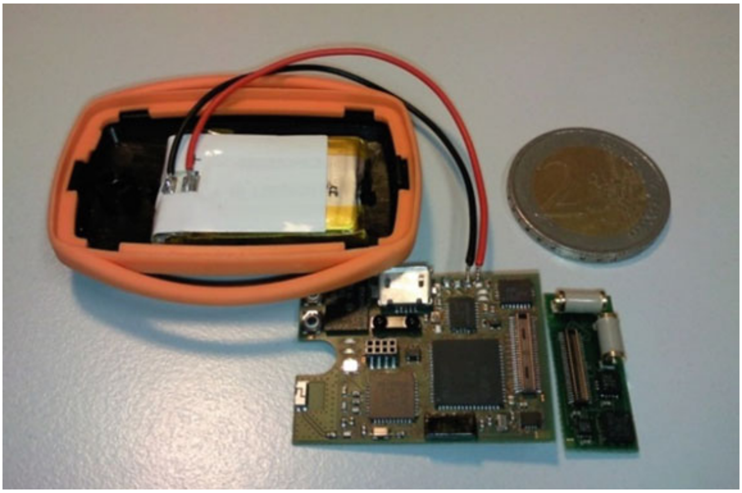

Fig. 3.9 StrokeBack sensor node with LiPo cell and sensor case

coil of 10 µH, see Figs. 3.9 and 3.10. The weight of the fully packaged sensor system is about **21 g** only. The packaged sensor can be recharged by any Qi-compliant charging module, see example in Fig. 3.11.

3.9.6 Usage and Performance Characteristics

The performance of the sensor platform in terms of power consumption is key to meet the desired working time of the platform. In current setting, the applied LiPo cell has a nominal power capacity of 250 mA h, which is one of the smallest LiPo

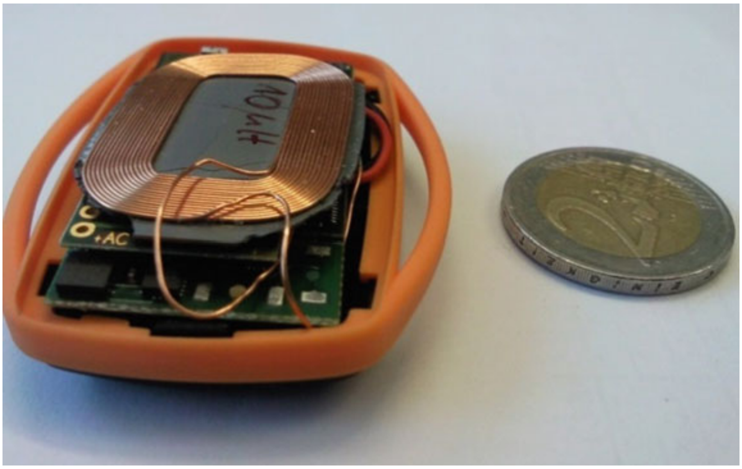

Fig. 3.10 Complete sensor node with battery pack and receiver coil in package

Fig. 3.11 StrokeBack sensor system using a Qi-compliant state-of-the-art charging station

cells available on the market. In contrast to that, the power consumption of the platform during storage of movement data, i.e. when the sensor is worn throughout the day, is at a maximum of 10 mA at the maximum sensing rate if accelerometer, gyroscope and magnetometer are used at 50 Hz data output in parallel. The power consumptions of different working modes of the GHOST platform are presented in

Table 3.2 Power consumption of GHOST platform at different settings

Platform setting	Power consumption
Basis platform (standby/no active sensing, low frequency) @ 3.3 V	<0.5 mA
Operational (StrokeBack setting) @ 1–4 MHz @ 3.3 V (only accelerometer and gyroscope used)	2–5 mA
BT-LE module @ 3.3 V	≤21 mA
All sensors @ 3.3 V	<10 mA max; typical 3–5 mA
Total maximum (StrokeBack setting) @ 3.3 V @ 1 MHz	<40 mA

Table 3.2. The average power consumption of GHOSTv1 is about 5 mA depending on the working frequency of the microcontroller. Thus, the platform might be in theory runnable for 50 h without recharging. However, all experiments done with the battery cells showed that the 250 mA h could not be reached in a real setting.

Whereas the first cells had a real power capacity of less than 100 mA h only, though being sold with a 250 mA h labelling, the capacity of the finally used cells have been tested to provide in between 150 and 220 mA h. That means the working time of the sensor platform when collecting movement data far exceeds the envisioned 10–12 h of data collection during a single day. Please note, the power consumption is of course much higher in case of the wireless data transfer via BT-LE is activated, but this mode is activated only when the sensor resumes in the charging station overnight.

In addition, the embedded temperature shutdown while charging the LiPo cells has been tested in a climate chamber to satisfy a maximum of safety for the patient. To circumvent possible failures and safety risks in overheating of the LiPo cell by over-charging (the might even catch fire) or degradation by sub-zero temperatures, the battery charging module interrupts charging the cell if the cell temperature is not in between 5 and 45°C.

3.10 StrokeBack GHOSTv2

This section will describe the design of the final StrokeBack sensor system, called GHOSTv2. The key design goals have been to reach a more integrated version of the platform as well as incorporating strong security means based on the crypto-microcontroller of IHP.

3.10.1 New Features in Comparison to GHOSTv1

The unique feature of GHOSTv2 is the empowerment of the platform by the IHP-crypto-microcontroller, which in particular allows using the advances of asynchronous cryptography means based on ECC on low-power sensor nodes. In contrast to

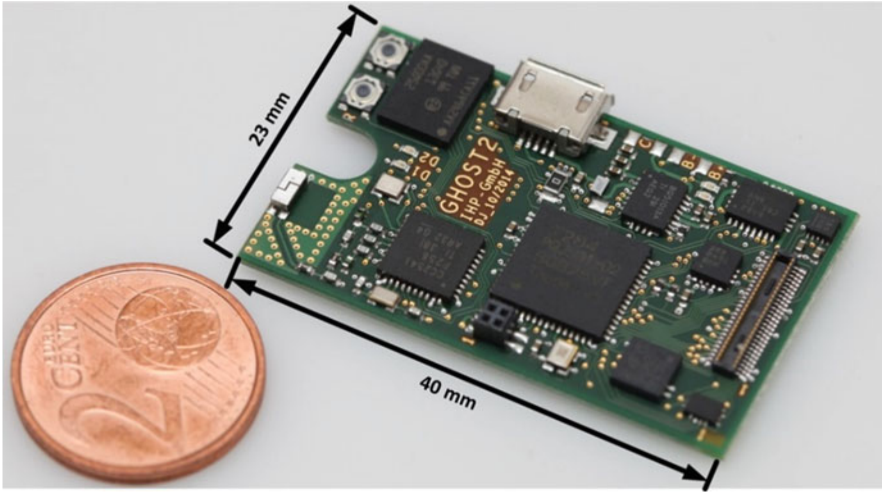

Fig. 3.12 GHOSTv2 sensor platform in comparison to a 2 Euro cent coin. This platform implements all components and sensing required for StrokeBack on a single board

standard AES encryption, the crypto-microcontroller enables using a significantly more secure public–private encryption infrastructure, where each sensor node in the BAN can take part in the encrypted communication without the need of exchanging a session key. In addition, knowledge about the public key of a data provider, which here is the sensor node worn at the wrist, enables the base station to authenticate the data transferred as well as the data source itself. Secondly, the sensors needed for the project, i.e. accelerometer, gyroscope and magnetometer have been incorporated into a single board to minimise the sensor node size, depicted in Fig. 3.12.

3.10.2 Features and Assembly Parameters

The size of the sensor platform has been further reduced from 10.8 cm^2 of the GHOSTv1 platform to 9.2 cm^2 of the GHOSTv2 platform, which in summary is a reduction about 15 % of the sensor board size. The other components and sensor board features are functionally equal to GHOSTv1. Figure 3.13 overviews the features and assembly components of the GHOSTv2 sensor platform.

3.10.3 Attachment to the Body

Two different sensor node placements at the patient's body are investigated as shown in Fig. 3.14. It is currently planned to use three sensor nodes per patient attached to the sternum and to the upper arm and wrist of the affected arm as

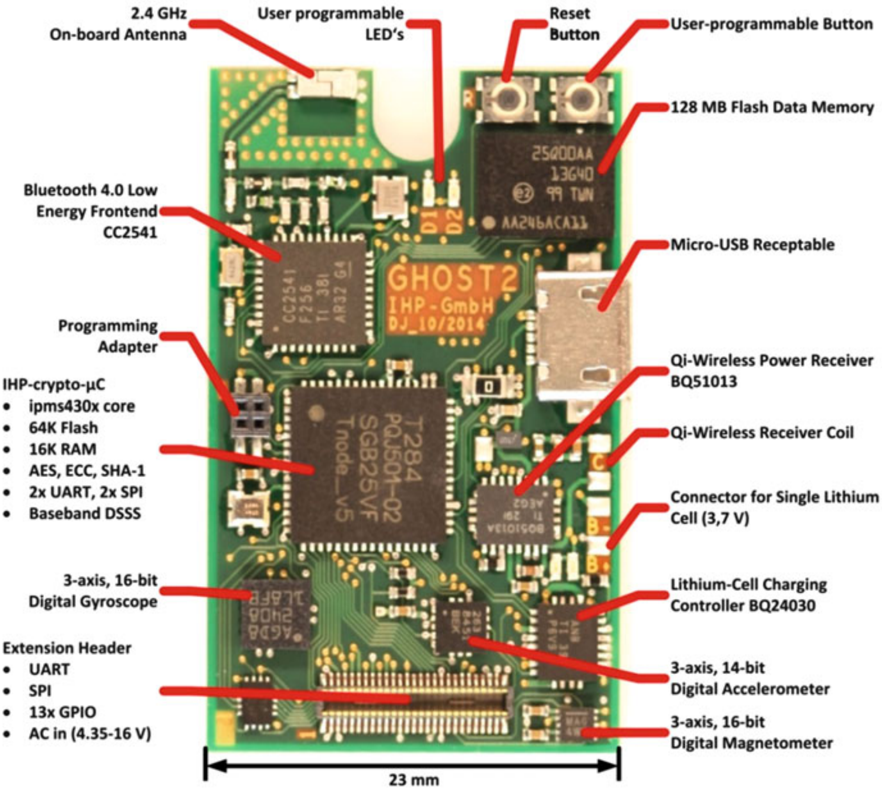

Fig. 3.13 Structure and features of the StrokeBack sensor platform GHOSTv2 at a glance

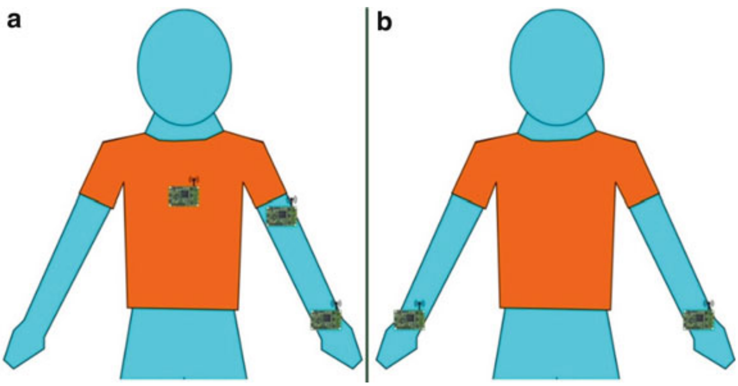

Fig. 3.14 Investigated placement of sensor nodes on the patient's body

Fig. 3.15 StrokeBack sensor node worn at the wrist

Fig. 3.16 Investigated sensor case with slap attachment (strap that self-roles around an arm)

depicted in part (a) of Fig. 3.14. However, the most comfortable setting for patients looks as presented in part (b) of Fig. 3.14, where only two sensors are placed at the wrists of both arms. In addition to the usability aspects, the second setting may allow to compare directly to what daily activities are carried out with which arm. Nevertheless, the second setting definitely provides less data that may not be enough to classify properly daily activities.

Having decided where to place the sensors on the patient's body, the final question is how to fix them at the patient's body? As the investigations of suitable algorithms and sensor placement for detection of ADL have found out that a single sensor worn at the wrist of the affected arm of a patient can satisfy basic detection needs, a watch-like attachment to the wrist is desired. For the beginning, a flexible strap is used to fix the sensor node to the wrist as presented in Fig. 3.15.

However, this strap might not be easily handled by all patients, especially not by patients with increased impairments. To solve that issue, the use of a self-rolling strap for single-handed use was investigated. Therefore, the sensor node is integrated into a slap bracelet as depicted in Fig. 3.16. This memory-metal

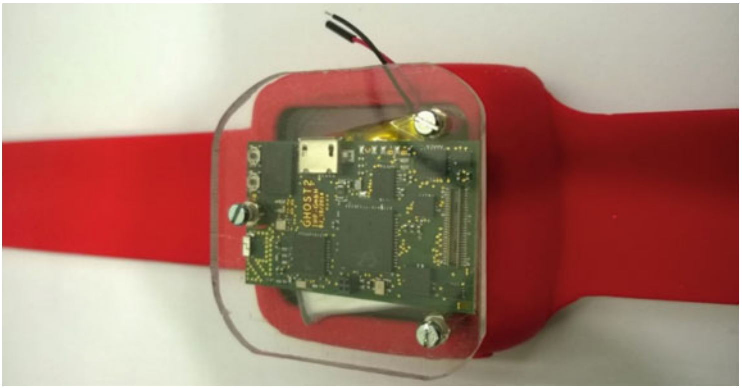

Fig. 3.17 GHOSTv2 sensor platform integrated into the selected self-rolling strap for automatic wrist attachment

wristband is enclosed with soft silky silicone and originally used to as housing for an iPod nano [38]. The spring-steel band lies flat and rigid until it is 'slapped' onto the arm. A slap band self-adjusts to comfortable fit, exactly the size of a patient's wrist.

As depicted in Fig. 3.17, a lithium cell battery and a GHOSTv2 sensor node was successfully embedded into such strap. It is obvious that such embedded design is useable for pre-prototype design investigations, but a fully integrated and fashionable design is out of scope of the project.

The same way of attachment might be feasible for the upper arm sensor too, depending on the perimeter of the arm. Otherwise, the chest and upper arm sensors will be attached by elastic textile straps with hook-and-loop fastener. Investigations of other potential attachment methods, e.g. integration of sensors into clothes, are out of scope of the project, since it would limit everyday use of the sensing devices.

3.11 Sensor-Instrumented Objects

The primary purpose of the BAN is to identify particular types of movement of the affected arm of a patient, but in reference to the therapy means reflected in former deliverables, the sensors may also be embedded into object for therapy means. We investigated two types of such therapy means, presented below.

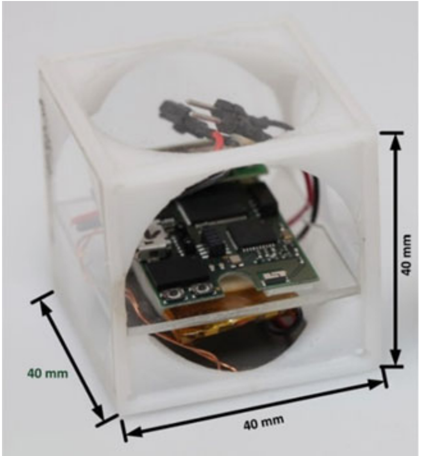

Fig. 3.18 Example of minimised sensor-equipped therapy cube using GHOST platform

3.11.1 Sensor Cube

The use of small coloured cubes for training of fine-grained finger skill is common in occupational therapy. Thereby, the patient has to spin a cube laying in his palm with his fingers of the same hand only. The goal of this 'game' is to spin the cube until the targeted colour appears on top. Each target colour has to be reached as fast as possible. The target colour is thereby pre-given by the therapist. To use such a therapy in StrokeBack, we embedded a sensor node into such a coloured cube on the one hand, and have implemented dedicated software with a GUI that wirelessly communicates with the sensor node on the other hand. A showcase (not-coloured but transparent) prototype of the cube design is shown in Fig. 3.18.

While running the 'cube game', the GUI randomly sets a target colour and assesses orientation data from the sensor cube. The orientation of the cube is calculated from data provided by the inertial sensors of the GHOST node inside the cube, which is streamed in real time to the software running on the training device. Based on that, the software can determine which colour is currently shown on top of the cube and set a new colour of a targeted one has been successfully detected. At the end of such 'game', the software provides user statistics about the gaming time, successfully detected (top) colour, fasted level, slowest levels and average results as result file for the PHR. For patient use in the clinic, we have developed a 'prototype' of such coloured cube made of paperboard, see Fig. 3.19, where we have embedded the receiver coil for wireless power transfer too (Fig. 3.20).

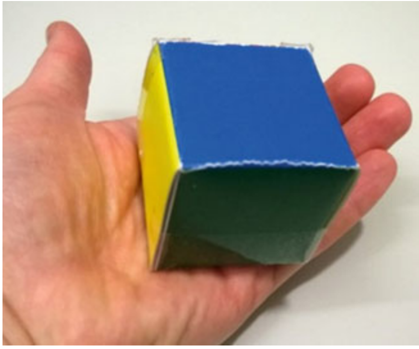

Fig. 3.19 Sensor cube for use in therapy

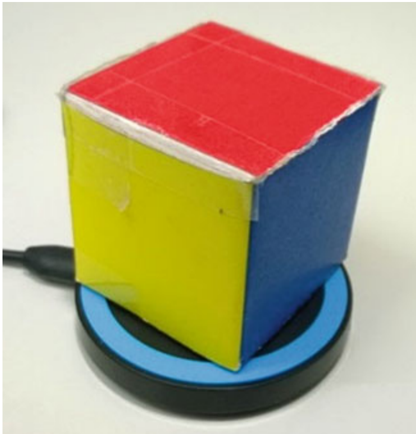

Fig. 3.20 Wireless charging of a cube

3.11.2 Multi-Function Board

As a second means of therapy with instrumented objects, an electronic variant of the multi-function board was investigated. Such board consists of a matrix of 8×8 holes, where the patient has to put object into those in a pre-given way and as fast as possible. An electronic variant used a sensor node for remotely controlling such a device and allowing active interplay of the patient with a multi-function board. Thereby, the patient is visually instructed where to put objects in the holes, whereas the board automatically detects whether task was successfully completed.

The technical concept was using configurable RGB LEDs for illuminating holes with different colours and respective photo-resistive diodes in each hole to determine whether objects have been placed or not. An example of such application is depicted in Fig. 3.21. There, the task was to put bars into each hole of a row that was illumined by red light. When the sensor node detects a bar inside a hole—by sensing

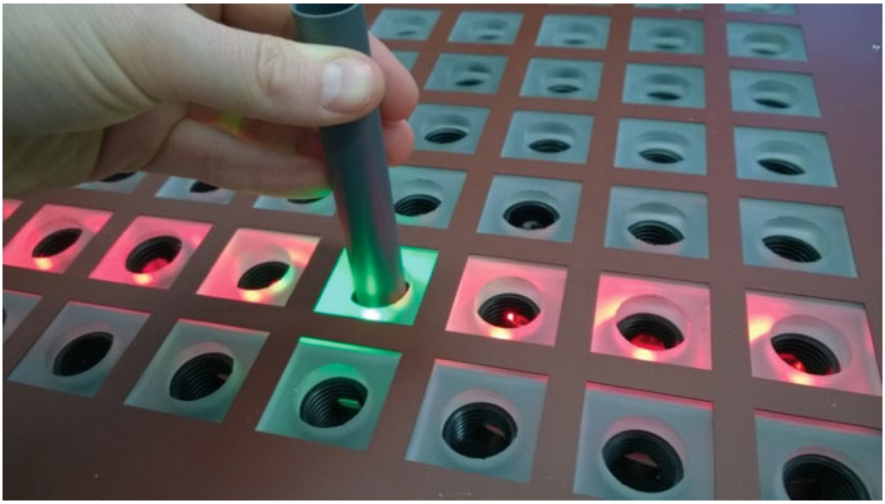

Fig. 3.21 Example use of the sensor-fitted multi-function board. The board automatically recognises plugging objects in and provides optical feedback for the patient (here *green light* for correct input of bar in respective hole)

changes of reflected light by diodes—it changes the luminous colour from red to green. Note that this work is still under development.

3.12 Conclusions

This chapter introduces the design and performance of the GHOST platform, which is a tiny sensor platform with inertial sensors, Qi compliant wireless power transfer and an embedded BT-LE (Bluetooth 4.0) front end. In full package, the complete GHOST sensor platform is of matchbox size only, including a Lithium cell battery pack and a receiver coil for wireless power transfer. In addition, the second version of GHOST features a novel security chip offering efficient data encryption means using a highly secure ECC hardware.

The GHOST sensor allows detection of daily living activities of people under rehabilitation. Following the prerequisites set by therapist and physicians, the use case scenario for patients is extremely user-friendly. The GHOST system is worn on the wrist of the affected arm like a watch. There are only two actions per day required by the patient, i.e. the patient has to take the sensor from the charging station and put it on the wrist in the morning, and merely put it back to the charging station in the evening. The sensor will automatically collect necessary data during the day and transfer it into a PHR over night while charging.

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Chapter 4
Body Area Sensing Networks for Remote Health Monitoring

Dwaipayan Biswas, Andy Cranny, and Koushik Maharatna

Abstract This chapter explores the field of remote sensor systems using wearable technologies that play a significant role in monitoring activities of patients in home and community settings. The focus is on body area sensing networks incorporating the primary enabling technologies: sensors for capturing the physiological and kinematic data, and data analysis techniques for extracting the clinically relevant information. With respect to the StrokeBack project, the majority of this chapter is dedicated towards physical activity monitoring—a key component in stroke rehabilitation. In particular, the domain of upper limb rehabilitation is examined since reduction of upper limb motor function is a common effect of stroke and significantly impairs the performance of patients as they engage in activities of daily life. As an example, a case study is presented where different arm movements are recognized in real time using data from inertial sensors attached to the arm. Tracking the occurrences of specific arm movements (e.g. prescribed exercises) over time can give an indication of rehabilitation progress since the frequency of these movements is expected to increase as motor functionality improves.

4.1 Introduction

Increased life expectancy due to better medical facilities in developed nations has increased the prevalence of health impairments among the ageing population. Among the many diseases afflicting the elderly is cerebrovascular accident (CVA), more popularly referred to as stroke, which ranks second to coronary heart diseases [1–3]. Stroke is considered as a medical emergency due to its impact, generally causing some degree of physical disability and potentially leading to death. The effect of stroke is different for each individual based on the degree and region of the brain that suffers damage and can result in partial paralysis, impaired vision, memory loss and speech problems [4, 5]. The after-effects of stroke pose a serious socio-economic challenge in terms of loss of lives, disability among the survivors and the expenses incurred towards their rehabilitation and care.

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Patients who are left paralyzed post-stroke are often treated with physiotherapy in order to restore their motor functionality. The level of physiotherapy needs to be as intensive as possible in order to ensure fast recovery [6]. Apart from conventional physiotherapy, rehabilitation therapies have been provided in clinical settings using functional electrical stimulation (FES), often involving the use of a controller like an iterative learning control (ILC) [7, 8]. Robotic technology has also been used in FES systems to assist patients in performing their rehabilitation exercises [9]. Other methods employed include virtual reality [10] and constrained induced movement therapy [11, 12]. Although there has been some success in achieving motor recovery in patients by these rehabilitation methods, a major disadvantage is that they are restricted to use in clinical settings because they involve many appliances and hence require unnecessary patient transfer to the clinic. Moreover, the use of sophisticated robotic frameworks, the need to correctly place sensors and the use of specialized software necessitate trained personnel to use the systems, which diminish their practicality in home settings. Hence, the clinical outcome of rehabilitation is often unsatisfactory among a wide group of stroke survivors [3]. The high socio-economic impact of post-stroke rehabilitation demands the development of a telemedicine system for devising a long-term and effective treatment strategy in home settings, thereby also helping to reduce costly human intervention [13]. A specialized application of telemedicine for stroke rehabilitation called "Telestroke" has been in practice for quite a long time and has had major success in delivering "around-the-clock" specialist clinical evaluation of stroke survivors in home settings [14].

Rehabilitation is primarily aimed at restoring a level of physical and psychological functioning within patients that allows them to re-integrate themselves back into their daily life [15]. Rehabilitation guidelines are specifically bespoke to the requirements of each individual with an aim towards optimizing balance, mobility and gait functionality. Monitoring of physical activity and specific physiological parameters are the key components in interventions aimed at maintaining health and well-being, preventing falls and reducing motor functionality loss and the risk of recurrent stroke [16]. Measurements of various physiological parameters such as heart rate, respiratory rate, blood pressure, blood oxygen saturation and muscle activity are also useful for clinical evaluation of patients during rehabilitation [17].

Physical activity has traditionally been monitored by questionnaires, citing its usefulness in covering large subject groups and cost-effectiveness [18, 19]. These questionnaires can be completed by the patients themselves on a daily basis at home; manually or electronically through computing facilities. This data helps to formulate a patient activity log which is monitored periodically by the respective clinicians. There are also a wide range of clinical tests that are quite popular and performed by the therapists to assess rehabilitation of survivors within a clinical environment. The Wolf motor function test (WMFT) [3, 20, 21], Box and Block (B&B) test [22] and the Nine Hole Peg (NHP) test [23] are some of the popular means to assess the patient's motor ability while they perform designated tasks under the observation of a therapist. These tests are generally associated with a scoring system which is used to quantify the performance of the subjects. However, subjective measures of physical activity may overestimate activity levels as compared to assessments made by objective measures [24]. Hence, sensor-based telemedicine modalities provide an alternative towards objective measurement for patient monitoring [25, 26].

Recent developments in the fields of wearable technology, sensor miniaturization, communications and advanced processing techniques have enabled a new paradigm in patient monitoring within the home environment. They have led to the development of body area network (BAN) or body sensor network (BSN) systems which comprise miniaturized wireless-enabled sensor nodes positioned directly or indirectly (e.g. clothes, belts, shoes, wristwatches, mobile devices) on the human body. They are used to capture physiological signals that are reflective of the physiological state of the subject and also used for capturing kinematic data when the subject wearing them performs any movement or activities. Apart from sensing, front-end amplification, microcontroller functions and radio transmissions have all been integrated into a single circuit, thus resulting in a system-on-chip (SoC) implementation [27].

A holistic overview of a typical wireless BAN system for remote healthcare monitoring is shown in Fig. 4.1. Measurements obtained from the sensor nodes are transmitted to a central hub which can be in the form of a personal digital assistant (PDA), a smartphone, a personal computer or a microcontroller-based device.

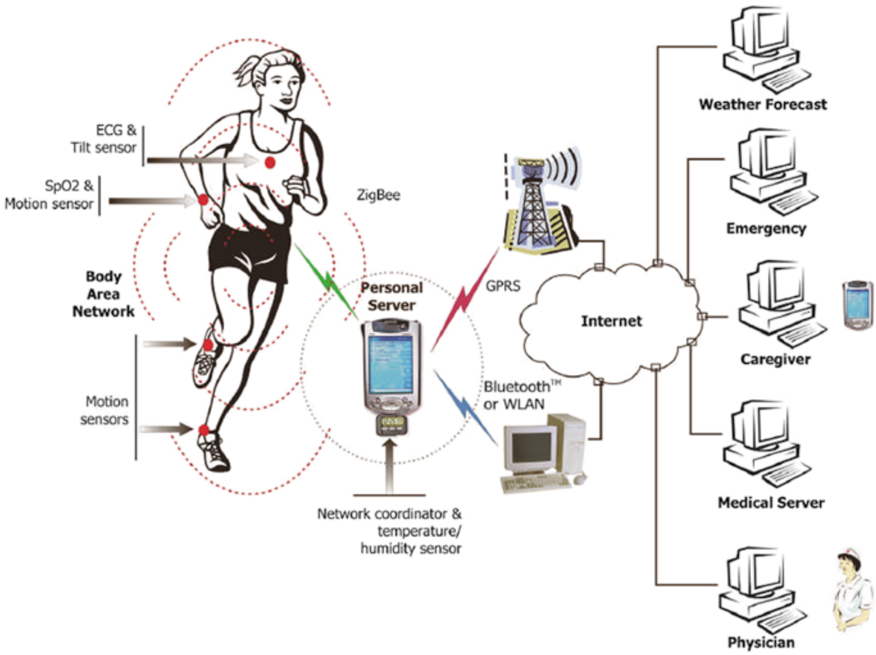

Fig. 4.1 Overview of a wireless body area network system for remote healthcare monitoring. On-body sensors monitor physiological parameters (ECG, SpO2) and motion and postural data. The collected data is transmitted to a PDA and/or transmitted through GPRS/Bluetooth to a medical server, physician or caregiver for further intervention [28]

The central hub acts as a gateway and can be used for displaying the vital information on a user interface or transmitting the clinically relevant information to a remote medical centre or authorized caregiver [28].

The sensor nodes may contain accelerometers, gyroscopes, magnetometers and bio-amplifiers and can be attached to the body and used for recording kinematic data. Additionally, sensors for monitoring vital physiological parameters, such as electrocardiography (ECG) and electromyography (EMG), may also be included. Recent advances in material science have led to the development of e-textile-based systems which integrate sensing capability into garments. The sensors embedded on the garments can be used for collecting ECG and EMG signals, by weaving the electrodes into the fabric, and also used for gathering kinematic data by printing elastometer-based substances on the garments and sensing changes in their electrical characteristics (resistance or capacitance) associated with stretching of the garments when movements are performed by the wearer [24, 28]. Some remote health monitoring systems have also combined wearable sensors and ambient sensors (sensors and motion detectors on doors, objects of daily use such as RFID tags) with an aim of developing smart homes that provide intelligent systems for health assistance in the subject's living environment, also referred to as ambient assisted living (AAL) [29, 30]. In this context, information collected by body-worn sensors can be augmented by the data from ambient sensors, such as motion sensors, distributed throughout the home environment to determine the pattern of activities performed by the patient and provide feedback concerning exercises and living behaviours for better health management.

4.2 Physiological Monitoring

Research into remote health monitoring over recent years has led to the development of many research prototypes [31–34], commercially available systems [35–41] and smartphone-based systems [42–46]. These developments have enabled long-term physiological monitoring of various clinically important parameters including heart rate, blood pressure, oxygen saturation, respiratory rate, body temperature and galvanic skin response, thereby improving the diagnosis and treatment of life-threatening incidents involved in cardiovascular or neurodegenerative disorders [47].

A medical sensor platform, Code-Blue, was developed at Harvard University which could monitor multiple patients and consisted of custom-designed biosensor boards for pulse oximetry, three-lead ECG, EMG and motion activity [48]. It also caters to the transmission of data from the sensors to multiple receivers which include PDAs with the clinical staff. Live-net is another system developed by the MIT Media Laboratory for detecting Parkinson-like symptoms and epileptic seizures by using sensors to measure three-dimensional acceleration, ECG, EMG and galvanic skin conductance [35].

As part of the research initiatives undertaken by the European Commission over the years, some of the projects worth mentioning in the field of remote health monitoring employing a wearable sensor platform are: MyHeart [49], WEALTHY [50] and MagIC [51]. These projects mainly led to the development of garment-based wearable sensors for general health monitoring of people within the home and community settings. One such project was AMON that led to the development of a wrist-worn device capable of monitoring blood pressure, skin temperature, blood oxygen saturation and ECG [52].

A custom-built u-healthcare system consisting of ECG and blood pressure sensors as well as a cell phone for signal feature extraction, communication and display was developed in [53]. Only abnormal or alarming ECG and blood pressure (BP) patterns are transmitted to the hospital server, rather than transmitting all collected data, to save power. A wrist-worn sensor was used to record blood pressure readings and transmitted to the hospital server if found to be out of range.

A BAN including sensors to measure ECG, PPG and PCG was developed in [54]. Another embedded sensor system named Bi-Fi was developed for wireless bio-signal recording, incorporating ECG, EEG and SpO2 sensors which performed on-board signal processing to cut-off transmission power [55]. A system named BASUMA [56] was developed with custom non-invasive sensors for monitoring parameters such as ECG, air and blood content of a thorax, body temperature, breath rate and cough control, blood pressure, pulse rate and oxygen saturation.

A research project in the Netherlands (Human++) developed a BAN consisting of three sensor nodes for acquiring, amplifying, filtering, processing and wirelessly transmitting multi-channel signals of ECG, EEG and EMG [57]. An autonomous pulse oximeter was developed in Belgium research centre IMEC that transfers the body heat of the wearer into electrical energy storing it in a super capacitor for short-time storage, replacing batteries [58].

There have been some designs which have targeted novel sensor locations like the one mentioned in [59], where a sensor worn as a ring measures blood oxygen saturation (SpO2) and heart rate. The ring sensor has techniques integrated within for motion artefact separation to improve measurement accuracy. This system was used for diagnosing hypertension and congestive heart failure.

A microphone was used for measuring respiratory rate by placing it on the neck to capture acoustic signals associated with breathing. The signals obtained were band-pass filtered to remove noise and artefacts and used for detection of obstructive sleep apnea (OSA) [60]. A low-power flexible, ear-worn PPG sensor was developed for heart rate monitoring which was suited for long-term monitoring owing to its unobtrusive design [61]. However, the system suffered from motion artefacts which adulterated the sensor signals.

Chemical sensors have also been used in wearable systems to detect and monitor the presence of harmful compounds and alert people working in hazardous environments. A non-invasive wearable closed-loop quasi-continuous drug infusion system was developed by researchers for measuring blood glucose levels and infuses insulin automatically [62].

4.2.1 Mobile Phone-Based Physiological Monitoring

The use of mobile phones has also been very popular in recent years, where the inbuilt inertial sensors have been used for collecting data. With the advent of smartphones having Internet connectivity and expandable low-cost memory, they have also been used as a base station with which other sensors communicate and also used as a display unit. We will review a few phone-based wearable health monitoring systems.

A prototype system developed by Microsoft (HealthGear) consists of a noninvasive blood oximeter, a sensor assembly to measure oxygen saturation and heart rate signals, Bluetooth-enabled wireless transmission and a cell phone for user interface. This has been used for detecting mild and severe OSA. The system also had satisfactory feedback from the users in terms of wearability and functionality [47].

A cell phone-based real-time wireless ECG monitoring system (HeartToGo) was developed for the detection of cardiovascular abnormalities [46]. A mobile care system developed in [44] utilizes a Bluetooth-enabled blood pressure monitor and ECG sensor. A mobile phone was used as the processing core with an alert mechanism generated depending on the detection of an emergency situation. Finally, an application for detecting arrhythmia events has been described in [43] which used a handheld device as a PDA. The PDA serves as the smart device for processing and analysing the continuously transmitted ECG signals. It also communicates remotely with a clinician, transmitting alarm signals and minute long raw ECG samples.

A wearable system for stress monitoring depending on the emotional state of an individual (AUBADE) has been developed by researchers [63]. It consists of a 3-lead ECG sensor and a respiration rate sensor strapped to the chest, a 16-lead EMG sensor embedded in textile and a galvanic skin response sensor attached within a glove. It employs an intelligent emotion recognition module with a three-dimensional facial representation mechanism to provide feedback.

4.2.2 Commercially Available Systems

A range of wearable health monitoring systems are already commercially available, such as the wrist-worn device called Vivago WristCare for monitoring skin temperature, skin conductivity and movement [42]. A similar device known as SenseWear Armband monitors ambient temperature and heat flow [41]. Both communicate collected data to a base station and report any alarming situations for further evaluation by responsible clinicians. A washable lightweight vest including respiratory rate sensors, one-lead ECG for heart rate measurements and an accelerometer for activity monitoring was developed by VivaMetrics and known as LifeShirt [38]. Another garment-based physiological monitoring tool for monitoring heart rate, respiration rate, posture, activity, skin temperature and GPS location was developed in [37], known as Watchdog. Sensatex also came up with a smart

T-shirt-based wearable system for measuring ECG, respiration rate and blood pressure working on conductive fibre sensors [64]. A mobile cardiac outpatient telemetry (MCOT) system was developed by CardioNet for measuring ambulatory ECG aimed at treating patients with arrhythmia [36].

Manufacturers like Philips [65], Nellcor [66], Agilent [67] and Nonin [68] are providing low-cost, lightweight fingertip pulse oximeters providing real-time display of heart rate and blood oxygen saturation. Chest-worn belts and wristwatch for displaying heart rate measurements have been developed by Polar [69] and Omron [70].

4.2.3 Safety Monitoring Systems

A number of devices designed for safety monitoring are already commercially available. Simple systems such as Life Alert Classic [71] and AlertOnce [72] provide the basic facility of manual alarm activation through the use of a push button contained in a wristwatch. When activated by the user, an alarm message is transmitted to the nearest remote care facility, and the appropriate emergency response is initiated. By comparison, the Wellcore system is more sophisticated and uses accelerometers and advanced microprocessors to monitor the body position and is able to detect falls and generate an alarm message in times of emergency that is relayed to the nearest response centre [73]. Another such device in the form of a chest strap is MyHalo [74], which can be used for detecting falls, monitoring heart rate, skin temperature, sleep/wake patterns and activity levels. The BrickHouse system also employs an automatic fall detector and an alarm generation facility [75].

Reliable fall detection using wearable sensors has also been a well-researched topic, and there exists various research prototypes. An automatic fall detection and alarm generation device was developed by researchers at CSEM [76]. They achieved high recognition precision with simulated falling situations with a wrist-worn sensor, which was easy to put on. There have been other alternative approaches where researchers have embedded a tri-axial accelerometer in a custom-designed vest to detect falls. A barometric pressure sensor has also been used to measure altitude and discriminate fall situations from normal bending down or sitting down activities [77]. An accelerometer embedded in an assistive device such as a cane, which is used by many elderly people for maintaining balance, was used as a fall detecting mechanism in the Smart-Fall system [78].

Smartphones have also played a major part in modern fall detection systems, where it is augmented by the GPS facility within the phone to detect the location of the subject who has fallen [79]. The accelerometer within the smartphone was used effectively for robust detection of falls along with the Google map facility for locating the event, and an associated alarm was generated to the respective caregiver or to the family members through a messaging facility (sms) [80].

More recently, there has been a paradigm shift towards prevention of fall-related injuries by pre-empting a falling incident and using airbag technology to minimize impact [81]. However, further development in the miniaturization of airbags is necessary to produce unobtrusive and comfortable systems that would be acceptable to the user. A system designed to detect freezing of gait (FOG) events that are commonly associated with neurological disorders such as Parkinson's disease was developed in [82]. It provides subjects with a rhythmic auditory signal for stimulating them to resume walking when an FOG episode is detected. An android application, iWander, using GPS and communication facilities available on the smartphone was developed to provide assistance with tracking location for subjects suffering from dementia [83].

4.3 Activity Monitoring

Activity monitoring is a well-researched and broad topic. Human activity monitoring has gained prominence with the use of wearable sensors and video-based sensing technologies and is a major area of remote health monitoring systems. For post-stroke rehabilitation, tracking the number of times a patient performs specific movements (e.g. exercises) with their impaired body parts (e.g. paretic arm) during training and also throughout the day can provide useful information on the progress of the patient. The frequency of specific movements and the quality of the movements performed (e.g. fluidity/smoothness) are likely to increase as the motor functionality of the patient improves. It can also provide information on the patient's compliance to the specific guidelines set by the respective clinicians during rehabilitation training.

Rehabilitation is primarily carried out by repeated exercises of the impaired limb to maximize the chances of recovery [84]. However, it is well perceived in the medical community that exercises alone do not suffice for achieving a speedy recovery due to various factors. This is due to the lack of motivation among patients to exercise for sustainable period of time and the fact that exercises comprise only a minor proportion of time and energy spent by a subject as compared to the wide range of activities performed throughout the day. Moreover, patients tend to compensate their paretic arm with their non-impaired arm, making rehabilitation progress slower [85–87].

Home-based rehabilitation through monitoring of specific activities has gained prominence over the recent years through the development of various exercise platforms [88–90], virtual reality (VR)-based systems [91, 92], gaming consoles [93, 94] and the widely popular Kinect camera-based system [95]. These approaches mainly aim to monitor the rehabilitation progress of the patients during the exercise or the training phase in a controlled environment within a designated zone (exercise/gaming platforms and vicinity of camera systems). The main difficulty with this approach is that it offers no possibility to monitor the movement quality of the patients and their compliance with the prescribed exercises in their natural environment (i.e. while performing daily activities) which are more objective reflections of the actual rehabilitation state and of the effectiveness of the prescribed therapy.

Hence, there has been a growing demand to monitor subjects as they perform their daily activities within their home and community settings. Quantifying the daily activities performed by patients would help to ascertain their degree of participation and thereby formulate a qualitative index of their lifestyle [96]. A taxonomy of activities known as Activities of Daily Living (ADLs) developed by [97] gained prominence in the research community owing to its relevance to real-world applications. Typical examples of ADLs include brushing teeth, combing, washing, cooking, bathing or walking [98–102]. Accordingly, there have been extensive research efforts to assess the accuracy of wearable sensors in classifying ADLs [103–107] which has supported medical diagnosis during rehabilitation and augmented traditional medical methods in recovery of chronic impairments [108].

Human activity recognition (HAR) is a challenging and highly researched topic in many diverse fields which include pervasive and mobile computing [109, 110], context-aware computing [111, 112] and remote health monitoring systems which also include AAL [113–117]. Advances in wireless sensor technology have caused a paradigm shift from low-level data collection and transmission to high-level information integration, processing and activity recognition [118]. The different approaches are variants of the underlying sensor technology, the machine learning models and the environment in which the activities are performed. Before embarking on activity modelling and recognition methodologies, it is imperative to understand the different levels of granularity inherent in human behaviour.

4.3.1 Movement Categories

Depending on the complexity of activities performed, they can be categorized into mainly four different levels: gestures, actions, interactions and group activities. Gestures are movements performed by the subject's body parts which are atomic components comprising any holistic movement. Some common examples of gestures are raising the hand or stretching the leg. Actions are activities performed by individuals that are composed of multiple gestures aligned together to form a meaningful movement. For example, walking or reaching and picking a cup can be described as completed actions. Interactions are used to describe human–object or human–human interaction like making tea. Group activities, as the name suggests, are performed by multiple persons, for example, a group marching together [118, 119].

Activity recognition is a complex process and can be categorized into four main steps: (1) choice and deployment of appropriate sensors and the environment in which the activity will be performed; (2) collection, storage and processing of information through data analysis techniques and knowledge representation formalisms at appropriate levels of abstraction; (3) creation of computational models which allows reasoning and manipulation and (4) to develop reasoning algorithms from sensor data that helps to recognize activities performed.

4.3.2 Modalities of Activity Recognition

Home-based activity recognition can be classified as: vision-based and sensor-based recognition. Vision-based activity recognition uses visual sensing facilities, such as video cameras and still cameras, to monitor a subject's movement in a designated area. The generated sensor data are video sequences or digitized visual data. Recognition of activities further takes place by the use of computer vision techniques which include feature extraction, structural modelling, movement segmentation, action extraction and movement tracking to analyse visual observations. The use of gaming consoles with camera systems and also the Microsoft Kinect has been quite popular in the field of rehabilitation. However, they suffer from occlusion problems since they are designated to mostly indoor activities with their surveillance restricted within a specific zone. Moreover, inferring the movements performed often involves the use of complex image processing algorithms [120].

Sensor-based activity recognition was further explored owing to a paradigm shift towards monitoring of activities in unconstrained daily life settings. The sensors used in activity recognition mainly generate time series data of various parameters or state changes. The data is processed through statistical analysis methods, probabilistic models, data fusion or formal knowledge technologies for recognizing the underlying activity. Sensors for activity recognition are generally attached to the body of the subject as wearable sensors or are inherent in portable instruments such as smartphones. Sensors can also be embedded within the living environment of the subject and thereby create ambient intelligent applications such as smart environments. For example, sensors attached to objects of daily use can record human–object interaction. Recognition methodologies utilizing multimodal miniaturized sensors present in the environment is referred to as dense sensing approach. In this approach, activities are characterized by the objects that are manipulated during the performed movements in real-world settings. They are widely used in AAL through the smart home paradigm [121–123]. Sensors in smart homes are used to initiate a time-bound context-aware ADL assistance. For example, a pressure mat or force plate can indicate position and movement of a subject within a defined environment, and a pressure sensor in a bed can suggest sleeping activity of the subject [31]. In general, wearable sensor-based monitoring is used in pervasive and mobile computing, while the dense sensing-based approach is more suitable for intelligent environment-enabled applications. Both approaches are not mutually exclusive, however, and in some applications they can work well together such as in RFID-based activity monitoring, where objects in the environment are instrumented with tags, and users wear an RFID reader fixed to a glove or a bracelet [117, 124].

4.3.3 Inertial Sensor-Based Activity Recognition

Activity recognition using wearable inertial sensors primarily involves the capturing of kinematic signals which are used to measure acceleration, velocity, distance, rotation, rate of rotation, angle and time. These measurements help to determine position of a limb segment or the angle of flexion of a limb joint. These classes of signals are widely used as health indicators encompassing gait, posture, spasticity, tremor and balance, some of which are subjective parameters in clinical assessment. Most of these parameters can be measured with the help of kinematic sensors like accelerometers, gyroscopes and magnetometers [125, 126], thereby removing the subjective quotient from symptomatic data [127].

Kinematic sensors are based on the transformation of physical parameters to an electrical signal which is further processed. Microelectromechanical systems (MEMS) play a key role in remote health monitoring applications, where size and power consumption are of vital importance. In MEMS-based transducers, changes in the electromechanical characteristics of the silicon are used to generate resistive or capacitive variations when the microstructure within the transducer is excited by external forces such as compression, pressure, temperature and acceleration. [128]. Some of the popular kinematic sensors used in the field of HAR are accelerometers, gyroscopes and magnetometers [125, 127].

An MEMS accelerometer is probably the most frequently used wearable sensor used for activity recognition. Gyroscopes are used primarily for computing rates of rotation (°/s) and, when combined with accelerometers, form an inertial measurement unit (IMU) [129], in which the gyroscopes are additionally used to compensate for errors in the accelerometers due to changes in orientation. Hence, IMUs can be used to measure acceleration, velocity, distance, rotation and orientation [128]. A magnetometer is another device that is sometimes used in remote monitoring applications that responds to the strength and direction of the Earth's magnetic field. Considering that the magnetic field vector has a constant direction and magnitude within a predefined area on the Earth's surface (given by the latitude and longitude), a magnetometer can be used to track orientation with respect to this localized constant field vector [128]. Magnetometers are not extensively used in health monitoring applications due to the fact that the Earth's magnetic field can be distorted by the presence of ferromagnetic materials [130]. Patients requiring wheelchair support (with steel frame) or the presence of other ferromagnetic substances within the home environment (e.g. in the kitchen) are likely to distort the reference magnetic field.

4.3.4 Data-Driven Versus Knowledge-Driven Approach

Processing of sensor data for recognizing activities can be categorized into two approaches: data-driven and knowledge-driven. Development of activity models is important for interpreting the sensor data to infer activities. In the data-driven approach, sensor data collected as a result of the movements performed by the subjects are used to build activity models with the help of data mining techniques and relevant machine learning algorithms. Since this involves probabilistic or statistical methods of classification driven by the data, the process is generally referred to as data-driven or bottom-up approach. Although this approach has its advantages in being robust to uncertainties and temporal variation in information, it requires the availability of a large dataset for training the activity model. Further it suffers from reusability and scalability as often it has been seen that activity models developed and evaluated on a particular subject's data does not work on the movement data of another subject owing to the large degree of variability inherent in human movement [118].

The knowledge-driven approach, on the other hand, is used to exploit the rich prior domain knowledge to build upon an activity model. This involves knowledge acquisition, formal modelling and representation and is hence referred to as knowledge-driven or top-down approach. It is based upon the observation that most activities are performed in a relatively specific location, time and space. A suitable example would be an act of brushing teeth, which takes place in the morning, evening or at night and involves the use of a toothbrush. Similarly, cooking in the kitchen involves the use of the microwave or cutlery. This implicit relationship between activities, temporal and spatial context and the entities involved provides a rich domain knowledge and heuristics for activity modelling and pattern recognition [118]. This approach is semantically clear, logically simple but weak in cases of uncertainty and temporal information.

Having discussed the different modalities and approaches of HAR, we will take an in-depth look into the process of activity modelling, classification and recognition using the data-driven approach. Prior to this, we shall first examine the various challenges concerning activity recognition.

4.3.5 Challenges in Activity Recognition

Activity recognition presents more degrees of freedom with respect to system design and implementation when compared to language processing or speech recognition [131]. However, owing to the diversity inherent in the data collected by different individuals performing the same action or by the same individual performing an action in different environments, it requires careful consideration of the type and placement of sensors and data analysis techniques used, depending on the application scenario and activities to be monitored [132].

4.3.5.1 Class Variability

A recognition system has to be robust enough to handle intra-class variability. In this context, class refers to the activities that are to be detected by any recognition methodology. This variability is primarily due to the fact that a same activity is performed differently by different individuals. Further this might also happen with an individual who repeats the same activity over time due to factors as fatigue or environmental changes. Therefore, there can be two approaches towards training an activity recognition system.

A system trained with movement data of more than one subject, or a person-independent training system would be susceptible to considerable inter-person variability [132]. To address this issue, the number of data points for each subject can be increased or an alternative approach can be person-dependent training, i.e. training the system on the movement data of single person. This might as well be robust enough towards capturing considerable intra-person variability. This system, however, requires the collection of a large set of data collected from one individual to train the system, thereby capturing as much variability as possible. The choice of the training sample is application dependent and hence a trade-off is required between the selection of a highly specific and discriminative dataset or a generic dataset which is potentially less discriminative but robust across multiple subjects [131]. In general, for remote health applications, formulating a person-centric training data would be beneficial when applied to monitoring of individual patients who demonstrate differences in levels of impairment depending on their stage of rehabilitation [133]. Another interesting challenge in recognizing activities is the similarity in characteristics prevalent across activities [134]. For example, if we would like to distinguish between drinking water from a glass and drinking coffee from a cup, it would be very difficult to differentiate from the kinematic data pertaining to both the movements. Therefore, in such cases sensors deployed in the environment like RFID tags attached to objects can prove to be helpful. Therefore, this is dictated by the requirements of the application [124].

An intriguing problem occurs during activity recognition on continuous streaming data or real-time monitoring applications where the data needs to be segmented depending on the activities we want to monitor and those that are irrelevant to the application. This is referred to as the NULL class in the relevant literature [135] and is difficult to model since it represents a plethora of activities in infinite space. It can however be identified if the signal characteristics gathered from the sensor data are completely different to the ones that are being monitored and hence involves a threshold-based mechanism to filter out the unwanted data. Class imbalance is a major problem, especially during long-term monitoring where all activities being tracked do not have the similar number of occurrences. A common example would be the number of instances of a drinking action and a walking action [136]. There are however a couple of techniques which can be adapted to get around this problem of class imbalance. Firstly, generating artificial training data for a class that is under-represented to balance out inequality; secondly, oversampling or interpolating smaller class sizes to match a bigger class size [137].

4.3.5.2 Ground Truth Annotation

Annotating the ground truth of activities being monitored in real-life scenarios is another interesting challenge, especially with data from wearable inertial sensors as opposed to data obtained from video recordings. With activities performed in the laboratory or controlled environment, annotations of the training data can be performed post hoc based on video footages. However, in nomadic settings, ground truth annotation of activities is a very difficult problem to solve. Researchers generally depend on self-recalling methods [138], experience sampling [139] and reinforcement learning, all of which involves testimonies from the subject themselves. Therefore, many researchers have based their work on a list of activities performed under a semi-naturalistic condition, where the subjects perform the movements as they would do in normal daily life, and another person annotates their activities by means of visual inspection in real time [100]. This therefore helps in gaining the ground truth information required for evaluating the recognition methodology.

4.3.5.3 Sensor Requirements

The experimental design gives rise to another challenge that of data collection, sensor selection, placement and the number of sensors to be used. As opposed to other computer vision problems like heart monitoring, brain activity modelling or speech recognition, HAR does not have a standard allocated dataset to start with the data analysis as it is completely dependent on the requirement, and experiments are designed in pursuit of recognizing only the selected movements. Sensor characteristics also present a significant amount of challenge for long-term monitoring of activities as hardware failures, sensor drifts and errors in the software aimed at capturing the data can lead to erroneous situations. External factors such as temperature, pressure and change in positioning due to loose straps can cause the need for frequent recalibration, thereby affecting the sensor data being recorded [140, 141].

One of the last challenges is power requirement of the battery-operated wireless sensors which are increasingly being used in the field of remote health monitoring. The remote monitoring system in place at present transmits the captured signals collected by the sensor nodes placed on the patient's body to the remote server at the back-office service platform wirelessly, where the signals are analysed [142]. This system requires continuous transmission of data from the sensors to the server using wireless protocols taking into account the nomadic environment. The fundamental problem with continuous data transmission is the energy requirement. A result from respective investigations into continuous data transmission at 1 kHz suggests that it can be supported for 24-h monitoring using a 1200-mAh battery [143].

The analysis presented in [143] regarding the power consumption and longevity of batteries pertains to transmission energy only, added to it the energy involved in pre-processing the physiological data at the sensor nodes including analogue-to-digital conversion, quantization, filtering and the microcontroller operation would bring down the effective time of monitoring to 8–10 h, thereby making the entire system power hungry and affecting the life of the batteries. An increased battery capacity like the prismatic zinc–air battery—1800 mAh operating at 1.4 V used recently in the medical community would increase the respective sizes of the sensor nodes. Furthermore, the use of Bluetooth transceivers consuming 40–55 mA with operating voltage in the range of 3–3.6 V would necessitate the use of three such zinc–air batteries, making it non-ideal in terms of volume for body-worn applications. The supply voltage is quadratically proportional to the power dissipation and therefore an optimal power supply to sustain the continuous Bluetooth transmission would have an adverse impact on the operational lifetime of the battery-powered sensor nodes. Considering Bluetooth as the primary means of communication, the energy dissipation is directly dependant on the packet format of the data being transmitted which can be optimized using standard duty cycling and might eventually lead to delays and packet loss of data which would be highly undesirable for applications involving remote health monitoring [142].

Therefore, from the long-term system operation perspective, when implementing a wireless body area network (WBAN) that comprises heterogeneous sensors, it is imperative to select data analysis algorithms having low computational complexity. This is because energy consumption is directly proportional to the computational complexity of the processing algorithms used. Therefore, for applications such as real-time movement detection requiring online operation, it is imperative to perform the data processing (feature extraction, classification) in a low-power way on a sensor platform [132, 142] itself while for applications supporting long-term behavioural or trend analysis, offline data processing may be sufficient [144].

4.3.6 Activity Recognition: Process Flow

In this section, we discuss the sequence of signal processing and pattern recognition techniques that help to implement a specific activity recognition behaviour using supervised learning methodologies. The process flow is shown in Fig. 4.2.

4.3.6.1 Data Acquisition and Pre-processing

Raw data is collected from multiple sensors attached to the body or sensors placed on objects or in the environment or from both, depending on the application requirement as discussed in Sect. 4.3.2. Data coming from each sensor sampled at regular intervals results in a multivariate time series. However, the sampling rates of different types of sensors might differ. Therefore, there is a need to synchronize multimodal sensor data. Inertial sensor data are generally sampled at low frequencies, 20–30 Hz, depending on the movements to be monitored. Certain sensors like accelerometers, gyroscopes and magnetometers can produce data that have multiple

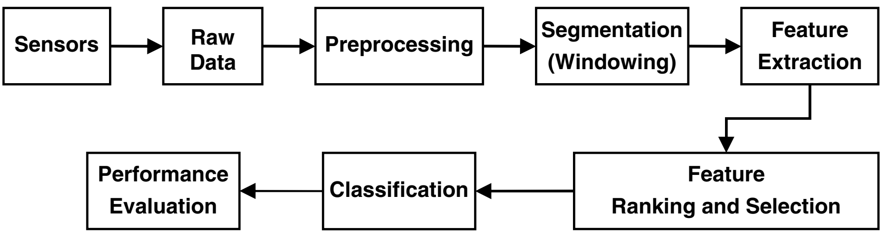

Fig. 4.2 Activity recognition process flow

dimensions (X-, Y- and Z-axis). Therefore, a multidimensional and a multimodal sensor output can be represented by (1), where S represents the sensor output, m represents the number of sensors and $d_1 \ldots d_n$ represents the sensor-specific data sampled at regular intervals.

$$S_i = [d_1, d_2 \ldots d_n], \quad i = 1, \ldots, m \tag{4.1}$$

The raw sensor data contains noise and is often corrupted by artefacts caused due to various factors. Artefacts are generally induced into the data due to sensor malfunctioning (e.g. drift) or due to unwanted movements of the body [131]. The pre-processing stage aims to remove the low-frequency artefacts and high-frequency noise components by using high-pass and low-pass filters [132]. The pre-processing algorithms also synchronize the data coming from various sensors and prepare it for the next stage of feature extraction. It preserves the signal characteristics which carries the relevant information about the activities of interest. Data from inertial sensors are in general calibrated; their units converted (as most sensor outputs are arbitrary units), normalized, resampled, synchronized, then filtered or fused in the pre-processing stage. Sensor fusion is generally performed where signals from multiple sensor axes are selected a priori, based on the activities being tracked. For example, specific accelerometer and gyroscope axes can be fused (both sensors placed on the wrist) for detecting a reach and retrieve action [132].

4.3.6.2 Data Segmentation

The pre-processed signal is segmented to identify only those segments that contain information about the activities that are being monitored. This process is also commonly referred to as event detection or activity spotting since it detects the signal frame representative of the activity of interest. The boundary of each segregated time series data is represented by the start and stop time. Thus, each segmented time series represents the potential activities to be monitored. Segmenting a continuous stream of data is a difficult task, especially for monitoring ADL. For example, consider a drinking activity. This may be considered as starting when reaching for a cup or glass. Alternatively, it may be considered as starting when the cup is raised to the lips. But what about when the cup is simply resting in the hand between individual sips? Should this still be classified as a drinking activity? In such circumstances, it is difficult to determine the boundaries of the activity from the signal. There are various segmentation algorithms that are used in relevant research, popular among them being the sliding window technique, energy-based segmentation, rest-position segmentation and using data from one sensor to segment another sensor reading [131].

The sliding window technique is one of the most popular segmenting schemes followed in diverse applications. As is suggested by the name, a fixed-size window representing definite time duration is used to extract segments of a signal [108]. If a very small interval is chosen, there is a possibility of missing out on a relevant activity whereas a longer window size would pertain to multiple activities, thereby affecting the classification decision. Hence, a dynamic window selection technique based on a data-driven or a probabilistic approach for segmenting each individual activity would be an optimal solution although this increases the computational load [118].

Another popular approach adopted for segmenting different activities is based on the energy content of the signal reflecting the change in intensity levels. The differences in energy levels in the signal are representative of the intensity variations of the activities that produce these kinematic signals. The energy content of a signal $s(t)$ is given by (4.2).

$$E = \int_{-\infty}^{\infty} \left| s(t) \right|^2 dt \tag{4.2}$$

Therefore, a threshold-based mechanism based on the value of E can help to identify segments of activities which are identical [145]. Researchers have explored energy-based segmentation with the assumption of a rest period between each activity which is particularly useful for gesture recognition involving discrete activities and momentary pauses [146].

4.3.6.3 Feature Extraction

The choice of features is a fundamental step for classification and a highly problem-dependant task. Although each of the sensors exhibits signal patterns that are distinctive for each of the movements and may be recognizable to the human eye as shown in Fig. 4.3, in order for a machine to recognize these patterns a set of characterizing features must be extracted from the data. Features represent the transformation of the raw data into another space known as the feature space. It is a measure to define the raw data in a quantitative as well as a qualitative manner such that it characterizes the raw data. The total number of features extracted from a feature space, where ideally identical activities should be clustered together whereas features corresponding to different activities should lie far apart. The selection of features is dependent on the activities that are to be classified.

The patterns shown in Fig. 4.4 clearly stress the importance of deciding on the right feature. Typical feature sets for HAR include statistical functions, time and/or frequency domain features, as well as heuristic features [147]. Some of the commonly used time-domain features extracted from sensor data and reported in the literature are: arithmetic mean, variance, median, skew, kurtosis, inter-quartile range, root mean square, standard deviation and correlation between axes [148, 149]. Correlation between accelerometer axes can improve recognition of activities involving movements of multiple body parts. For example, the activities of walking and climbing stairs might exhibit the same degree of periodicity and magnitude of a kinematic signal, but walking involves translation in one dimension whereas climbing stairs involves translation in multiple dimensions [150]. The often used mathematical features of variance, inter-quartile range, root mean square and standard deviation are useful measures of the variation in the data representing an action.

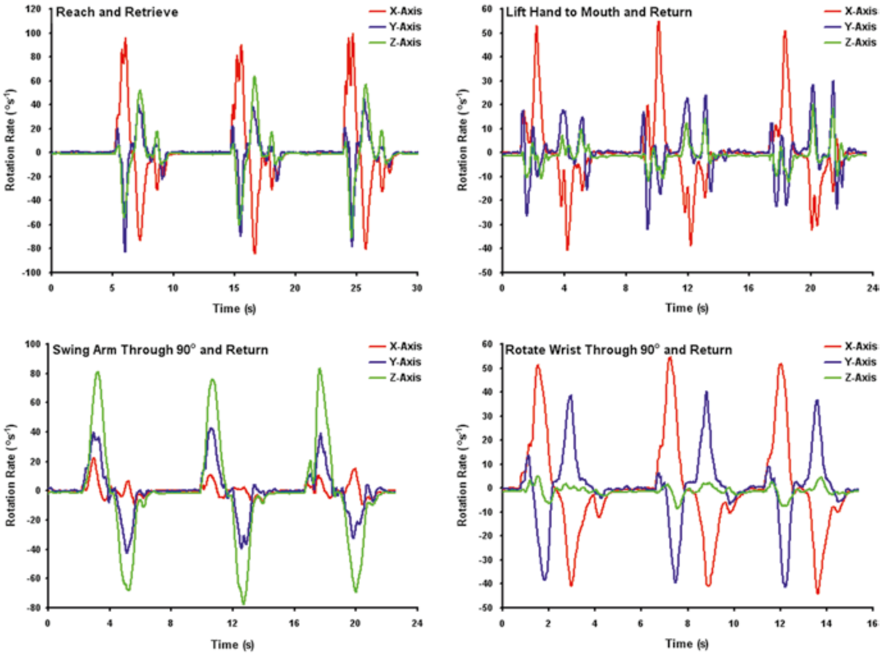

Fig. 4.3 The signal patterns generated by a tri-axial gyroscope placed near the elbow for three repetitions of four different actions—reach and retrieve, lift hand, swing arm and rotate wrist

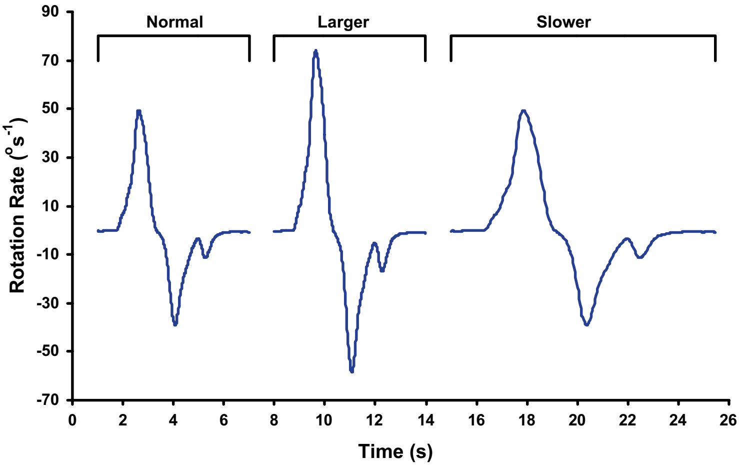

Fig. 4.4 Examples of movement patterns that exhibit obvious differences but are essentially the same movement

The statistical functions of kurtosis and skew may appear out of place when considering human activity since these are more usually associated as descriptors of the shape of a probability distribution. Nevertheless, these functions can still return values that uniquely identify different classes of activity, and therefore are rightly considered as appropriate classification features.

Commonly used frequency domain features are extracted from the coefficients of various time–frequency transforms such as the Short Time Fourier transform (STFT), Fast Fourier transform (FFT) and the Continuous or Discrete Wavelet transform (WT). The high-frequency component of an accelerometer signal also known as the AC component is primarily related to the dynamic motion of the subject like walking, running and handshaking while the low-frequency DC component of the signal is related to the gravitational acceleration and hence is informative about the orientation of the body in space and can be used to classify static postural positions [151].

The signal energy and its distribution at different frequency bands are popular choices for discriminating activities of differing intensities. More specifically, some of the commonly used features are spectral centroid, spectral spread, estimation of frequency peak and estimation of the power of the frequency peak and signal power in different frequency bands [148, 151]. Frequency domain entropy, calculated from the normalized information entropy of the discrete FFT component magnitudes of the signal, helps to discriminate activities with similar energy content. For example, cycling and running might result in similar values of energy if captured with an accelerometer placed near the hip. Cycling involves a uniform circular motion, and discrete FFT of the acceleration data in the vertical direction may show a single dominant frequency component at 1 Hz and low magnitude for all other frequencies. By comparison, the action of running may produce major FFT components in the low-frequency range 0.5–2 Hz [100].

4.3.6.4 Feature Selection

With a higher dimensional feature space, learning the parameters becomes a difficult task for the classifier because in such cases a large number of data samples (i.e. more training data) are required for the parameter extraction of the model and hence the computational complexity of the classification increases. The performance of the classification algorithm depends on the dimension of the feature space and hence methods to reduce the dimensionality are considered in the field of activity recognition. Particularly for real-time activity recognition, it is imperative to use the minimum number of features with an eye on computational complexity and memory utilization. If features with minimum discriminatory abilities are selected, the subsequent classification would lead to poor recognition whereas if information-rich features having a large between-class distance and small within-class distance in the feature space are selected we can expect to have a better classification. This would imply that features would take distant values in different classes and closely located values in the same class. However, before proceeding with feature selection, the feature vectors need to be pre-processed to remove the outlier points and feature normalization [152].

An outlier is a point that appears as a result of noisy measurement and lies far away from the mean of the corresponding feature vector causing large errors during the training of the classifier. For normally distributed data, a threshold of up to three standard deviations from the mean is used to filter out the outliers. For non-normal distributions, more complex measures like cost functions are considered [152].

Feature normalization is another key step adopted for feature values lying in different numeric ranges, such that features with large values do not dominate the cost function in the design of the classifier. A common technique is linear normalization as shown in (4.3), where the features are normalized by removing the mean from each sample and dividing the samples by their standard deviation. This ensures that each feature has zero mean and unit variance and can be represented as:

$$\tilde{x}_i = \frac{x_i - \mu}{\sigma}, \quad i = 1,2,3,\ldots,N \tag{4.3}$$

where x_i represents the respective feature values, μ is the mean value, σ is the standard deviation and $\tilde{x}_i$ represents the normalized feature values. Alternatively, other linear techniques can be used to normalize the feature values by restricting them between a minimum and a maximum value as expressed in (4.4). Selecting the range depends on the nature of the data.

$$\tilde{x}_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \quad i = 1,2,3,\ldots,N \tag{4.4}$$

Non-linear methods of normalization are also applied for data which are not evenly distributed about their mean. In such circumstances, non-linear functions like logarithmic or sigmoid can be used to transform the feature values within specific intervals [152]. Another option is scaling the feature vectors by the Euclidean length of the vector.

The normalization step is followed by the feature ranking step. Fisher's Discriminant Ratio (FDR) and Bhattacharyya distance are such techniques used to quantify the discriminatory ability of each individual feature between two equiprobable classes. Another class separability technique, based on scatter matrices, can be used for a multiple-class scenario [152]. The rank of each individual feature is determined, where a high rank represents a small within-class variance and a large between-class distance among the data points in the respective feature space [153]. The class separability based on scatter matrices is further explained.

The rank of each individual feature for a multiple-class scenario is determined by the J value [152] as calculated below:

$$J = \frac{S_{\mathrm{m}}}{S_{\mathrm{b}}} \tag{4.5}$$

$$S_{\mathrm{m}} = S_{\mathrm{w}} + S_{\mathrm{b}} \tag{4.6}$$

S_{w} and S_{b} are the within-class and between-class scatter matrices, respectively, and S_{m} is the mixture scatter matrix. The respective expressions are presented below:

$$S_{\mathrm{w}} = \sum_{i=1}^{c} P_i S_i \tag{4.7}$$

where P_i denotes the priori probability of a given class $i = 1, 2, \ldots c$ and S_i is the respective covariance matrix of class i.

$$S_{\mathrm{b}} = \sum_{i=1}^{c} P_i \left(m_i - m_0\right)\left(m_i - m_0\right)^T \tag{4.8}$$

$$m_0 = \sum_{i=1}^{c} P_i m_i \tag{4.9}$$

m_0 is the global mean vector. A high value of J represents a small within-class variance and a large between-class distance among the data points in the respective feature space [152].

The ranked features are sorted in a descending order to determine the one having the highest rank. As opposed to other popular multi-class feature ranking algorithms used in activity recognition like the ReliefF algorithm [3] and Clamping technique [108], the use of scatter matrices is computationally less complex and at the same time it quantifies the scatter of feature vectors in the respective feature space [152].

We come to the core problem area wherein we have to now select a subset of l features from the best ranked m features (where $l \leq m$). The two major approaches are—scalar feature selection and feature vector selection. In the scalar feature selection technique, each feature is treated individually and their class separability measure is ascertained using any of the above-mentioned criterion $c(k)$ (FDR, Scatter Matrices) for each feature. Features are then ranked in a descending order according to criterion $c(k)$, and l best features are considered for classification. Considering features individually involves low computational complexity but is not effective for complex classification problems and for cases where features are mutually correlated. Feature vector selection can be approached in two ways:

1. *Filter approach*: The features are selected independent of any classification technique. For each combination of features chosen, we apply the class separability criterion as mentioned above and select the best feature combination. Considering $m = 10$ and $l = 5$, we can have 252 feature vector combinations which are very large, and the number l is also not known a priori.
2. *Wrapper approach*: The selection of the feature is based in association with the classifier to be employed. For each chosen feature vector combination, the classification error probability of the classifier is estimated, and the feature combination with the minimum error is chosen. This approach can be further computationally complex depending on the choice of the classifier.

However, to reduce the complexity there are some effective searching techniques, which have been proposed to select the best feature vector combination: sequential backward selection, sequential forward selection and floating search method [152]. We will discuss the sequential forward selection technique (*sfs*) with a working example of a feature vector comprising four different features [X_1, X_2, X_3, X_4]. First, we compute the best ranked feature, say X_2, and evaluate the classification performance with X_2. Secondly, we compute all two-dimensional feature vector combinations with X_2: [X_1, X_2], [X_2, X_3], [X_2, X_4] and evaluate the classification performance for each of the combinations. Thirdly, we compute all three-dimensional feature vector combination with X_2: [X_1, X_2, X_3], [X_1, X_2, X_4] and evaluate the classifier performance with both the combinations. Finally, we select the best feature vector combination as the desired features [152]. Similarly for the sequential backward selection technique, we start with a combination of three features, eliminating one feature from each of the combinations and then evaluate its performance with respect to the classification algorithm employed. From each respective feature combination, we again eliminate one feature and evaluate the two-dimensional feature combinations.

Both these methods suffer from the fact that once a feature is selected or discarded in the forward or backward selection technique, respectively, there is no possibility for it to be discarded or reconsidered again. This problem is referred to as the nesting effect. Therefore, a flexible technique to reconsider previously discarded features and vice versa is known as the floating search method [152].

A popular analytical technique often reported in the literature is Principal Component Analysis (PCA), or the Karhunen–Loeve transform, which transforms feature vectors into a smaller number of uncorrelated variables referred to as the principle components [150, 151]. Another popular approach is Independent Component Analysis (ICA), often applied in problems of blind source separation, which attempts to decompose a multivariate signal into statistically independent non-Gaussian signals [154]. The choice of relevant features and choice of ranking or selection technique are completely dependent on the activities, type of sensors and the application scenario.

4.3.6.5 Classification

A wide range of classifiers have been used for activity recognition in recent years [155]. The determining factors for the selection of the classifier are accuracy, ease of development and speed of real-time execution [131]. Two distinct approaches can be used in classifying human activities—supervised and unsupervised learning. In supervised learning, the association of the training dataset comprises selected feature vectors with each class label is known beforehand [151]. In unsupervised learning, only the number of classes is known and the system assigns a class label to each instance in the training dataset. Clustering-based unsupervised learning has been used in the field of activity recognition [153, 156].

In HAR, the classification schemes used can be broadly categorized into three themes: probabilistic models, discriminative approach and template-based similarity metrics, as described below.

1. *Probabilistic models*: Probabilistic models are quite commonly used for behaviour modelling since they are an efficient means of representing random variables, dependence and temporal variation. In this approach, the activity samples are modelled using Gaussian mixture, yielding promising results for offline learning when a large amount of data is available for training. Generative probabilistic models such as HMMs have been used to model activity sequences and have been extended to hierarchical models like Conditional Random Fields (CRFs) and Dynamic Bayesian Networks (DBNs) [156]. Hidden Markov Models (HMMs) have been very popular in speech recognition and have also been used in applications for hand gesture recognition [157, 158]. In general, the HMM is trained on pre-defined class labels using the Baum–Welch algorithm and is tested on new instances. The Baum–Welch algorithm is a generalized Expectation Maximization (EM) algorithm that computes the maximum likelihood estimates of the parameters of an HMM given the observations as training data [159, 160]. The problem with HMMs is the first-order Markov assumption where the current state depends only on the previous one. Further, the probability of a change in the hidden state does not depend upon the time that has elapsed since entering into the current state. Therefore, a time dependence has been added to HMMs and they have been augmented to semi-HMMs where the hidden process is semi-Markovian rather than Markovian. Coupled HMMs have also gained prominence which is considered as a collection of HMMs, where the state at time t for each HMM is conditioned by the states at time t-1 of all HMMs in the collection. They are used to model the dynamic relationships between several signals [161].
2. *Discriminative approach*: The classification is based on the construction of the decision boundaries in the feature space, specifying regions for each class. The decision boundaries are constructed on the feature vectors of the training set, through an iterative or a geometric consideration. The Artificial Neural Network (ANN) commonly used for detecting ADL consists of inputs and outputs with a processing or a hidden layer in between. The inputs are the independent variable, and the outputs represent the dependent variable. The internal (hidden) layers can be adjusted through optimization algorithms such as the resilient back-propagation or scale-conjugate algorithms [106].

   The k-Nearest Neighbour (k-NN) [162] and the Nearest Mean (NM) classifiers work directly on the geometrical distances between feature vectors from different classes [163]. Support Vector Machines (SVMs) work by constructing boundaries that maximize the margins between the nearest features relative to two distinct classes. SVM is a very popular technique in machine learning community and generally produces high accuracy rates with moderate computational complexity (depending on the number of support vectors used) [108, 164]. In principle, it is a binary classifier but has been extended to handle multiple classes using the "one-versus-all" or the "one-versus-one" scheme [165].

However, both of these methods can be computationally intensive depending on the number of target classes. The Naive Bayes classifier has also been successfully used over the years [116, 149]. It assumes conditional independence among all feature vectors given a class label and learns about the conditional probability of each feature. They require large amounts of data and do not explicitly model any temporal information which is very important in activity recognition [118]. Finally, binary tree classifiers have been widely popular in the field of HAR, where the classification process is articulated in several different steps. At each step, a binary decision is made based on different strategies like the threshold-based or template-matching. With each stage, the classification is progressively refined as the tree descends along the branches [166]. The *C4.5* Decision Tree (DT) algorithm is by far the most popular algorithm and has been used to achieve successful recognition of daily living activities [100, 148].

3. *Template-based similarity metrics*: The template-matching technique exploits the similarity between the observed data (testing dataset) and the pre-stored activity templates which are user defined or obtained from the training dataset. They can employ, for example, a *k*-NN classifier using the Euclidean distance computed between the testing and training dataset having a fixed window size or dynamic time warping [167, 168] in the case of varying window size. Another popular template-matching technique used is string matching [169]. The choice of a classifier depends on the trade-off between the computational complexity, memory requirements and the recognition accuracy.

4.3.6.6 Cross-Validation

One technique quite common in classification problems is the use of cross-validation. During estimation of the model parameters, validation of the employed classification algorithm is essential to judge its robustness. This is particularly applicable in supervised learning techniques, i.e. where the class labels of the dataset are known. The available cohort of data is divided into training and testing datasets. The training set is used to train the classifier whereas the test set is used to estimate the error rate of the trained classifier. The cross-validation technique is also known as the re-sampling method and can be divided into three approaches: random sampling, *k*-fold cross-validation and leave-one-out cross-validation [131].

1. *Random sampling*: The available dataset is split into K parts, where each split randomly selects a fixed number of elements. Each training set is used to retrain the classifier, and the error E_i is estimated after classifying the test set. The true error estimate could be obtained by averaging the separate error estimates E_i.
2. *K-fold cross-validation*: It is used to independently partition the whole dataset into K parts. For each K experiment, *K-1*, folds are used as the training dataset to train the classifier and the remaining one dataset is used as the test dataset. The advantage of K-fold cross-validation over random sampling is that in this technique all data samples in the dataset are eventually used for training and testing. The error computed over each run could be averaged to estimate a true error.

3. *Leave-one-out cross-validation*: In this method, an exhaustive validation is performed, where out of the total N available data samples, N-1 data samples are used to train the classifier while the one remaining sample is used to test the classifier. This is repeated such that each individual data sample takes the role of the classifier test data. The true error could then be calculated as the mean of the error over all N runs performed.

The number of folds is determined by the size of the available dataset. With a large number of folds, we can achieve a near accurate estimation of the classifier's performance though this requires a longer computation time. With a smaller number of folds, we can gain on the computation time but sacrifice on the performance of the classifier. Hence, a large number of folds on a sparse dataset lead to a more robust classifier. In the literature, the value of K is generally chosen as 10 and therefore 10 runs of tenfold cross-validation are performed. The accuracy is calculated by averaging the performance of the classifier over the 10 runs [170].

4.3.6.7 Performance Evaluation

The recognition performance of an activity recognition system can be evaluated in terms of correct classification through true positives (TPs) or false negatives (FNs). Classification can also lead to false detection of activities that did not occur and can be estimated through false negatives (FNs) and false positives (FPs). There are a few well-known performance metrics that are widely used, such as confusion matrices, accuracy, precision, recall or receiver operating characteristics (ROC) curves.

A confusion matrix is a popular means of evaluating the classifier performance for multi-class problems. It summarizes the misclassifications of the different activity classes. The rows of the matrix represent the actual number of instances in each activity classes while the columns represent the predicted instances in each activity classes. Precision [TP/(TP+FP)], recall [TP/(TP+FN)] and the overall accuracy [(TP+TN)/All] can be easily computed for each activity class from the matrix. Normalized confusion matrices are commonly used for unbalanced datasets where there is a significant amount of difference in the number of ground truth annotations of the activity classes [131, 171, 172].

For binary classification problems (i.e. involving two classes), the overall (average) correct classification or accuracy is used as a measure of the classifier's performance which might not always be applicable for multi-class classification because of possible dissimilar classification rates of different classes affecting the overall performance measure. Hence, we can measure the sensitivity of a given class from the confusion matrix N following the scheme proposed in [173]. The sensitivity S of class i estimates the number of patterns correctly predicted to be in class i with respect to the total number of patterns in class i [173]:

$$S_i = \frac{N_{ii}}{f_i} \times 100 \tag{4.10}$$

	Predicted 'A' $j = 1$	**Predicted 'B'** $j = 2$	**Predicted 'C'** $j = 3$	**Predicted 'D'** $j = 4$
Actual 'A', $i = 1$	0.9	0.1	0	0
Actual 'B', $i = 2$	0	0.9	0	0.1
Actual 'C', $i = 3$	0.02	0	0.98	0
Actual 'D', $i = 4$	0.05	0	0.05	0.9

Fig. 4.5 An example of a confusion matrix for four classes

$$f_i = \sum_{j=1}^{c} C_{ij} \tag{4.11}$$

where $i = 1 \ldots c$, and c is the total number of classes. The diagonal and the off-diagonal elements of the confusion matrix correspond to correctly classified and misclassified patterns, respectively. C_{ij} represents the number of times that the patterns are predicted to be in class j when they really belong to class i. A sample confusion matrix N is shown in Fig. 4.5.

This example shows near perfect classification since all left to right diagonal elements approach unity and all off-diagonal elements approach zero. Therefore, the sensitivity of class A (expressed as a percentage), can be computed as $S_A = \frac{0.9}{(0.9 + 0.1)} = 90\%$ and the overall accuracy (expressed as a percentage) can be computed as $\text{Accuracy} = \frac{(0.9 + 0.9 + 0.98 + 0.9)}{4} = 92\%$.

4.3.7 Movement Quality Estimation

As mentioned in Sect. 4.3, one of the prime objectives of activity monitoring is to have a qualitative feedback on the state of the patient or the subject undergoing rehabilitation. The recognition of activities, as mentioned in Sect. 4.3.3, includes the detection and classification of particular limb movements, which is beneficial in many neurodegenerative pathologies, where regular exercise of the impaired limb is necessary to achieve rehabilitation. A system capable of tracking the use of the impaired limb (during exercises and ADL) and classifying the type of movements performed over time would indicate improvement in motor functionality.

Movement smoothness has been widely used to determine the motor performance of both healthy subjects and stroke survivors [174]. One visible feature in the earliest movements performed by early stroke survivors is the lack of smoothness. Their movement profile appears to be comprising a series of discrete and episodic sub-movements. However, the movements become suppler as the recovery proceeds.

For upper arm impairment post-stroke, the rate of recovery is usually rapid in the first few weeks. The B&B test [22] and the NHP test [23] have been traditionally performed by the clinicians to assess rehabilitation in clinical settings, which are reliable measures of gross manual dexterity and arm functionality. However, with the advent of lightweight, low-cost, wireless body-worn sensors capable of recording kinematic movement for long durations, there is an increasing demand for assessing the functional ability of patients within the home settings.

Data from inertial sensors, especially those from accelerometer have been used to quantify the degree of smoothness in the kinematic movements recorded. The jerk metric and the variations in the speed profile are the most common features used to represent smoothness in movements. The jerk metric characterizes the average rate of change of acceleration in an underlying movement. It is calculated by dividing the negative mean jerk magnitude by the peak speed. Normalizing the jerk to the maximum speed helps to make it a measure of movement smoothness [175].

The normalized mean speed, average speed normalized by the maximum speed, is another important metric and essentially captures the discontinuities in the underlying episodic sub-movements of the subjects [174]. The peak metric is a common metric used to quantify movement smoothness usually obtained by counting the number of peaks from a gradient analysis of the raw acceleration data or on the speed signal (first integral of acceleration). A smaller number of peaks indicates fewer occurrences of changes in acceleration or deceleration and hence reflects the smoothness of the movement [175].

Relevant studies performed have shown that features extracted from the sensor data conform to the clinical findings [175]. The B&B and the NHP scores showed an improvement in arm functionality over the experimental duration of 3 weeks. The trends observed with the extracted features (jerk metric and number of peaks) from the acceleration data support the clinical observations. Hence low-cost body-worn sensors can be used in a pervasive manner to determine the rehabilitation of patients in the home environment.

4.3.8 State-of-the-Art Activity Recognition Systems

Table 4.1 lists a few state-of-the-art activity recognition systems that have been developed in recent years, mainly aimed towards ADL monitoring. Here, we have highlighted the activities being monitored, the sensors and their positioning, the classification schemes used and the accuracies obtained.

4.4 Case Study

Our review of the existing modalities reveals that the majority of the published work on activity recognition has been devoted towards monitoring of gross dynamic human movements such as sleeping, sitting, standing, cycling and running.

Table 4.1 State-of-the-art systems developed in recent years for ADL monitoring

Sensors	Activities	Evaluation	Ref.
Inertial sensor on the thigh for activity recognition; marker-based system using 12 cameras to track the three-dimensional location	Lying, sitting, standing, walking, and transitions from sit-to-stand, lie-to-sit, stand-to-sit and sit-to-lie	HMM; overall accuracy about 90 %; accuracy increases with location data; high setup cost and a fixed coverage area for location tracking using the camera system	[120]
Wristwatch-based sensor containing accelerometer, altimeter and temperature sensors	BADLs—brushing, dressing, walking upstairs/downstairs and sleeping; IADLs—washing dishes, ironing, watching television	Neural networks and SVM; average accuracy of 90 %; dressing, ironing, brushing and washing are sometimes confused; system is cost-effective and non-intrusive	[108]
Two tri-axial accelerometers in a smartphone	ADLs such as sitting down, standing up, walking and stopping	SVM; Accuracy of 92–100 %; limited by the number of activities and the charge on the smartphone	[176]
Five bi-axial accelerometers	20 different activities including walking, sitting, standing, lying down, climbing stairs, folding laundry, etc.	Decision tree; accuracy of 44–94 %; riding elevator and stretching confused with other activities; large number of sensors; wired connectivity and need for real-time synchronization are drawbacks	[100]
Accelerometer on thigh and waist; RFID reader on hand glove; RFID tag on objects of daily use	18 activities—handshaking, rope jumping, brushing, making phone calls, reading, using umbrella and other ADLs	Decision trees; overall accuracy of 95 %; walking was detected by 84 %—confused with standing/running. The glove "iGrabber" is too big to wear for elderly people and tagging of different objects with RFID is exhaustive	[177]
Infrared sensors to detect location and movement; door contacts; microphones; digital temperature and hygrometry sensor; tri-axial accelerometer; and magnetometer	Bathing, dressing, resting, use of toilet, moving in/out of bed/chair, feeding	SVM; accuracy of 90 % except for dressing (75 %) and hygiene (64 %) which had fewer occurrences in the training database; use of multiple ambient sensors is expensive; needs to be tested on the elderly population	[178]
Four accelerometers on the thigh, sternum and lower arm	Posture of human body, lying, sitting, standing, walking, climbing stairs, cycling, driving, use of wheel chair and running	Average accuracy of 90 %, uses wired sensors and hence is intrusive	[179]
Tri-axial accelerometer placed on the wrist	8 tasks from the WMFT—reach and retrieve, card flipping, grasping, etc.	Dynamic Time Warping; average accuracy of 96.5 %, the system is small, non-intrusive and uses only one sensor; which is advantageous	[180]

Apart from these, efforts have also been made to ascertain the activity levels of subjects in daily activities like bathing, personal grooming, toileting and drinking. Compared to those, very little work has been done in terms of activity recognition for elementary arm movements in nomadic environment, which can help to track the involvement of the impaired arm in daily living activities and thereby help in upper limb rehabilitation for stroke patients.

Let us consider a case study where we report on a systematic exploration to recognize three fundamental movements of the upper limb that are generally associated with ADL, using data collected only from a wrist-worn, wireless tri-axial accelerometer. The motivation was to detect the occurrence of these specific arm movements in a real-world scenario (i.e. unconstrained environment), using the minimal number of body-worn inertial sensors. Enumerating occurrences of particular arm movements (e.g. prescribed exercises) during daily activities over time can provide a measure of rehabilitation progress in a wide range of remote health monitoring applications. It will be particularly useful in the monitoring of arm rehabilitation progress in pathologies associated with neurodegenerative diseases such as stroke or cerebral palsy.

Continuous monitoring of activities in an unconstrained scenario involves data segmentation and activity recognition. Here, we concentrate only on the activity recognition part as a proof-of-concept methodology owing to the qualitative non-uniqueness of an activity pattern exhibited by a subject and due to inter-person variability. The accuracy of any movement recognition technique is dependent on the system components and requirements, covering areas such as type of activities, number of activities, type of sensors, number of sensors, placement of sensors [108], level of data fusion and most importantly the classification methodology adopted. Further, there is a requirement for subject-specific training, especially when tracking activities that are susceptible to individual and temporal variation [100]. Recognition strategies generally follow one of three themes. Firstly, data collected under controlled conditions (e.g. in the laboratory) is used for training as well as testing, resulting in high accuracies [148]. Secondly, controlled and uncontrolled data (e.g. out-of-laboratory) are used for both training and testing, which results in reasonably higher movement recognition accuracy [100, 181]. Finally, using controlled data for training and only uncontrolled data for testing, results in lower accuracies but is more realistic of real-world applications [100, 181]. To explore the levels of recognition accuracy for a robust classification mechanism applicable in the field of home-based rehabilitation, in this study we use controlled data for training and uncontrolled data for testing. Here, a subject with arm dexterity is requested to follow a particular exercise regime involving the impaired arm in a controlled environment (clinic or home) and is later monitored to track occurrences of these specific movements while they perform daily activities, involving the impaired arm.

This facilitates a measure of rehabilitation progress. In this exploration, we consider three specific arm movements (i.e. actions) all of which involve rotations of the forearm about various axes. In principle, the three chosen elementary movements (*Action A*, *B* and *C*) constitute a significant proportion of the complex movements performed with the upper limb in daily life and also resemble three of the tasks (8, 9 and 15, respectively) in the streamlined WMFT [182, 183]. The selected movements are:

Action A—Reach and retrieve an object (extension and flexion of the forearm).
Action B—Lift cup to mouth (rotation of the forearm about the elbow).
Action C—Perform pouring or (un)locking action (rotation of the wrist about long axis of forearm).

The fundamental concept of this exploration is to first form a set of three clusters in multidimensional feature space, using selective features from a ranked set of features generated from person-centric data collected in a constrained *training* phase (e.g. in the laboratory). Each cluster formed represents a particular type of movement. Data collected subsequently during an unconstrained *testing* phase (e.g. out-of-laboratory) is tested for its proximity to each of the clusters by using a minimum distance classifier. The basic philosophy of our methodology is illustrated in Fig. 4.6, where three clusters A, B and C are formed on the *training* dataset corresponding to the three movements (*Actions A*, *B* and *C*), respectively, in a two-dimensional feature space (Feature 1 (f_1) and Feature 2 (f_2)).

The distance of the *test* vector T from each of the three cluster centroids is represented by the distances d_A, d_B and d_C. These three distance measures are compared to estimate the proximity of the *test* dataset T to each cluster and assigned to the nearest one. This methodology can be further scaled up by forming more clusters corresponding to new categories of movements and associating a new dataset (corresponding to the movement to be detected) to the proximal cluster. The formation of unique clusters corresponding to each performed movement can be achieved by selecting the optimum number of features which help to discriminate movement patterns in the respective feature space.

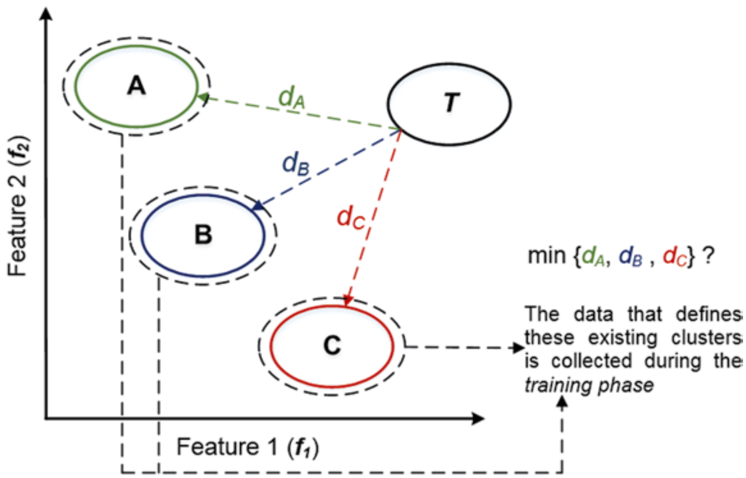

Fig. 4.6 Illustration of the clustering and minimum distance classifier-based methodology

We used the regularized Mahalanobis distance-based *k*-means clustering technique to form the clusters on the person-centric *training* data (collected in the *laboratory* setup) and use 10 runs of a tenfold cross-validation technique to determine the best combination of cluster forming features. A minimum distance classifier based on Euclidean and Mahalanobis distance was used for associating the *test* data (collected during "*making-a-cup-of-tea*") to the formed clusters in the same feature space [170]. We adopted a person-dependent, i.e. personalized approach, thereby formulating the clusters on a set of person-centric *training data* in view of the large degree of inter-person variability reflecting on the different levels of impairment and rehabilitation stage applicable in the field of remote health monitoring. This would be beneficial in monitoring the stage of rehabilitation of each individual.

Although it is generally accepted that cluster analysis is primarily used for unsupervised learning (where the class labels for the training data are not available), the *k*-means algorithm can also be used for supervised learning where the class labels of the training data are known a priori [184, 185]. In our exploration, the class labels for the training data relating to the three movements performed in a constrained *training* phase are already known. This helps to have a definitive estimate of the underlying cluster structure to be formed on the data (three clusters), thereby facilitating a faster convergence during cluster formation for reduced time complexity [152]. The primary steps involved in our overall approach are illustrated in Fig. 4.7 and described in detail in the following sections.

4.4.1 Data Acquisition and Pre-processing

A Shimmer 9DoF wireless kinematic sensor module containing mutually orthogonal tri-axial accelerometers, rate gyroscopes and magnetometers was used as the sensing platform.

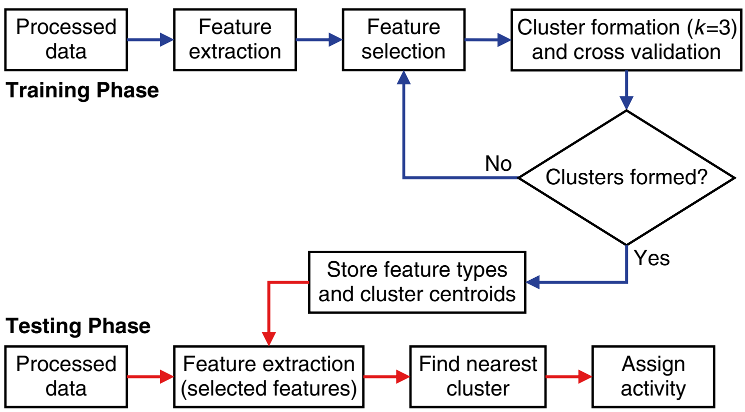

Fig. 4.7 Training and testing phases of the data processing [153]

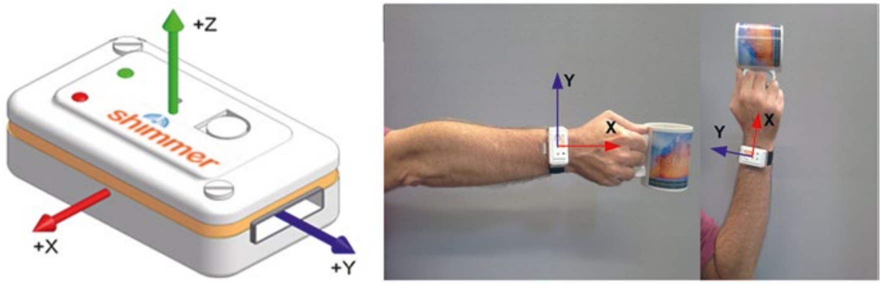

Fig. 4.8 Sensor module showing the coordinate system for the positive direction of the accelerometer axes (*left*) and when worn on the wrist showing the *X*- and *Y*-axis, the *Z*-axis points away from the plane (*right*)

For our experiments, we only use the tri-axial accelerometer with ±1.5 g range selected and exclude the magnetometer since it can be affected by the presence of ferromagnetic materials which are expected to be present in the natural environment [130]. We also leave out the gyroscope in view of using a minimal number of sensors aimed at reducing the amount of data processing involved. The dorsal side of the forearm proximal to the wrist on the dominant arm was chosen as the sensing position since it was likely to produce significant sensor responses to the arm movements being investigated. The dorsal side was in contact with the *XY* plane of the sensor with the *X*-axis pointing towards the fingers and the *Z*-axis pointing away from the dorsal aspect (cf. Fig. 4.8). Sensor data was collected at a rate of 50 Hz, deemed sufficient for assessing habitual limb movement [164, 108]. In this exploration, experimental data was collected from four healthy subjects (age range 24–40, male, all right arm dominant) within an open laboratory, with an attached kitchen at the University of Southampton. To generate the *training* phase data for the target cluster formation, all four participants performed 240 trials of *Action A*, 120 trials of *Action B* and 120 trials of *Action C*, separated into groups of five repetitions, with each group of trials being separated by approximately 3 min. This was done to avoid unrepresentative data due to fatigue and to minimize the effects of unconscious self-learning of the activities. The data collection produces a large *training* set offering greater convenience for accurate recognition [23] since the cluster formation on the *training data* inherently captures the person-centric nature of movement patterns.

On a separate day, participants were recalled and requested to perform four repetitions of the activity list in Table 4.2 at a comfortable speed in a kitchen, with a 10-min rest period between repetitions. The activity list was designed to emulate the process of "*making-a-cup-of-tea*", a common activity performed in daily life, having repeated occurrences of the three elementary types of arm movement (*actions*). The activity list in our experiment protocol comprises 20 individual activities including 10 occurrences of *Action A*, and 5 each of *Action B* and *Action C*. There were no restrictions on the various physical factors of the experiment such as the seating position or standing position with respect to the kitchen surface or the time required to complete the actions. The experiment was unconstrained to ensure a

Table 4.2 Use case activity list—"making-a-cup-of-tea"

Activity		Action
1.	Fetch cup from desk	A
2.	Place cup on kitchen surface	A
3.	Fetch kettle	A
4.	Pour out extra water from kettle	C
5.	Put kettle onto charging point	A
6.	Reach out for the power switch on the wall	A
7.	Drink a glass of water while waiting for kettle to boil	B
8.	Reach out to switch off the kettle	A
9.	Pour hot water from the kettle into cup	C
10.	Fetch milk from the shelf	A
11.	Pour milk into cup	C
12.	Put the bottle of milk back on shelf	A
13.	Fetch cup from kitchen surface	A
14.	Have a sip and taste the drink	B
15.	Have another sip while walking back to desk	B
16.	Unlock drawer	C
17.	Retrieve biscuits from drawer	A
18.	Eat a biscuit	B
19.	Lock drawer	C
20.	Have a drink	B

Table 4.3 Data structure used in the training and testing phases

Attributes	Quantification
Number of subjects	4
Training dataset	[Action A—240; Action B—120; Action C—120] = 480
Testing dataset	[Action A—10; Action B—5; Action C—5] × 4 trials = 80

wider range of variability in the data paving the way for a robust arm movement recognition system which will produce acceptable levels of accuracy in a real-world application. The activity list was prepared to facilitate the evaluation of the recognition methodology under semi-naturalistic conditions. The start and stop time of the activities were noted down by the researcher observing them as they performed their designated tasks. The corresponding data collected was segmented using the annotations from the researcher and used for the testing phase.

The data structure for the *training* and *testing* phase used in this analysis is summarized in Table 4.3.

The tri-axial accelerometer located on the wrist transmits data along with a time stamp to a host computer using the Bluetooth wireless transmission protocol, and each activity performed by a subject is marked to record the start and end of the

Table 4.4 List of features considered in this investigation

No.	Features	Description
1	Standard deviation	Measure of the variability from the mean of the signal
2	Root mean square (rms)	Measure of the signal energy normalized by the number of samples
3	Information entropy	Measure of the randomness of a signal [186]
4	Jerk metric	rms value of the second derivative of the data normalized with respect to the maximum value of the first derivative [3]
5	Peak number	Obtained from gradient analysis of the signal
6	Maximum peak amplitude	Measure of the amplitude of the peaks obtained after gradient analysis
7	Absolute difference	Absolute difference between the maximum and the minimum value of a signal
8	Index of dispersion	Ratio of variance to the mean
9	Kurtosis	Measure of the "peakedness" of a signal
10	Skewness	Measure of the asymmetry of a signal [187]

movement for all trials performed during the *training* and *testing* phases. The raw sensor data is band-pass filtered with a third-order Butterworth filter having cut-off frequencies of 0.1 Hz and 12 Hz to respectively attenuate the low-frequency artefacts and high-frequency noise components introduced in the data due to physical effects such as drift [13].

4.4.2 Feature Extraction

Each sensor data stream exhibits signal patterns that are distinctive for each of the arm movements, which is characterized by a set of features extracted from the signals [164]. In this investigation, we consider ten time-domain features which are listed in Table 4.4.

We compute 10 one-dimensional features from the data produced by each accelerometer axis (*acc_x*, *acc_y*, *acc_z*) for each movement trial of each subject. The subsequent process of feature selection and cluster formation is performed on the sensor-specific feature space (comprising 30 features), represented as:

$$\mathrm{FS} = \left[f_1\_x \ldots f_{10}\_x, f_1\_y \ldots f_{10}\_y, f_1\_z \ldots f_{10}\_z \right] \tag{4.12}$$

where FS represents the respective feature space formed by considering the ten individual features ($f_1 \ldots f_{10}$) computed on each tri-axial data segment together. The suffix (x, y or z) represents the sensor axis on which the respective feature was computed. The movements performed by the subjects were segmented using the annotations from the researcher, therefore each feature was computed on data segments of varying lengths representative of the time taken to complete each movement trial.

4.4.3 Feature Selection

The extracted features are linearly normalized, and the best features for each subject are selected by using the low-complexity class-separability measure based on scatter matrices (cf. Sect. 4.3.6.4) which ranks the 30 features. The ranked features are sorted in descending order with respect to their R values. We employ a sequential forward selection (*sfs*) technique (cf. Sect. 4.3.6.4), selecting the first i features of the ranked feature set in each iteration ($i=2\ldots30$) and check if the data from the *training* phase can be correctly clustered in a multidimensional feature space as described in the next section.

4.4.4 Cluster Formation on the Training Dataset

The fundamental concept of cluster analysis is to form groups of similar objects as a means of distinguishing them from each other and can be applied in any discipline involving multivariate data [188]. With a given dataset $X=\{x_i\}$, $i=1\ldots n$ to be clustered into a set of k clusters, the k-means algorithm iterates to minimize the squared error between the empirical mean of a cluster and the individual data points, defined as the cost function, J:

$$J(\theta,u)=\sum_{i=1}^{n}\sum_{j=1}^{k}u_{ij}\parallel x_i-\theta_j\parallel^2 \tag{4.13}$$

where θ_j is the cluster centre, and $u_{ij}=1$ if x_i lies close to θ_j or 0 if otherwise [189]. Initially, k centroids are defined and the data vectors are assigned to a cluster label depending on how close they are to each centroid. The k centroids are recalculated from the newly defined clusters, and the process of reassignment of each data vector to each new centroid is repeated. The algorithm iterates over this loop until the data vectors from the dataset X form clusters and the cost function J is minimized [152].

The Euclidean distance used to compute the squared distance between the vectors x_i and the mean of each cluster θ_j has an undesirable effect of splitting large and elongated clusters, since most real datasets do not have a well-defined, isolated and spherical underlying cluster structure. By comparison, the use of the Mahalanobis distance, which involves computing the covariance matrix of the data vector, causes a large cluster to absorb nearby smaller clusters, leading to the creation of unusually large or small clusters. Hence, we use the regularized Mahalanobis distance as mentioned in [189] which prevents the clustering algorithm from producing unusually large or small clusters. The distance measure J is given by:

$$J(x_i,\theta_j)=(x_i-\theta_j)^T\left[(1-\lambda)(\Sigma_j+\varepsilon I)^{-1}+\lambda I\right](x_i-\theta_j) \tag{4.14}$$

where Σ_j is the covariance matrix of the k-th cluster and I is the $d \times d$ identity matrix, d is the input dimensionality (no. of feature vectors representing the data vector) and $\varepsilon(10^{-6})$ is the regularization parameter. The value of λ can be used as a parameter to control the choice of distance measure to be used, with $\lambda = 0$, J is the squared Mahalanobis distance and when $\lambda = 1$, J is the squared Euclidean distance [189]. In our exploration, we start with an initial value of $\lambda = 1$ (Euclidean) and after three iterations change it to $\lambda = 0$ (Mahalanobis). The cluster formation on the *training* dataset is associated with a cross-validation step to determine the best combination of the features, discussed in detail in the following section.

4.4.5 Cross-Validation on the Training Dataset

We perform 10 runs of tenfold cross-validation on the feature vectors computed from the accelerometer data which characterizes the movement trials of the *training* phase (480 trials for each healthy subject) to form three clusters representing the three arm movements [170]. The key steps involved in the cross-validation process have been highlighted below:

- The cluster formation using the regularized Mahalanobis distance (as discussed in Sect. 4.3.4) runs on the *training* dataset for each subject that comprises feature vectors (30 features) extracted from each sensor data segment.
- The algorithm runs in conjunction with the *sfs* algorithm sequentially selecting a combination of 2–30 ranked features in each step (i).
- For a particular set of feature vectors selected (i), 10 runs (n) of tenfold cross-validation are carried out whereby ten segments of the *training* data are created.
- In each run (n) of the stipulated 10 runs, one segment is used as the *test* dataset while the rest of the nine segments are used as the *training* dataset.
- We set a threshold of 25 % of the expected number of data points for each of the three clusters formed (i.e. 240 ± 60 for *Action A* and 120 ± 30 for *Action B* and *Action C*). This threshold value was experimentally selected since it produced the best results [153]. If the number of data points in each cluster is within the threshold, we consider it as correctly clustered for that particular combination (i) of features selected (where $i = 2,\ldots,30$).
- We compute the distance of the mean of the *training* dataset for each class label from the cluster centroids and thereby assign each cluster with the class label that has its closest proximity to that particular class of a *training* dataset.
- We then use a minimum distance classifier to compute the distance of the *test* dataset (one segment of the stipulated tenfolds) from the centroid of each cluster in a multidimensional feature space (considering the feature combination of the current step, i) based upon: Euclidean distance and Mahalanobis distance. The Mahalanobis distance is used to measure the distance of a point from a data distribution. The data distribution is characterized by the mean and the covariance matrix which defines the shape of how the data is distributed in the feature space and is generally hypothesized as a multivariate Gaussian distribution. Here, the

Mahalanobis distance takes into consideration the covariance of the clusters along with their mean for the maximum likelihood estimation of the covariance matrix and hence is effective for clusters with larger variance along one or many directions and in general having an ellipsoidal shape [152].

- The *test* dataset is assigned to a particular cluster depending on the minimum distance computed for each of the two measures.
- The predicted label is verified with respect to the known annotations, thereby ascertaining the accuracy of the prediction for a single run (n).
- The accuracy of prediction for a particular feature combination is determined by averaging the results produced over the runs ($n \leq 10$) forming successful clusters. This process is repeated for each of the sequentially selected best ranked feature combinations ($i = 2 \ldots 30$).

Therefore at the end of all iterations (i.e. $i = 30$), we have a detailed list of the feature combinations that resulted in a successful cluster formation and the corresponding accuracies achieved both with Euclidean and Mahalanobis distance measures, for each subject. This information (minimal number of feature combination, resulting in the best accuracy) is used for the target classification of the *testing* phase data collected in the semi-naturalistic setup by associating them to the formed clusters in the chosen feature space. For all the subjects, the number of features chosen was in the range of 2–27 (selected out of total of 30) and the individual sensitivities were in the range of 90–100 %.

4.4.6 Prospective Evaluation with the Testing Dataset

The data from the *testing* phase (cf. Table 4.2) collected in the semi-naturalistic setup during the "*making-a-cup-of-tea*" session (80 test vectors for each healthy subject [$(10A + 5B + 5C) \times 4$ trials] and 40 test vectors for each stroke patient [$(10A + 5B + 5C) \times 2$ trials]) is pre-processed for each type of sensor, and only those features are extracted from each test vector which resulted in the best accuracy in the cross-validation of the *training* data. We use a Euclidean and Mahalanobis distance based classifier to compute the distance of each test vector (represented by the extracted features) from the centroid of each cluster in a multidimensional feature space. The test vector is assigned to a particular cluster depending on the minimum distance computed for each of the two measures. Predicted label is verified with respect to annotations in the activity list of Table 4.2.

4.4.7 Results and Analysis

Typical variations in accelerometer data recorded during a single example of each action are illustrated in Fig. 4.9. We had in total 80 movement trials (*actions*) to be recognized (40 of A, 20 of B, 20 of C) for each subject. The results of the prospective

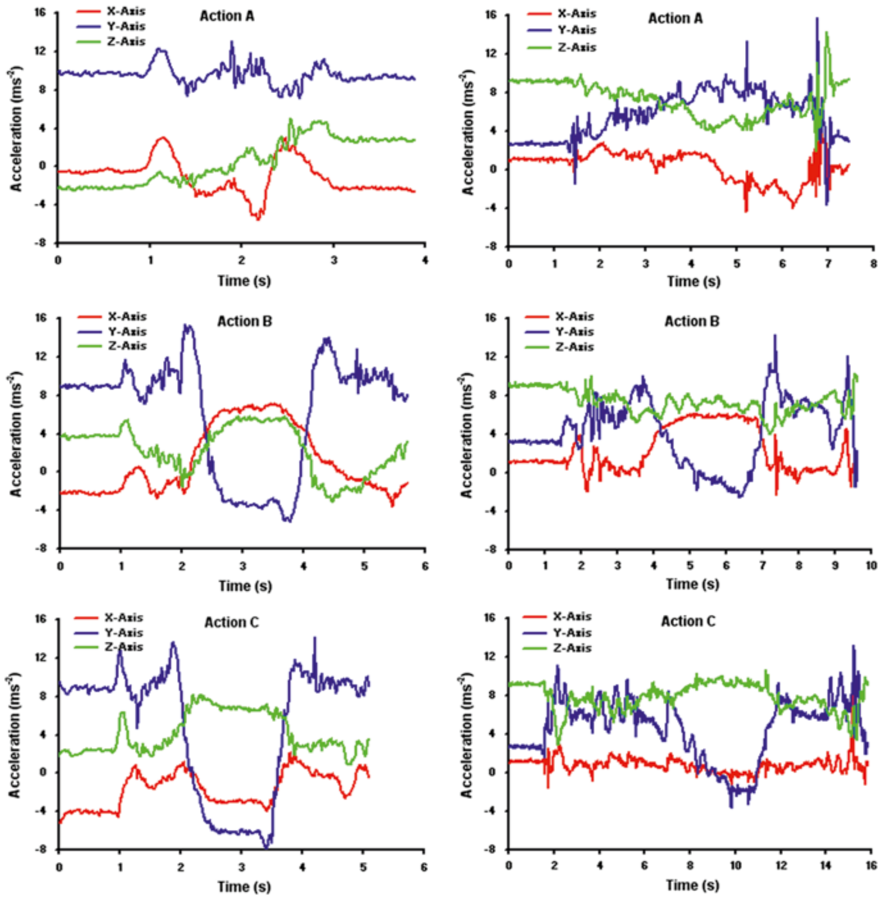

Fig. 4.9 Data from a tri-axial accelerometer located on the wrist collected while performing arm actions A, B and C with a healthy subject (*left*) and a stroke survivor (*right*) [170]

evaluation in terms of the sensitivity of recognizing the movements performed in the *testing* phase are presented in Table 4.5. The table also shows the minimum number of features that were required to successfully form the three clusters for each subject. The number of features has been determined by 10 runs of tenfold cross-validation on the *training* phase data as discussed in Sect. 4.4.5. The results in general show that each subject required a different minimum number of features to successfully form three separate clusters from the *training* data, reflecting the variability in arm movement patterns between individuals. The final two columns in Table 4.5 show the overall detection accuracy (total number of recognized actions expressed as a percentage of the total number of actions performed) for each subject, which covers the range 61–100 % (average of 88 %) and 61–93 % (average of 80 %) for the two different distance measures (Euclidean and Mahalanobis).

Table 4.5 Calculated recognition accuracies and number of features required for each subject performing the activity "making-a-cup-of-tea" when using Euclidean (Euc) and Mahalanobis (Mah) metrics to assign clusters

		Recognition accuracies (%)							
		A	A	B	B	C	C	Overall	Overall
Subject	Features	Euc	Mah	Euc	Mah	Euc	Mah	Euc	Mah
Subject 1	11	100	98	100	100	100	75	100	93
Subject 2	2	80	75	5	5	80	95	61	61
Subject 3	7	95	85	100	100	90	60	95	83
Subject 4	23	95	63	100	100	85	100	94	81

Table 4.6 Number of features and their ranked order for each subject required to accurately classify the three separate arm movements in the activity "making-a-cup-of-tea"

Subject	Ranked features
Subject 1	stddev_y, rms_y, rms_z, stddev_z, rms_x, diff_y, stddev_x, diff_z, max_mag_y, diff_x, max_mag_z
Subject 2	stddev_y, rms_y
Subject 3	rms_z, rms_x, stddev_y, stddev_x, rms_y, entropy_z, stddev_z
Subject 4	stddev_y, rms_y, stddev_x, rms_x, diff_y, max_mag_y, diff_x, max_mag_x, kurtosis_x, kurtosis_z, skewness_z, entropy_y, diff_z, max_mag_z, kurtosis_y, stddev_z, entropy_x, skewness_x, peaks_y, skewness_y, entropy_z, rms_z, peaks_x

A list of ranked features is presented in Table 4.6 (sorted in descending order), highlighting the features selected for each subject. This shows that for each subject, the ranked order of features is different (reflecting on the different ways in which they perform a movement) and also shows the difference in the number of features required to form the clusters. In general, we can consider the recognition accuracies achieved as being favourable, with the obvious exception of detecting *Action B* with Subject 2 with both the Euclidean and Mahalanobis minimum distance classifiers. It is worth noting that this subject required the smallest number of features to form clusters from the *training* data. This is somewhat counterintuitive—fewer features imply sufficient differences in arm movement patterns to make unique cluster formation easier. While this may be the case, however, the low detection accuracy for *Action B* could be accounted for by poor repeatability by the subject in this particular arm movement.

Changes in the detection accuracies for Subject 2 using additional features are shown in Fig. 4.10, which reveals that increasing the number of features beyond 2 does not necessarily improve accuracy. In comparison with the results achieved, the minimum distance classifier based on Euclidean distance appears as the favourable choice of distance metric. This is favourable since computation of the Euclidean distance is far less complex than that of the Mahalanobis distance which involves the maximum likelihood estimation of the covariance matrix.

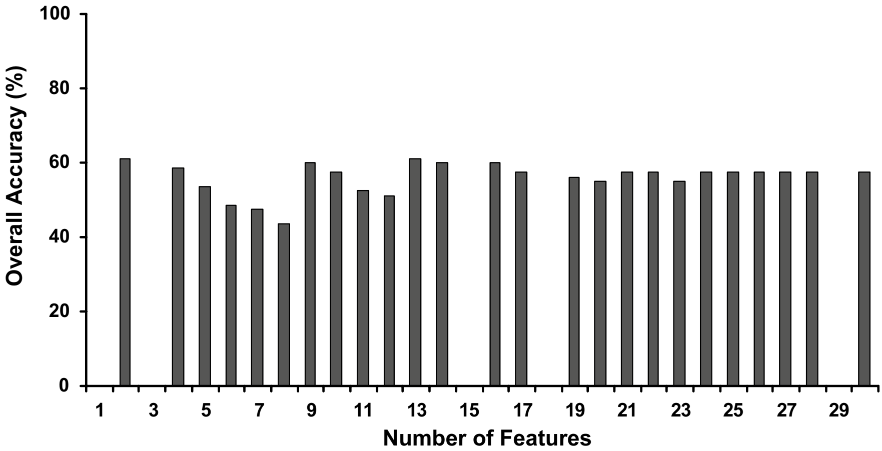

Fig. 4.10 Change in accuracy with number of features selected (for Subject2) using Euclidean distance [170]

4.4.8 Application Framework

In view of this exploration and the achieved results, we believe that the proposed clustering and minimum distance classifier-based methodology can be implemented in real life for monitoring arm rehabilitation progress in remote health monitoring applications. This methodology could be used to track the number of times a patient performs specific arm movements with their paretic arm throughout the day. Therefore, we highlight the application framework for a patient monitoring system.

It is evident from the results that there is a need for a completely personalized approach of detecting elementary arm movements. Various factors like stage of rehabilitation and whether the affected arm was originally dominant play a significant role in detection since they affect the level of repeatability of individual movements as well as introduce a high degree of temporal variation. For any patient suffering from arm dexterity, the specific movements (or exercises) that need to be tracked as defined by clinicians need to be performed multiple times, following an exercise regime or a gaming session, in a controlled environment (clinic or home). The sensor data collected during this phase can be analysed through cross-validation to determine the best cluster forming features and obtain the centroids of each cluster corresponding to each movement. This helps to perform a clinical profiling of the individual patient with respect to their movement quality. Movements performed in the uncontrolled nomadic environment (which can involve daily activities) can be associated to the proximal cluster centroid using the minimum distance classifier.

It is also important to mention that this methodology can be adaptable to the changing movement patterns of the patients over time reflective of an improvement in their motor functionality depending on the rehabilitation. The patient's training data can be collected periodically as and when requested by the clinician and the

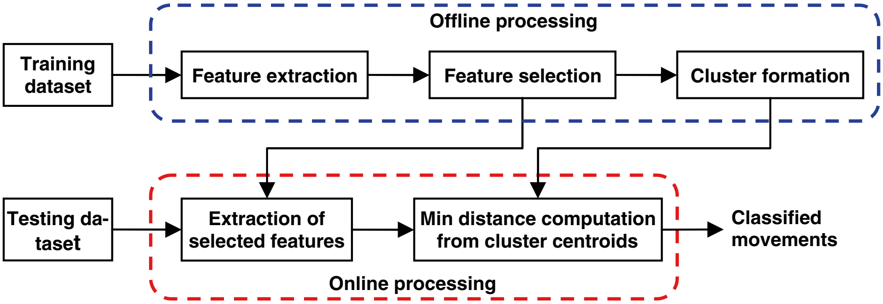

Fig. 4.11 Overview of the offline–online processing—the *training* dataset is processed offline and the *testing* dataset is processed online. The computation of the selected features on the *testing* data and computation of the minimum distance from the pre-computed cluster centroids were done in ASIC for real-time detection of arm movements

cluster centroids and the associated features can be recomputed to reflect the new movement patterns. This information can be further used by the minimum distance classifier to recognize movements performed in daily life. In StrokeBack, this methodology has been implemented in an offline–online resource sharing mechanism aimed at detection of arm movements in real time. The processing overview is illustrated in Fig. 4.11.

The time and memory intensive process of feature computation, selection and cluster formation, on the *training* data were done in an offline mode. The computation of the selected features on the *testing* data and computation of the minimum distance (Euclidean) from the pre-computed cluster centroids in near real time were implemented as a low-power hardware (i.e. application-specific integrated circuit—ASIC). The fabricated ASIC, implementing the minimum distance classifier, is envisaged to be embedded on a sensor node, illustrated in Fig. 4.12, along with a microcontroller and other processing components like A/D converter, memory and de-noising circuit (digital filters), which can be used to recognize arm movements performed in daily life for real-time remote monitoring. This provides an energy-efficient solution for WSN operation over long durations [142].

The cluster centroids and *feature-code* (selected features) are uploaded to the on-board memory when the sensor module is plugged into the docking station for charging at the end of a monitoring session. The on-board microcontroller is aimed at controlling the address and the data signals to and from the ASIC, placed within the sensor node. The classification results produced in real time can also be stored within the memory along with the raw sensor data, which can be uploaded to a local host computer and also to the patient health record system (PHR). The ASIC chip takes $(9n+30)$ clock cycles (where n is the number input of data samples) in the worst case, considering it has to compute all the 30 features from the *testing* dataset and compute the Euclidean distance to the three cluster centroids (cf. Fig. 4.6). In our implementation, we consider a signal of the *testing* dataset to have 256 data samples, which can be represented on a dyadic scale and therefore we can implement any multiplication or division through a shift operation, which is important for

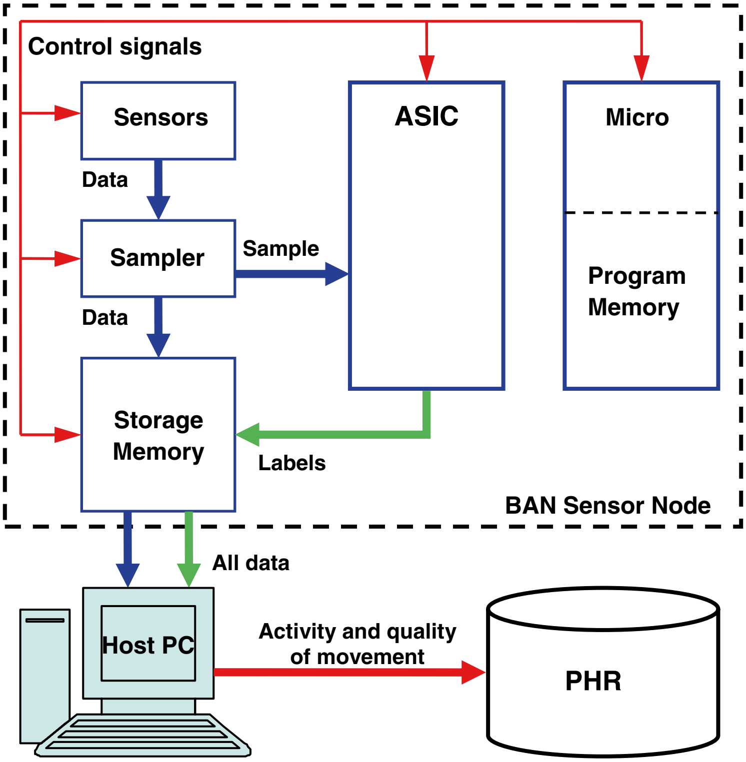

Fig. 4.12 Overview of an envisaged sensor node with ASIC, microcontroller and memory

obtaining low-power circuit operation. The design when synthesized on a 20-MHz clock frequency consumes a dynamic power of 25.9 mW and takes 0.12 ms [$(9 \times 256 + 30)$ @50 ns] to recognize a performed arm movement. This offline–online processing approach satisfies the application requirements of remote monitoring for arm rehabilitation. The processing (feature extraction, feature selection and clustering) of data collected during exercise (*training* data) needs only be done in an offline mode when requested by the clinician, depending on the rehabilitation progress of the patient. The online detection module can be used to associate the activities performed in nomadic settings (*testing* data) to the pre-computed cluster centroids in real time.

4.4.9 Discussion

In this proof-of-concept methodology, we demonstrate that we can detect all three arm movements performed in a real-world scenario with an accuracy of 61–100 % using between 2 and 23 time-domain features and both the Euclidean distance- and the Mahalanobis distance-based classifiers. Furthermore, our methodology exhibits an overall average accuracy of 88 % across all subjects and arm movement types using the Euclidean distance metric where the number of features used is subject specific, reflecting the variability inherent in human movement. The methodology will be scalable when applied to a larger group of subjects as it looks for the best combination of features to achieve the highest overall accuracy for each individual subject which when applied in the field of remote health monitoring will provide a gross measure of subject-specific rehabilitation. This methodology can help to augment clinical findings and provide a quantitative measure on the rehabilitation progress of patients over time outside of clinical environments.

Since this methodology has been implemented as offline–online processing system, it can be trained to detect any category of movements in an offline mode and the ASIC can be used to detect those movements in real time. This methodology could be extended for use with patients suffering from other neurodegenerative disorders exhibiting less fluidic movement profiles. It can also be extended towards monitoring of lower limb movements. Real-time detection of arm movements can be very useful in a wide array of applications in the field of sports, human–computer interaction, or other treatments of arm dexterity. Therefore, the developed system can be used to track movements of required body segments in these respective fields outside a controlled environment. Hence, through this exploration, we have touched upon majority of the activity recognition steps as illustrated in Fig. 4.2 and discussed in Sect. 4.3.6.

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Chapter 5
Motivating Rehabilitation Through Competitive Gaming

Cecilia Sik Lanyi and Veronika Szucs

Abstract This chapter presents the games and animations developed for the "StrokeBack" project. After a detailed introduction—which is quite a detailed overview of the current available literature—showing the multimedia and virtual reality-based games and rehabilitation systems made all over the world. The second chapter deals with the presentation of the development environment of the "StrokeBack" projects' games. This is followed by the third chapter which describes in detail the games themselves from the initial games' ideas and from the first developing steps to the final version of the games. Finally, from the suggested several games only three games (Break the Bricks, Birdie, and Gardener) have been installed into the system. The goal of these games is to make it possible for the patients to practice at home. The patients have exercised various repetitive movements. The fourth part of this chapter presents the redesign of the games based on the therapists' and patients' opinions. The description of the level editors is in the fifth part of the chapter. The sixth section presents the motivation and teaching animations. Motivational animations were necessary for the patients to have a short rest between the completion of a level and stepping to the next level of the game. The teaching animations teach the clients the proper movements that he/she must exercise both during the game and music therapy. Particular transactions to the games and the animation should have a great motivating effect.

5.1 Introduction

The literature reviews of the topics stroke rehabilitation and movement rehabilitation with computer games should be considered since the early 1990s. Later the Multimedia and Virtual Reality (VR)-based games have become more and more popular. This section presents the research and development around the world as addressed not only technical and rehabilitation but also motivational aspects.

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The increasing number of people living with post-stroke aftermath has stimulated the search for novel ways of providing post-stroke rehabilitation without putting additional stress on overburdened healthcare systems [30]. Early rehabilitation in the intensive care unit improves patients' physical function. After going home, the rehabilitation and the repetition of everyday practices are more important. Researchers from both the healthcare and the technology side are working on developing new rehabilitation systems. In this part of the chapter these new ways are introduced since the last 15 years.

5.1.1 Virtual Reality

In recent years, virtual reality has grown immensely with rapid advancement of Virtual Reality (VR) technologies in the field of stroke rehabilitation.

VR is an emerging technology with a variety of potential benefits for many aspects of rehabilitation assessment, treatment, and research. Through its capacity to allow the creation and control of dynamic 3D, ecologically valid stimulus environments within which behavioral responding can be recorded and measured, VR offers clinical assessment and rehabilitation options that are not available with traditional methods. Initial applications of VR in other aspects of medicine and psychology have yielded encouraging results, but continued research and understanding of this evolving technology will be crucial for its effective integration into rehabilitation [32].

Virtual reality technologies hold great opportunities for the development of effective assessment and treatment techniques for neglect because they provide rich, multimodal, and highly controllable environments [45].

Acquired brain injury affects considerable numbers of individuals every year, resulting in a range of functional impairments requiring rehabilitation. VR is a relatively new treatment approach being used increasingly for this purpose [16]. Therapists had positive attitudes toward VR, perceived it as being useful, and had positive intentions to use it more in the future [15].

The intervention involved 11 patients after stroke who received extra rehabilitation by training on a computer three times a week during a 4-week period in Göteborg. The control group involved 11 patients after stroke who continued their previous rehabilitation (no extra computer training) during this period. The mean age of all was 68 years (range = 47–85) and the average time after stroke 66 months (range = 15–140). The VR training consisted of challenging games, which provided a range of difficulty levels that allow practice to be fun and motivating. All the participants were novel computer game players. After an initial introduction they learned to use the VR system quickly. The treatment group demonstrated improvements in motor outcome for the trained upper extremity, but this was not detected in real-life activities [6]. The results of Broeren and his colleagues' research suggest the usefulness of computer games in training motor performance. VR can be used beneficially not only by younger participants but also by older persons to enhance their motor performance after stroke [5].

Conventional rehabilitation provides modest and sometimes delayed effects. Virtual reality (VR) technology is a novel adjunctive therapy that could be applied in neurorehabilitation [31]. VR and video game applications are novel and potentially useful technologies that can be combined with conventional rehabilitation for upper arm improvement after stroke [31].

Stroke is a frequent cause of adult disability that can lead to enduring impairments. However, given the lifelong plasticity of the brain one could assume that recovery could be facilitated by the harnessing of mechanisms underlying neuronal reorganization. Currently it is not clear how this reorganization can be mobilized. VR technology-based neurorehabilitation techniques hold promise to address this issue [10].

In the research, Turolla [46] evaluated the effectiveness of nonimmersive VR treatment for the restoration of the upper limb motor function and its impact on the activities of daily living capacities in post-stroke patients. Both treatments significantly improved scores, but the improvement obtained with VR rehabilitation was significantly greater than that achieved with upper limb conventional therapy alone. VR rehabilitation in post-stroke patients seems more effective than conventional interventions in restoring upper limb motor impairments and motor-related functional abilities [46].

Glegg's study was the first study to quantitatively examine the social, personal, external, and technology-specific barriers to VR use from the perspective of brain injury therapists. Barriers and facilitators identified can be targeted by management to support VR implementation. Therapist-identified knowledge and support needs have informed the refinement of knowledge transfer strategies employed in ongoing research [16].

A VR proprioception rehabilitation system was developed in Seoul for stroke patients to use proprioception feedback in upper limb rehabilitation by blocking visual feedback. To evaluate its therapeutic effect, 10 stroke patients (onset >3 month) trained proprioception feedback rehabilitation for 1 week and visual feedback rehabilitation for another week in random order. Proprioception functions were checked before, a week after, and at the end of training. The results show the click count, error distance and total error distance among proprioception evaluation factors were significantly reduced after proprioception feedback training compared to visual feedback training. Subjects were significantly improved in conventional behavioral tests after training. They showed the effectiveness and possible use of the VR to recover the proprioception of stroke patients [11].

5.1.2 Telerehabilitation and Serious Games

An early computerized system trains range of motion, finger flexion speed, independence of finger motion, and finger strength using specific VR simulation exercises. A remote Web-based monitoring station was developed to allow telerehabilitation interventions. The remote therapist observes simplified versions of the patient exercises that are updated in real time. Patient data is stored transparently in an Oracle database, which is also Web accessible through a portal GUI. The results are indicative of the potential feasibility of this exercise system for rehabilitation in patients with hand dysfunction resulting from neurological impairment [1].

Nu!Reha (trademark of Pragma Engineering srl. See http://www.nureha.eu) is an application of virtual reality applied to the telerehabilitation of patients with traumatic brain injury and stroke. This system, based on X3D and Ajax3D technologies, enhances the possibility of making telerehabilitation exercises aimed at the recovery of the neurological disease. The system is designed to allow the remote monitoring and assessment of the patients' activities by the medical staff at the hospital using the communication facilities of the telerehabilitation system [14].

Several years ago a VR-based system, the Rehabilitation Gaming System allowed the researchers to develop a Personalized Training Module for online adjustment of task difficulty. They studied task transfer between physical and virtual environments. The results showed that the Rehabilitation Gaming System effectively adjusts to the individual features of the user, allowing for an unsupervised deployment of individualized rehabilitation protocols [10].

The term "serious games" denotes digital games serving serious purposes like education, training, advertising, research, and health. Compared to traditional interventions, these games may help elderly people to improve their health by enhancing physical fitness and coordinative abilities by combining increased motivation, game experience like fun and game flow and training. Serious games, particularly adventure and shooter games, already play an important role in prevention and rehabilitation, e.g., to enhance health-related physical activity and improve sensory-motor coordination [48].

Brooks worked with stroke patients between 1996 and 2002. He made games-based and arts-based interactive gesture-controlled environments with patients in Aarhus regional hospital and then later at the main Centre for Brain Rehabilitation in Copenhagen. The research was based upon his self-made authoring environment that enabled adaptation and tailoring to each individual's ability, preference and desires to optimize motivation in intervention sessions. This emergent model ZOOM (Zone Of Optimized Motivation) is reported in Advanced Computational Intelligence [7, 8].

5.1.3 Motivation and Life Satisfaction

Kim argues that VR provides the motivation of gaming factors [21]. There is interdisciplinary evidence suggesting that key factors in game design, including choice, reward, and goals, lead to increased motivation and engagement. The authors maintain that video game play could be an effective supplement to traditional therapy. Motion controllers can be used to practice rehabilitation-relevant movements, and well-designed game mechanics can augment patient engagement and motivation in rehabilitation [23].

Effective stroke rehabilitation must be early, intensive, and repetitive, which can lead to problems with patient motivation and engagement. The design of video games, often associated with good user engagement, may offer insights into how more effective systems for stroke rehabilitation can be developed [9]. The emphasis is on the positive effects of virtual reality as a method in which rehabilitation and therapy can be offered and evaluated within a functional, purposeful, and motivating context [25]. So motivation has a crucial role, therefore several short (10–15 s) motivational animations were developed in the "StrokeBack" project too. These animations are running after each game [41].

Heo and Lee's study investigated factors that explain the life satisfaction of Senior Games participants. 193 older adults from the 2005 Michigan State Senior Games and the 2005 New York State Senior Games participated in the study. The results of their study show that one of the indicators of serious leisure (affective attachment) was positively correlated to optimism, age, and the number of years participated. It was found that dispositional optimism and perceived health were significant predictors of life satisfaction [19]. The study suggests to the reader that in 2005 there was no problem for the elderly to use the new technology. Therefore, we can trust that the patients who use "StrokeBack" project's game they will be able to use them easy [42, 44].

5.1.4 Commercially Available Technology

Pietrzah and his co-workers studied six papers and seven abstracts from healthcare's paper databases, wondering of the efficiency of commercially available technology for upper limb stroke rehabilitation. It was found using commercially available technology for upper limb stroke rehabilitation, like consoles and video games, Nintendo Wii, EyeToy PlayStation, and CyWee Z, the Nintendo Wii appears to provide the greatest benefits to patients, with improvements seen in upper extremity function measures such as joint range of motion, hand motor function, grip strength, and dexterity. At present, the evidence that the use of commercial video games in rehabilitation improves upper limb functionality after stroke is very limited [30]. The games developed under the umbrella of "StrokeBack" project have a level editor which allows adjusting level difficulty, i.e., makes the treatment more individualized. The level editor will be introduced in Sect. 5.5.

Nowadays a lot of games are controlled by Microsoft Kinect sensor as in the rehabilitation process at Royal Berkshire Hospital with computer games to engage patients with their rehabilitation following stroke and other brain trauma injuries. Initially off-the-shelf games were used, the ludic nature of the games, masking the treatment element of the exercises [27].

The controls of the games in the "StrokeBack" project are running by Microsoft Kinect sensor too.

5.1.5 Information Overload and Navigation

Ma's virtual reality system [24] enables the patient to perceive similar real-world performance in the virtual world. However, it might cause information overload, which makes the patient feel confused and distracted during training. During the evaluating tests it has been found that effective pre-training set could overcome the problem in the main task. Minor modifications on the pre-training set could overcome or aggravate the problem, which indicates the importance of choosing the correct pre-training parameters [24]. From this viewpoint the games in "StrokeBack" project are based on 2D and only the teaching animations are made in 3D. In this case the information overload might be avoided.

In recent years, the evolution of 3D graphics hardware and software has led to a growing interest for serious games in 3D virtual environments for learning, training, and rehabilitation. Many of these games are based on a first-person-shooter paradigm in which users navigate through the environment, select, and manipulate virtual objects. The target users of these applications are not necessarily usual gamers, and they often have difficulties in navigating and interacting in the 3D environment [28]. Therefore the navigation and control in the "StrokeBack" project's games were designed to be very simple [36, 37].

A new task-specific interactive game-based VR system, RehabMaster for post-stroke rehabilitation of the upper extremities was developed, and assessed its usability and clinical efficacy [33]. There was an observational study in which 7 patients with chronic stroke received 30 min of RehabMaster intervention per day for 2 weeks. The second was a randomised controlled trial of 16 patients with acute or subacute stroke who received 10 sessions of conventional occupational therapy only; or conventional occupational therapy plus 20 min of RehabMaster intervention. The requirements of a VR system for stroke rehabilitation were established and incorporated into RehabMaster. The reported advantages from the usability tests were improved attention, the immersive flow experience, and individualised intervention [33].

Lewis and Rosie found, seven common problems: technology limitations, user control and therapist assistance, the novel physical and cognitive challenge, feedback, social interaction, game purpose and expectations, and the virtual environments. Our key recommendations derived from the review were to avoid technology failure, maintain overt therapeutic principles within the games, encompass progression to promote continuing physical and cognitive challenge, and to provide feedback that is easily and readily associated with success [22]. "StrokeBack" project's games have visual-, audio feedback with reached score too [43].

5.1.6 New Technologies

New technologies are not necessarily easier to learn to handle than older ones, especially if they are treated as new innovations with longer adaptation time and used for everyday work [38]. Even if new technologies are often used in collaborative settings, the team aspects, team goals, and the underlying social interaction are often neglected in the evaluations [17]. The actual evaluation methods are not enough to know how to introduce new technologies in emergency management [2]. New approaches, for example, considering game patterns may lead to more effective training of many time-critical, time-consuming, or more complex tasks [18].

Barzilay and Wolf proposed a novel approach to neuromotor training by combining the advantages of a virtual reality platform with biofeedback information on the training subject from biometric equipment and with the computational power of artificial neural networks. The system was tested for upper limb rehabilitation on healthy subjects. They measured a 33 % improvement in the triceps performance (p=0.027) [3].

An extremity rehabilitation program was proposed based on inertial measurement units (IMU) and virtual reality. A single IMU consists of a three-axis accelerometer, gyroscope, and geomagnetic sensors. One IMU is attached to the upper arm (master) and another to the forearm (slave). The IMUs are connected using a distributed sensor network implemented with integrated circuit communication [21].

The games developed for "StrokeBack" framework are supporting the rehabilitation of patients with different degree upper arm dysfunctions. Each of the games can be controlled by simple repetitive movements, thus the boring physical exercises became the control resources for games. The emphasis moved from the practice to the control of the game, the users' viewpoint has changed and this makes them more motivated.

5.1.7 *Wolf Motor Function Test*

Jo [20] determined significant differences in Wolf Motor Function Test (WMFT) [49] score between before and after the intervention in the VR and control groups. Their study suggests that remote rehabilitation using functionally effective VR makes rehabilitation training an easy and pleasant experience for patients. Standen [39] showed a low-cost virtual reality system for home-based rehabilitation. Participants were assessed at baseline, 4 and 8 weeks using the WMFT and other tests of Daily Living [40].

The games showed in this chapter were developed based on WMFT test too. Success of the treatment relies then on the accuracy and repetition of the motor training. The games' controls in the "StrokeBack" project were based on these single repetitive movements. In this chapter we focus on serious games and animations designed for the "StrokeBack" project. The usability and special needs were in the focus of the development. In the development process we relied on our previous experience [26, 35].

5.2 Development

The aim of the development is to create an automated remote rehabilitation system for stroke patients, which needs minimal human intervention [34]. Objectives:

- Remote control of rehabilitation exercises
- Continuous monitoring of patients' movement coordination

- Database about patients for long-term evaluations
- Feedback for the doctors about the effects of rehabilitation exercises

There is also a plan to use a dress provided with sensors called BAN (Body Area Network) (see Chap. 4), which can be used for the monitoring of daily activities. With the use of a device, called rehabilitation desk, the patient can practice different exercises at his/her own home, or can consult with the doctors through a video conference. The framework and the games presented in our work will run on this device as well.

In the desk there is a high-definition camera and a Kinect motion detecting camera as well, with the help of which the patient should control the games. The results of the exercises will be uploaded to a database of the Patient Health Record (PHR) (see Chap. 8), which will be used for the further evaluations.

5.2.1 Applied Developer Devices, Technologies

Hereinafter a well-working development model will be presented. According to experiences, the usage of this method facilitates the task of the developers' team.

Since it is closely related to the GIT[1] versioning system, the authors start with the introducing of this one.

GIT is an open-source distributed versioning system. It's major advantage and main difference from the other versioning systems (e.g., CVS, SVN) is it's "branching" model. At versioning systems we create savings about a given workplace's state and we can restore to a saved state any time. The GIT gives the opportunity to create more local branches, which can be dealt with independently. We can freely experiment on the local branches, we can reenter the main branch, or we are able to merge these branches as well.

Since the system is distributed, all of the developers have a complete copy of the repository. Therefore every developer has a complete safety save. We may have any number of repositories and a great amount of work methods are attainable with it. Since every one of the developers has a complete capacity of repository, hence it is available to work on a given workplace without an Internet connection and can also be uploaded later for the server.

GIT is fast, thanks to the fact that nearly all of the operations are working locally and so it does not have to communicate with a distant server. GIT has primarily been written for the development of Linux kernel. It has been written in AnsiC and amongst its major aims was rapidness.

Further advantage is the so called "staging area". There is an opportunity to check the changes in the files before committing and also to commit only a part of the files. With the help of this it is easy to ensure that after each changing only those source code details should be added which are in close relationship with each other.

[1] GIT official website: http://git-scm.com

5.2.2 The Framework

A universal framework is also part of the system, which will include all of the serious games in the "StrokeBack" project. This framework handles the communication of the PCs and the controllers, supplies movement data to the games, and provides a main menu for the system.

The most important function of this framework is to support the communication of the games and the controller devices. The framework manages the connection of the PC and the Microsoft Kinect sensor, converts the sensor data received from the Kinect to the movement data used by the games, and provides this movement data to the games.

Another function provided by the framework is the PC client's main menu. In this menu, the user can reach the "Play games", the "Settings", the "About" and the "Help" submenus, and can quit the program. In the "Play games" menu the games inserted into the framework can be started. With the "Settings" submenu, the user can set some parameters of the PC client. In the "About" menu the user can find information about the authors and the game. The "Help" submenu's goal is to give a hand to the user with showing the controlling and setting up process of the framework.

A big advantage is that the framework can be easily expanded with other games and functions. This way if we design more games on the grounds of experience we gain from the first games' tests, we can easily add them to the system.

5.2.3 Specification of Requirements

At the beginning the functional requirements were the following:

- Simulating WMFT movements [49]
- Scoring system: cannot be negative, it should stimulate the patient
- The Feedbacks of the movements have to be very clear

Further requirements:

- Games should provide opportunity for using more themes
- After each game a motivating animation has to run which fits to game's theme
- Teaching animation has to show the right movement before each game
- Background events and supporting characters should appear
- For customization level, editors are needed

Nonfunctional requirements:

Under "StrokeBack" project, several rehabilitation games have been completed. To this a framework has also been developed, where these games and the associated level editors can be integrated, thus can be launched from the same surface.

Therefore, important nonfunctional requirements are as follows:

- All games should be fitting this framework
- In their structure and style they should be similar to the other games
- Use already written code sections of the framework to avoid redundancy

5.2.4 Saving the Score Results

During the games' developing process it was very important to test the games in every phase. These works ran parallel with the development of the projects' personal health record and e-Health Service Platform (see Chap. 8). Therefore we have to develop an own database to save the score results during the tests. In practical data mining tasks, high-dimensional data has to be analyzed [47]. One of the main focus was to develop the user interface and make knowledge defined in the expert system more exact in the hope of improving usability. It was based on the ideas of Werner-Stark [50].

As the first step of the system design process, the evaluation of the requirements had been completed. With the help of this, the definition of current services and requirements, the exhibition of data, and the identification of processes have been completed. The main aim was to define the functional and nonfunctional requirements, to evolve the cue, with special regard to the future users. This was followed by the modelling of actions, for which information support should be ensured in the project, more specifically for the databases.

For this reason a requirements catalogue has been created, which can continuously broaden through the whole period of the project: the contents of the initial catalogue will revolve with new date during the development process. This catalogue contains the functional and nonfunctional requirements. In the requirements catalogue every functional and nonfunctional requirement owes a requirement record, which contains the definition of the requirement in a table format, the suggested accomplishment method and an acceptable aim-value range.

The logical models of the MS SQL and SQLite-based databases have been created. The logical basic models of the databases are simple entity-relationship models, created based on a top-down evaluation. The requirements specification helped to know that what kind of new elements should the data model be expanded after the evaluation: new entities, new relations; but it also gave information about which contents can be left out from the models, which are the entities and relations not needed. The results have been normalized through more steps, thus abolishing the unnecessary connections and the unwanted redundancy in the planned databases. On the live system, the self-developed hardware of the consortium, the framework is not running as it was in the testing period, the games can independently be executed from a command line, with different options as switches.

In the games, the results of the scoring, the important game data, and the interesting information of the therapy are stored in a XML file, and with the help of excluded routine, get the contents of the XML result files to the central patients' health record (PHR) (see Chap. 8).

5.3 The Games

In the first development pace, the therapists said that games should be found out based on WMFT [49]. For the assessment of different motion abilities WMFT uses series of tests consisting of 21 tasks. For the development of the rehabilitative game we received a variant of this test restricted for 11 tasks. For these motions, which are all plain motions, we planned different skill developing and arcade games. These games are shown in Table 5.1. In Table 5.1 there is a summary, which sums up, which of the particular games are appropriate for the practice of which test tasks.

Out of these games five games have been completed (during the early development stage): "Break the Bricks" (BTB) (Fig. 5.1) [13], "Wordy Labyrinth" (Fig. 5.2), "Labyrinth" (Fig. 5.3), "Memory" (Fig. 5.4), and "Free Kick" (Fig. 5.5) [34, 35].

In the early development stage the games were tested over several cycles, but despite the positive feedback of the users the therapists took out four of the games from the further development process, only BTB remained. Therefore in the second step there were developed two more games: "Birdie" and the "Gardener" games.

5.3.1 "Break the Bricks" Game

BTB is a classic brick breaker game. It was a very famous arcade game in the 1990s. The goal of the game is very simple: smash the wall of bricks by deflecting a bouncing ball with a paddle (it could be a car, or a train, etc.). The aim of this game is to clear the screen by breaking the bricks appearing on the top of it. To break a brick, hit it with the ball several times (Fig. 5.6).

The brick types can be seen in Table 5.2.

For hitting bricks (if its type is not metal), $10 \times \frac{\text{the ball's speed}}{\text{the paddle's speed}}$ points are given,with smashing one, $20 \times \frac{\text{the ball's speed}}{\text{the paddle's speed}}$ points can be earned.

If the ball falls down it means −20 points from the score.

If the user finishes with a level within a shorter time than the previously set up average time, the points calculated from the time difference will be added to the score (1 s means one point).

The available themes of this game: default (original skin), car, cake, duck, ship, train.

To control the pad, the dedicated "left" or "right" movement should be done. The ball can be started with the dedicated "start" movement.

If controlled with the keyboard, the following keys shall be used: start the ball: space, movement: left and right or A and D, help: F1, menu: Esc.

Table 5.1 Relation of games designed for WMF test and movement that can be practiced

Planned game	Break the bricks	Free kick	Labyrinth	Memory game	Firework game	Puzzle	Obstacle course	Pick your phone	Bunny-jump	Gardener game	Birdie game	Virtual piano	SUM
1. Other movements	x	x			x	x				x	x	x	7
2. Lift basket					x	x							2
3. Fold towel									x				1
4. Turn key in lock				x		x						x	3
5. Lift pencil								x					1
6. Lift can					x	x							2
7. Reach and retrieve		x			x	x	x			x			5
8. Extend elbow-weight				x	x	x	x						4
9. Extend elbow-side				x	x	x	x				x		5
10. Forearm to box													0
11. Forearm to table													0

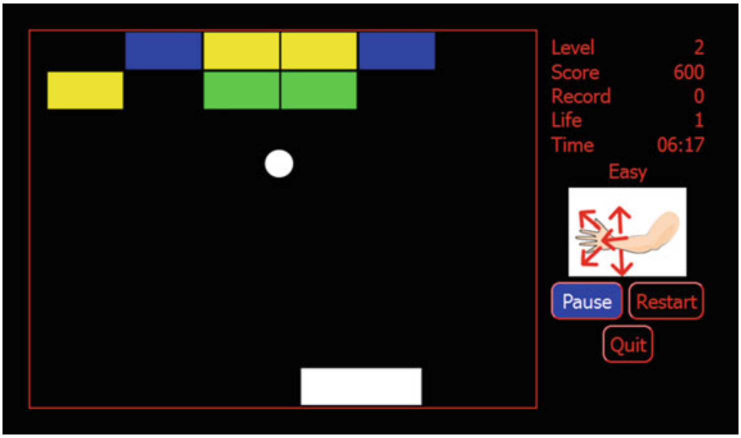


Fig. 5.1 Initial version of the BTB game

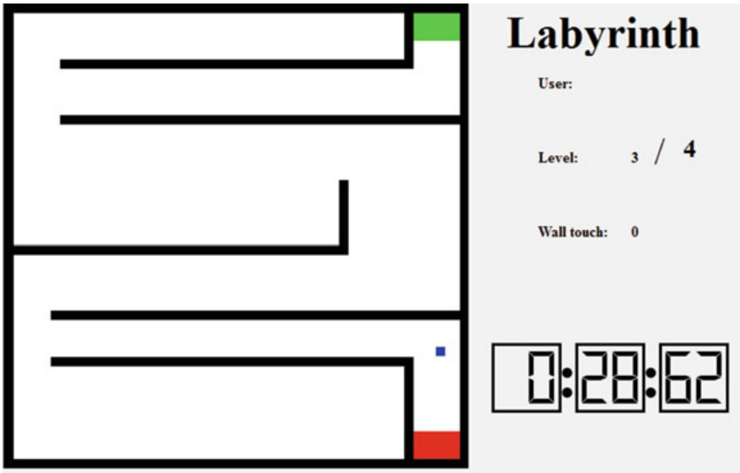


Fig. 5.2 Initial version of the Wordy Labyrinth game

5.3.2 "Birdie" Game

In this game the aim of the player is to help a bird to get back home. The birdie is flying home, and the goal is to keep it in the air and prevent it from colliding with the obstacles, which can be other birds, rocks, trees, etc. If the bird bumps into something, the game will continue from the actual point, and the level won't restart [41]. On the bottom of the screen a progress bar can be seen, which shows how much of the course is accomplished by the birdie, and how much is left (Fig. 5.7).

The main scores are derived from the distance travelled and the speed of the bird.

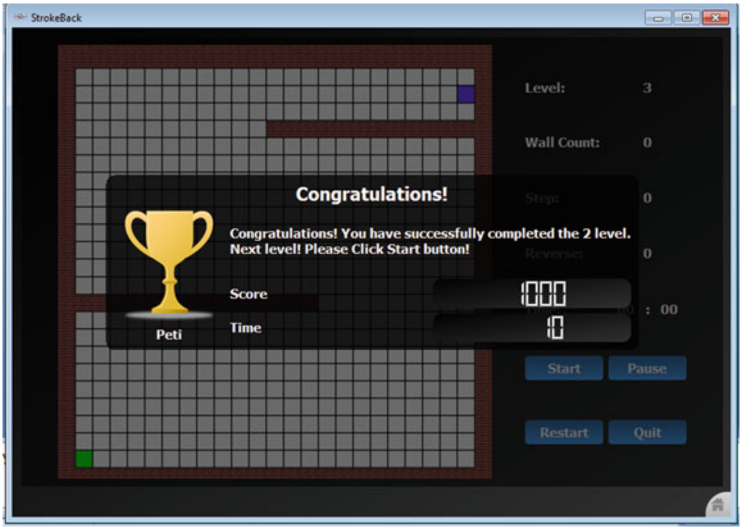


Fig. 5.3 Early version of the Wordy Labyrinth game

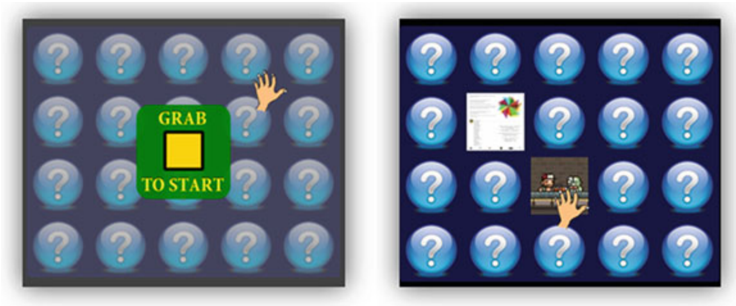


Fig. 5.4 Starting version of the Memory game

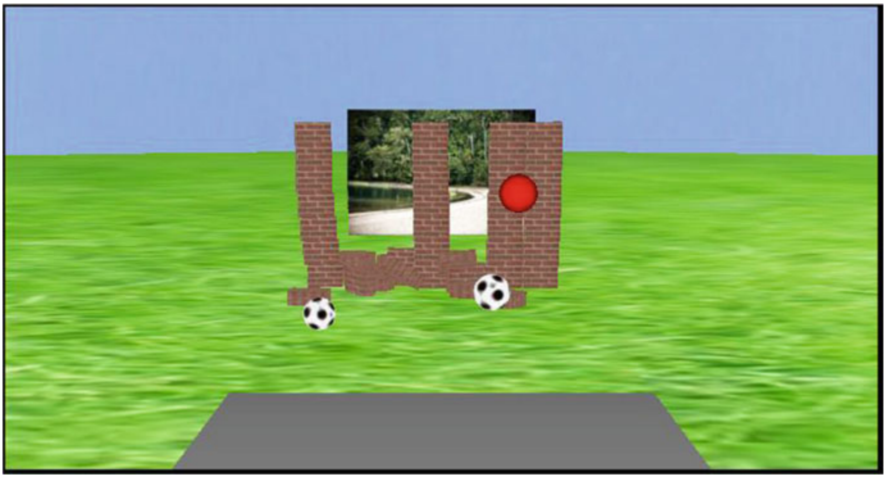


Fig. 5.5 Initial version of the Free Kick game

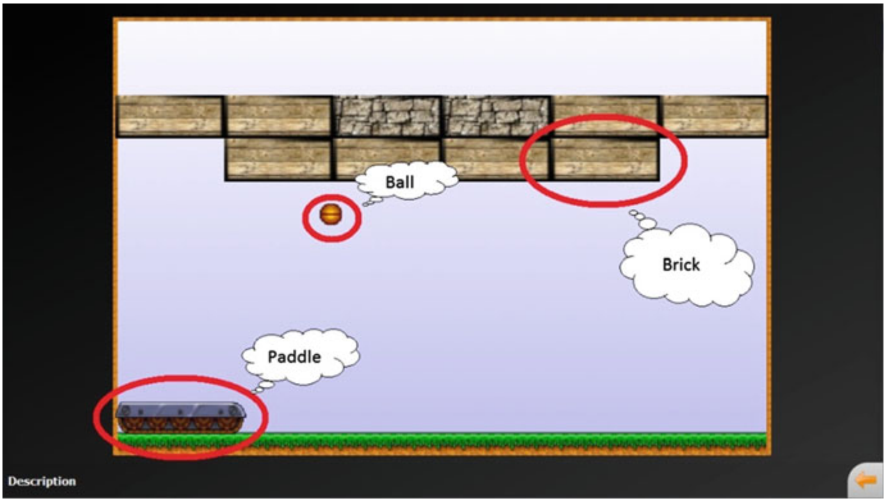
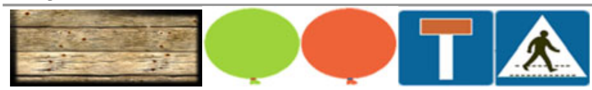
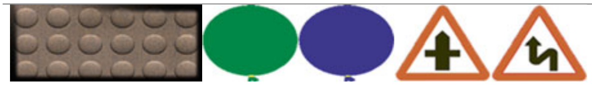


Fig. 5.6 The BTB game

Table 5.2 The brick types

Image	Type	Lives
	Wood	2
		
	Rock	3
		
	Brick	4
		
	Metal	Cannot be smashed
		

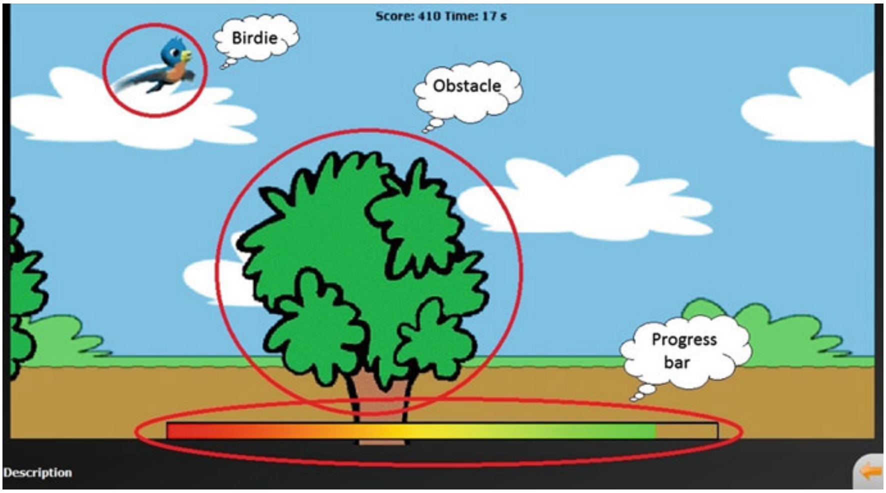


Fig. 5.7 The Birdie game

The player can get extra points by completing the level in a shorter time than the average, like in the BTB game.

If the player can finish a level without hitting any obstacles or falling down, extra points will be given.

If the little bird falls down, it means minus points from the score.

The available themes of this game: default (original skin), cave (played with a bat), circus, forest, jungle, mountain, sea, town, winter.

To fly the birdie, the player has to make an "up" movement. To descend faster, the player has to make a "down" movement.

If played with the keyboard, press "Up" arrow (cursor keys) to fly and the "Down" arrow to descend.

5.3.3 "Gardener" Game

The task of the player is to make the plants and flowers growing one by one [29]. To grow a plant, the player has to water it several times with a dedicated movement [36, 37]. After a plant grows up, the player can continue with the next one till all of the flowers or plants in the garden are grown up. The status bar shows how many times does the actual plant be sprinkled until it becomes fully grown (Fig. 5.8). The count of these sprinkles is called "Required" motions.

If the player waters the plants too slowly, they will start to wither (their color will turn to gray). There is a big exclamation point glowing above the withering plant to warn the player. The time interval between the last watering and the withering is called Fading time (Fig. 5.9).

The player can attend more kinds of plants, for example roses, grapes, or tomatoes.

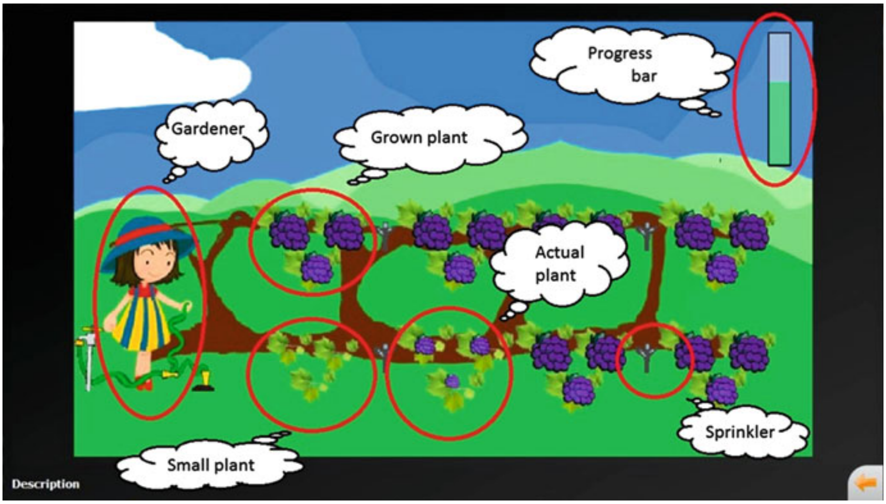


Fig. 5.8 Gardener game

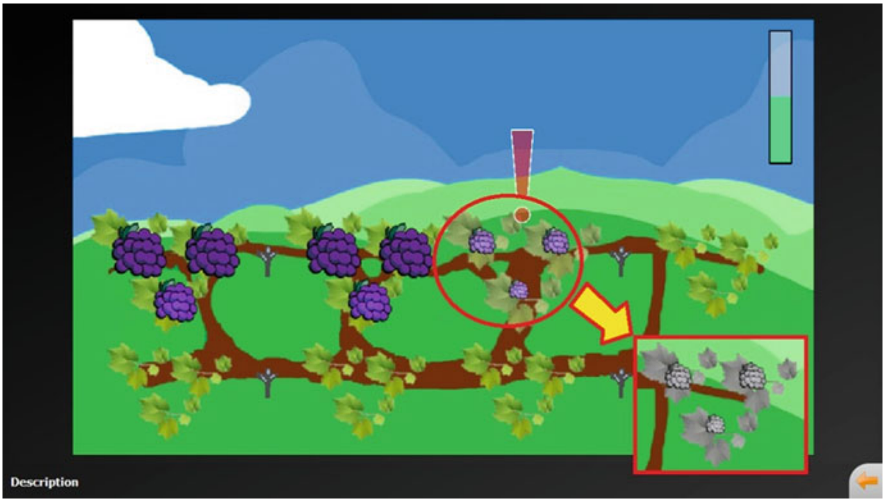


Fig. 5.9 Fading in the Gardener game

For each movement, the player will get $\frac{10}{\text{“Fading time”}}$ points, and completing a plant means $\frac{70}{\text{“Fading time”}}$ points. If the plant is grown up without withering, it means $\frac{100}{\text{“Fading time”}}$ points for the player.

There is an extra time bonus too, which is calculated based on the elapsed time, the number of the plants, and the count of the required movements.

The available themes of this game: bluebell, carrot, currant, geranium, grape, pepper, rose, strawberry, tomato, tulip.

To spray a plant, the player has to make a dedicated spraying movement.

If played with the keyboard, press “Space” to spray.

The movement of the gardener/hose is automatic; the player can only control the watering.

5.4 Redesign the Games

The first clinical test was made by nine stroke patients in the Brandenburg Clinic in Bernau (Berlin) early May 2013. We got several positive and negative feedbacks and good ideas from the patients too [36, 37, 43, 44].

5.4.1 Opinions of the Therapists and Patients

The BTB game was the most high-developed in the early testing phase; nevertheless the therapist opinion was not so high positive. They suggested more varied pictures on the bricks. A male patient’s opinion was that this train reminds him of a tank. After it the BTB game’s graphic design was improved.

The Birdie game also worked very well in the early test, and the graphics were really beautiful. But the therapist’s opinion was that we have to develop more interesting locations with a lot of objects. Another male patient’s opinion was that this game is very “girly”, and why do not we put into the game for example a bat. Based on these remarks some new locations were designed and added to the game, including a bat theme.

The least developed game was at that time the Gardener game, therefore its redesign is showing more details.

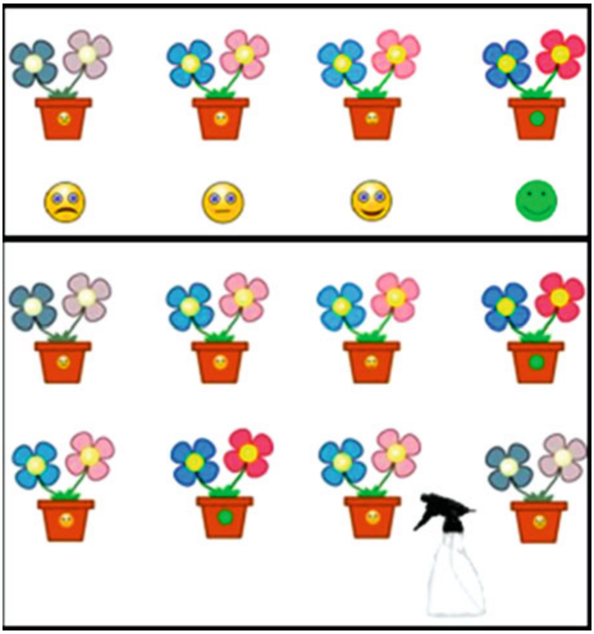
From the answers given for the open questions, it has also been found out that the users did not consider the “Gardener” game to be entertaining, they would not like to play with it again.

The main reasons may be the monotone character and the lack of motivating elements in the previous version of the game, for the correction of which the following solutions have been developed:

- The certain fields should appear in different environments, with different plants
- The plants should be watered by different characters
- Interesting events should be in the background (animals should appear in order to maintain the interest)
- After the completion of a level, motivating, reward animations should appear
- Levels with increasing difficulty should be introduced

Therefore the “Gardener” game in this chapter is only presented as a case study, because the patients found it “boring”.

Fig. 5.10 First plan of "Gardener" game



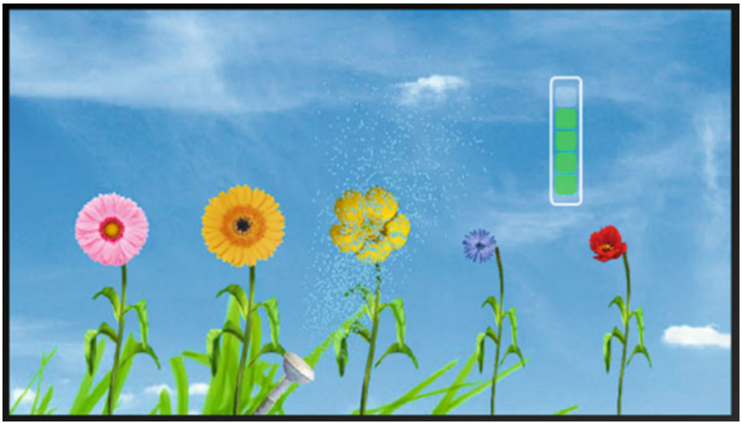


Fig. 5.11 First version of "Gardener" game

The "Gardener" game has undergone several versions and a series of redesign during the development process.

In Fig. 5.10, the first plan of "Gardener" game can be seen. According to this plan, a first version has been created, where the plants and the sprinkler have already appeared (Fig. 5.11).

Several functions have still been missing, as the fading of the plants, the alert, and a character that does the watering. According to these requirements a new

Fig. 5.12 Girl watering with a sprinkling-can

version has been created, where various themes and plants (bluebell, carrot, currant, geranium, grape, pepper, rose, strawberry, tomato, and tulip) were introduced, and a new character (girl) appeared with a sprinkling-can and passed along the plants (Fig. 5.12).

For this version, however, the therapists gave negative feedback that the game does not correspond to the rehabilitation process. The therapists referred to the girl sprinkling the plants (and passing along them), that she might be misleading, and the patients might think that they should do the same movement.

Such a visualization was needed which is realistic and inclines the user for the imitation of the movement. The movement in the case of this game is the repetitive movement of closing and opening the fingers 50 times or for 5 min (Figs. 5.13 and 5.14).

5.5 Level Editors

This part of the chapter shows the level editors of the games.

5.5.1 Break the Bricks Game Level Editor

To create a new level, the "new" icon should be selected at the top right corner of the screen. In this case, the name of the new level should be given in the dialogue window. To load an existing level, the "load" sign should be selected, which is placed next to the "new" icon (Fig. 5.15).

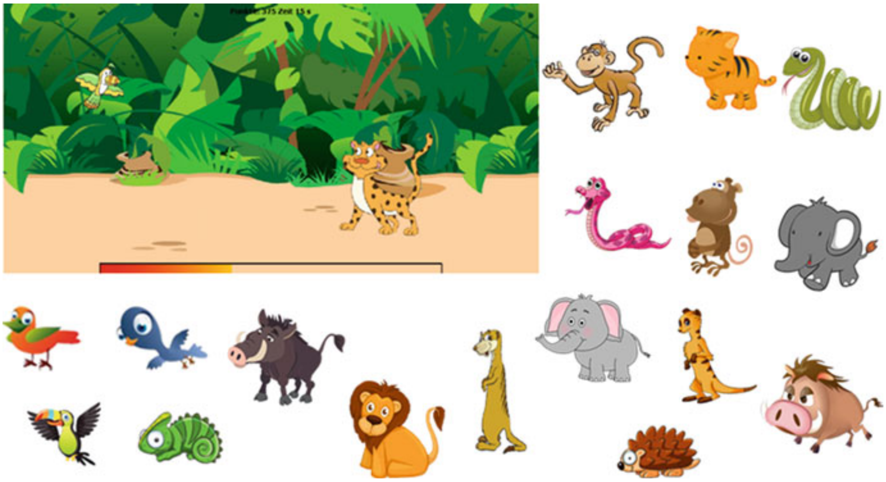


Fig. 5.13 Birdie game “jungle” theme with possible obstacles [43, 44]

Fig. 5.14 Birdie game “bat” theme and the possible obstacles

At the top left of the screen the file path of the actual level’s file can be seen. If there is a “*” (star) mark before it that shows the current state of the level has not been saved yet.

At the bottom of the screen the general settings of a level can be set: the previously mentioned average time, the speed of the pad (platform), the speed of the ball, and the theme (skin) of the level. The theme can be selected from the drop-down menu, which contains the available skins. It can be set to “Shuffle” also, which

Fig. 5.15 Level editor of the BTB game

means that the level will run with a randomly picked skin (two subsequent levels won't have the same theme).

On the right hand side the usable bricks can be seen; there are more types of bricks, depending on how many hits do they need to break (0–4). In the middle of the screen the game field can be seen (it's surrounded by a green rectangle). The bricks can be placed into the mentioned green rectangle, because they will appear there during the game. The placement of the brick on the field could be done with drag & drop from the right side to the game field.

The bricks cannot be placed on each other. Bricks can be replaced on the screen also with drag & drop. To delete a brick, it should be selected by clicking on it, and then deleted by clicking on the "X" sign at the bottom right of the screen. After finishing the level for saving, the "save" icon should be clicked in the top right corner of the screen.

5.5.2 *Birdie Game Level Editor*

The level editor of the Birdie game is very similar to the BTB game's level editor, except the obstacles, and the speed options (Fig. 5.16).

In this game, the speed which the nestling will fly with can be set up in the General setup area placed at the bottom of the screen.

Instead of bricks, the Birdie game has obstacles that shall be avoided by the little bird. There are four types of obstacles, based on their position and size during the game: top, big, middle, and bottom. The top is something floating or hanging at the top of the game field; the middle is also floating, but at the middle of the field; the bottom obstacle is something placed on the floor or land; and the big is also standing

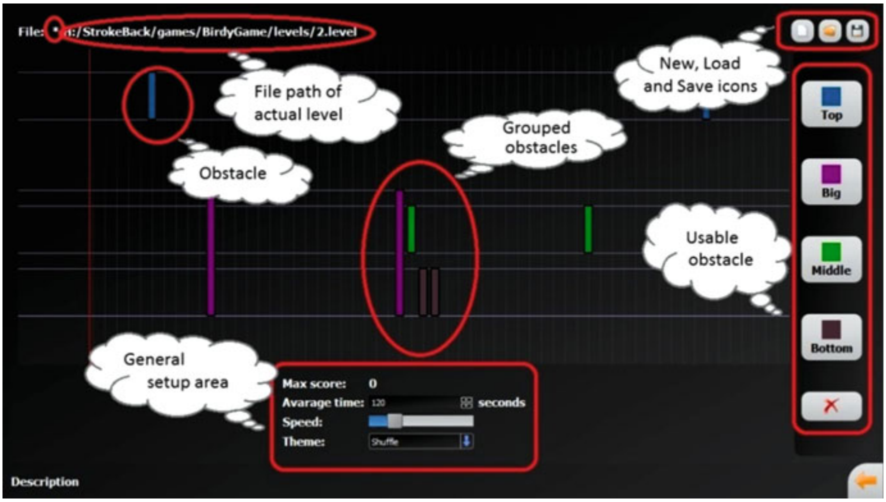


Fig. 5.16 Level editor of the Birdie game

on the ground, but compared to the previous obstacles, this is two times higher. These obstacles are represented with bars differing in colors and size based on the type of the object. The usable obstacles can be found at the right side of the screen. To place an obstacle, move it with drag & drop to the game field area in the middle of the screen, and place it to the desired spot. The grouped obstacles are also options to choose, if not one but more objects are needed. To make a grouped obstacle just place more of them next to each other.

5.5.3 Gardener Game Level Editor

The level editor of the Gardener game is very simple, because after setting up the main parameters of a level, the arrangement of the plants will be set up automatically according to the theme [29] (Fig. 5.17).

The "new", "load", "save" icons and the Actual level's file path area are the same as before. To create a new level, first the "new" icon should be selected.

The parameters of a level can be set with the tools of the General setup area. At the Theme label the level's theme can be selected from the drop-down menu, which contains only the available valid skins. Every skin is limited by the number of plants it can show on the game field. This is because some of the plants are bigger, so less can be placed from it. A skin is valid, if the selected plant number on a level is under its upper limit. The limitations are the following:

- Grapes, bluebell, strawberry, and currant: eight plants max.
- Rose, tomato and pepper: 16 plants max.
- Carrot, geranium and tulip: 20 plants max.

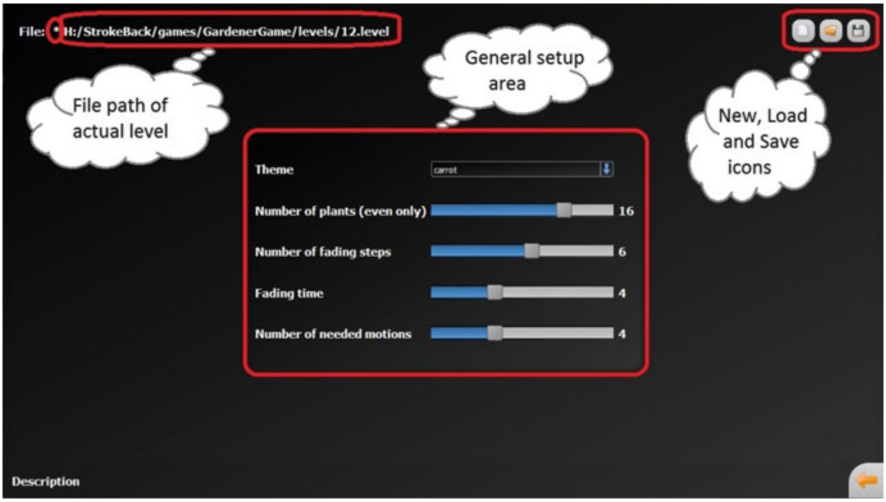


Fig. 5.17 Level editor of the Gardener game

The theme can be set to "Shuffle" also, which means that the skin of the level will be chosen randomly from the valid ones.

After this, the Number of the plants on a level can be set with a slider. It's important to notice that this should be an even number, which can be at least 4, and the maximum is specified by the chosen theme.

The next parameter is the Number of fading steps, which gives that how many steps does the plant need to wither when it's not watered. This can be set with a slider from 1 to 10. The next slider is for the Fading time parameter, which means that after the adjusted amount of time, the plant will start to wither. Its value can be between 1 and 10.

The last parameter is the Number of needed motions, which can take a value between 1 and 10. This value shows that how many movements are required to water a plant. This is only a scale value; the real amount of required movement can be calculated by multiplying the adjusted value with 4. So if the parameter is set to 5, the number of required movements to water a plant is 20.

5.6 Animations for Motivating and Teaching the Patients

In accordance with the request of therapists the motivational 2D animations are running after the completion of a level of a game before the next level. During this time the patient will be able to relax. Therefore, every theme has its own motivational animation. These animations run approximately 10–20 s. These animations are made in Director multimedia developing software [12] (Figs. 5.18, 5.19, 5.20 and 5.21).

Fig. 5.18 Birdie game theme

Fig. 5.19 Gardener game—strawberry theme

Fig. 5.20 Gardener game bluebell theme

Fig. 5.21 Gardener game default theme

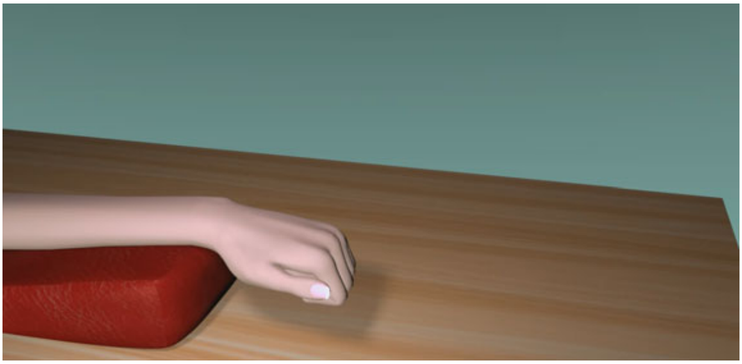


Fig. 5.22 Screenshot of the teaching animation to the Birdie game

The therapists' request was to get teaching animations of the repetitive movements to every game. These 3D animations show to the patients the repetitive movement to practice. The patients are able to control the games by these repetitive movements. These 3D animations are made in Blender 3D modelling software [4] (Figs. 5.22, 5.23 and 5.24).

The therapeutic process includes music therapy too, which is coordinated by the movements of the fingers. The task is to press the piano keys. The animations show to the patients the task. These 3D animations are made in Blender 3D modelling software (Figs. 5.25, 5.26 and 5.27).

These animations are motivating the patients to use the games to practice the repetitive movements. Everybody likes to play in every generation. The games in the "StrokeBack" project motivate the patients to reach the next level. The animations have some humor and little stories which motivate the patients.

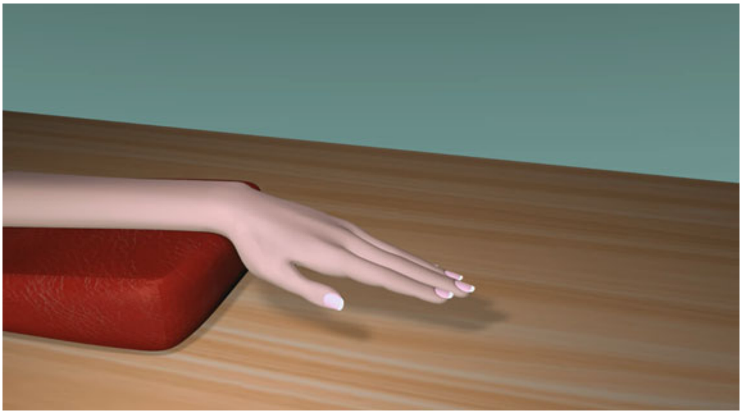


Fig. 5.23 Screenshot of the teaching animation to the Birdie game, finger extension

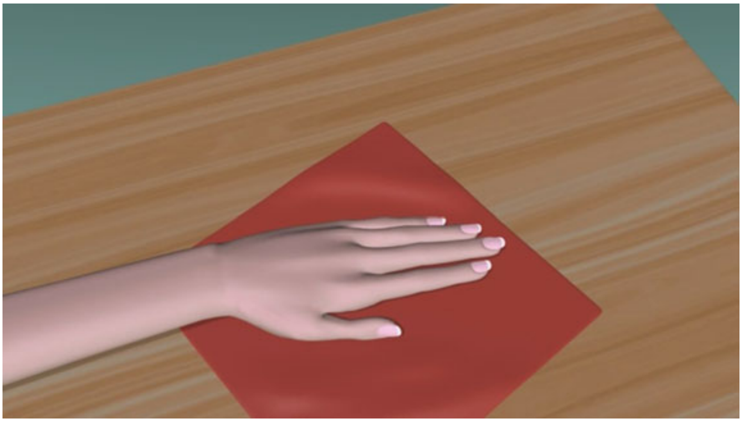


Fig. 5.24 Screenshot of the teaching animation to the BTB game

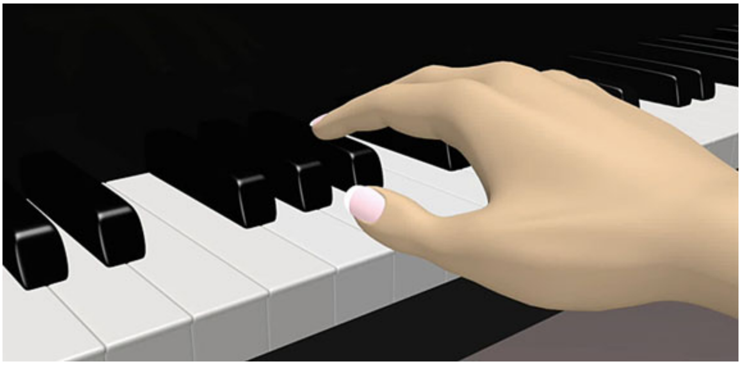


Fig. 5.25 Beginning the music therapy animation first screenshot

Fig. 5.26 Screenshot of the music therapy: index finger down

Fig. 5.27 Screenshot of the music therapy when thumb down

5.7 Results and Conclusion

In this chapter, after a detailed introduction, which includes the present state of our literature review, which is quite a detailed overview of the current available literature—the multimedia and virtual reality-based games and rehabilitation systems made all over the world are presented. The benefits and usability of these works are summarized too. After it the development process of the games for "StrokeBack" project is presented. The games were tested several times during the developing process. This helped in the redesign of the games based on both the therapists and the patients' opinions and suggestions. The games' difficulty can be set by level editor. The level editor is very important because it will help the therapists to customize the games to the needs and abilities of the patients properly. The therapists are able to modify every level of every game's theme very easily. So the games' difficulties are adaptable to the patient's skills and needs very easily and quickly.

The games in the "StrokeBack" framework were all developed for therapy purposes. In the therapists' hands, all of the games become a device which amends the traditional therapy and gives the opportunity to practice movements dedicated for WMFT tasks. With the help of the level editor surface the therapists have the opportunity to create unique, personalized action program for each patient, which helps the therapists' work to a great extent. The computer-aided healthcare-used programs amend, and after the learning process may even relay the presence of the healthcare professionals. The telemedicine system, besides kinesitherapy, accomplishes the aim to reach a greater self-dependence of the patients.

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Chapter 6
Kinect-Based Approach to Upper Limb Rehabilitation

Holger Jost

Abstract In this chapter, rehabilitation training is analyzed concerning the possible representation where real-time assessment of correct execution has the highest priority. In order to ensure proper execution of rehabilitation training, real-time feedback to the patients needs to be provided. As a first step in this task, the efficient means to process measured data to generate this feedback will be investigated and realized. Since rehabilitation exercises are sequences of body part movements, there exists a causal knowledge related to exercise movements. The complex relationship between body parts shall be represented by Answer Set Programming (ASP) allowing us to perform causal reasoning.

This chapter also discusses the tool used to create individualized training sequences or exercises for stroke rehabilitation patients with respect to design decisions, general architecture, usage, and adjustability.

The tool provides an interface to the depth sensor used to capture a patient and evaluates exercises via an interface to an ASP solver for causal reasoning. Additionally, the application offers a graphical user interface (GUI) as well as a general interface for the integration of the tool into the StrokeBack framework.

Furthermore, the steps a physical therapist has to perform to create a new training sequence or to create a compensation movement schema in cooperation with a stroke rehabilitation patient are explained and a detailed description on how compensations are handled in ASP is given.

6.1 Sensors for Exercise Supervision

The StrokeBack project means to provide a system for stroke patients in a post rehabilitation phase. The systems purpose is to support the patient in his daily exercises and thereby help the patient to improve on her/his fine motor function skills even without the supervision by a therapist.

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In the patient's home environment, the training in the post rehabilitation phase is supported by two approaches. The first approach facilitates the use of body-worn sensors. The group of sensors worn on the body is called Body Area Network (BAN) and monitors the patient's progress by analyzing the activities of daily living. The second approach consists of a training place in the home environment. This home-use system allows a computer-assisted supervision of the patient's exercises and progress. The exercises performed at this training place in the patient's home are monitored by sensors. A real-time analysis of the patient's performance can provide the patient with direct feedback. This feedback may give new impulses to the patient's motivation to improve her/his motor skills.

When monitoring the exercises performed by the patient with a sensor or a set of sensors, changes in the environment of the real world are mapped to sets of data. A model of the exercise which is performed in the real world is needed in order to interpret the data and subsequently making assumptions on the correctness of said exercise.

The representation of a training or exercise depends largely on the method chosen to monitor the exercise. Each type of sensor is able to monitor a fragment of the real world and therefore the sensor type chosen to observe the patient has a great influence on the accurateness of measurements. The sensors commonly used for observing motion depend on visual feedback (e.g., camera security systems). The advantages are clear: the observation of an exercise with a camera is a non-intrusive method. The stroke patient does not have to bother with straps, belts, or other means of fixation. Especially in the home environment, stroke patients may not be able to use fine motor skills necessary to fasten a belt due to the affection of the body without the help of another person.

Depth sensors like Microsoft Kinect are camera-like sensors that supply an image with depth information. Choosing depth sensors to monitor rehabilitation training has some consequences on the representation of exercises. The abilities and restrictions of depth sensors are summarized shortly below.

In the recent years, cameras with depth information became cheaper and more advanced with their use as modern video game controllers (e.g., Nintendo Wii, Microsoft Kinect). Compared to a conventional photographic camera, a depth sensor can provide either single point in three-dimensional space or an entire point cloud. This point cloud can be used to create a three-dimensional image of the world.

Two different approaches can be applied when using a depth sensor. It may be useful to either use raw data from the depth sensor, or utilize existing algorithms for pre-processing the raw data in order to monitor an exercise.

The raw data of a depth sensor delivers a three-dimensional view of an exercise from a single viewpoint.

The raw data of a depth sensor can be used, if the detection of an object or body part turns out to be too difficult to handle in real time or the intended use is not covered by available algorithms.

The data stream of the depth sensor can be used in every way imaginable. The depth measurements can be manipulated and objects can be identified by applying algorithms. The only constraint is the performance of the algorithm. The performance should allow for a real-time feedback.

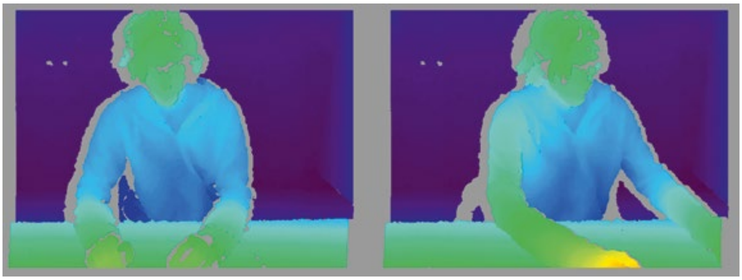


Fig. 6.1 The output of a depth sensor visualized in a two-dimensional picture. A person is sitting in front of the sensor. Some parts are registered to be space occluded by objects

The producers of depth sensors and other developers provide tool and libraries with existing algorithms to detect entire human bodies, hands, other parts of the human body, or objects in the data supplied by the sensor.

When detecting a human body the libraries mentioned above, an abstraction of the body, a skeleton, is projected in three-dimensional space. This skeleton resembles a stick figure, but in three-dimensional space. Depending on the library used, the number of body joints in the skeleton varies. Development kits are provided by Microsoft with Kinect for Windows [1]. Another software development kit comes from OpenNI [2].

The use of depth sensors has some requirements to the environment. Depth sensors measure the distance to the environment in the field of view of the camera by emitting electromagnetic radiation (usually infra-red light) and capturing the reflected radiation in a sensor. Therefore, a few environmental circumstances may interfere with the process. The existence of direct sunlight, reflective surfaces, and objects blocking the view may have a mild or severe influence on the accurateness of the measurements.

Depth sensors are often designed to work with ambient light. As the sun emits radiation across most of the electromagnetic spectrum, the impact of direct sunlight on a depth sensor results in inaccurate data. Reflective surfaces and mirrors may also lead to inaccurate data as they can give the impression of a larger distance. Finally, objects may block the view behind said object. Even arms blocking a person's upper body may induce a problem when not properly handled by an algorithm (Fig. 6.1).

6.2 Representation of Exercises

When describing the representation of exercises, it has to be differentiated between fine grained movements and more basic movements involving arms. When performing exercise that makes use of the fine motor skills of a patient, sensors may not be capable of capturing every delicate motion. Therefore, a model of the exercise has to be conceived which incorporates the basic movement in a simple manner. When using gross motor skills, the depiction of the exercise can be more sophisticated. In both cases, the number of exercises that may be wrongly recognized as having been carried out incorrectly has to be minimized. In the same fashion, exercises that are inadvertently identified as having been performed correctly should be minimized as well. By minimizing both false negatives and false positives, two goals can be achieved.

First, false positives distort the actual performance of a patient. Second, false negatives can be very frustrating for the patient. When performing a training in the right way but failing nonetheless, the patient may lose her/his interest in exercising.

In the following sections, the different approaches to represent basic and more sophisticated movements are presented.

6.2.1 Basic Movements

Very basic movements can be represented by basic techniques that check for the distance of a section of the camera's field of view. The distance could be tested for either just one point or an area. The area's shape depends on the exercise. This approach can also be used to detect objects without identifying them.

Every exercise is defined by a starting position and an ending position. In a training session, movements are often repeated. The motion from the starting position, across ending position, and back to the starting position could be repeated for a number of times.

An example for such an exercise would be the training of the dorsiflexion against gravity. In this exercise, the patient's forearm is resting on a wedge-shaped cushion. The wrist is positioned on the top edge of the wedge. In this position, the palm can be moved upwards and downwards. With the camera having a direct view on the palm of the hand, the exercise can be checked by considering the distance to the nearest object above the cushion.

Another approach is needed for more sophisticated movements, i.e., involving multiple body joints.

6.2.2 Sophisticated Movements

Sophisticated movements cannot simply be inferred from the raw data of a depth sensor. The data needs to be processed intelligently before interpreting it. For most of the body movements, it is advisable to use a library like Kinect for Windows or OpenNI that is able to detect a human body in the point cloud given by a depth sensor. The body or parts of the body are projected onto a stick figure, a skeleton, in three-dimensional space. This skeleton is not to be confused with the anatomical skeleton in the human body. The skeleton does not differentiate between ell and

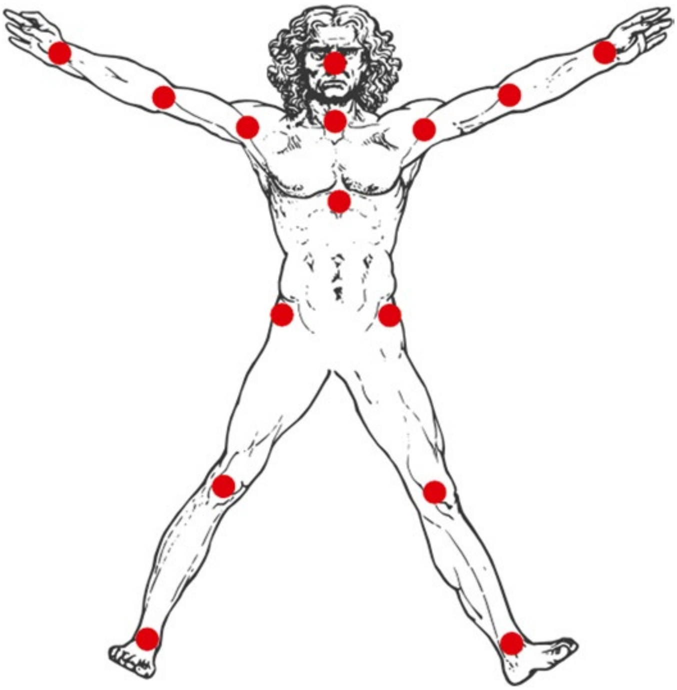


Fig. 6.2 The body joints detected by a skeleton detection algorithm from Microsoft. The *dots* indicate the detected joints

radius, the bones in the forearm. There is just one edge between wrist and elbow. The number of body joints detected by a skeleton detection algorithm depends on the library that is used (Fig. 6.2).

An exercise consists of a starting position and an ending position. The movement between these positions is a record of snapshots. In order to make the recordings comparable to later exercises, a few modifications are made. The absolute positions of the limbs have to be softened to be comparable. This is done by converting the edges between the body joints into vectors. Through simple vector conversion, some improvements to the data can be made. By extracting the alignment of the patient's upper body towards the camera, the vectors can be rotated around the vertical axis. This may be useful, if the patient is turned slightly to the left side or the right side.

Every human being has her/his own trademarks when moving around. Therefore, exercises are fitted specifically for each person.

The accuracy of the motion could be improved when recording the exercise multiple times. But this raises a few problems. As the patient will improve his performance over time, the exercise has to be recorded again to incorporate the improvements. Recording an exercise for 30 times in a row may annoy the patient. Other techniques have to be used to reduce the number of supervised recording sessions.

In summary, exercises are represented as a sequence of vectors. The vectors indicate the direction of the edges between body joints. The body joints are an abstraction of the skeleton of the human body captured by a depth sensor.

6.3 Evaluation of Exercises

The evaluation of basic movements using distance is quite simple. When using a point as a reference, the evaluation involves just one checking of the distance. When using a geometric shape one could either use the arithmetic mean of the points in the area or another kind of average. A weighted mean could focus on certain point of the area chosen for evaluating the training.

$$\frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} = \frac{w_1 x_1 + w_2 x_2 + \cdots + w_n x_n}{w_1 + w_2 + \cdots + w_n}$$

In an area with n points, the point x_i exists for all i. Every x_i has a weight w_i.

When dealing with a more sophisticated exercise involving multiple body limbs, another approach is needed. With the skeleton detection algorithms multiple goals are desirable. Primarily, the correctness of the exercise in general is a goal. Secondly, the lookout for indications of compensations made by the patient is desired.

6.3.1 Correctness of an Exercise

In general, a recorded exercise is compared to current online data when performing an exercise. As every movement differs from another, a threshold for successfully performing the exercise is allowed.

An abstract skeleton is identified by a skeleton detection algorithm and divided in vectors connecting the body joints (see Fig. 6.4). Each of the vectors is separately compared to the previously recorded exercise. This has two advantages. The conversion to vectors eliminates the need for the patient to sit at the exact same spot every time. Furthermore, a failed performance can be attributed to one of the vectors and hold as a basis for further analyses.

The vectors are compared by calculating the angles between them. A threshold determines how accurate angle has to be and thus how accurate the exercise has to be performed.

Further mechanisms allow for performing the exercise faster or slower. In some cases it may be possible that the patient does hesitant or jerky movements in either the wrong or right way. The evaluation allows for multiple states of progress. Therefore, such deviating moves are possible up to a certain degree.

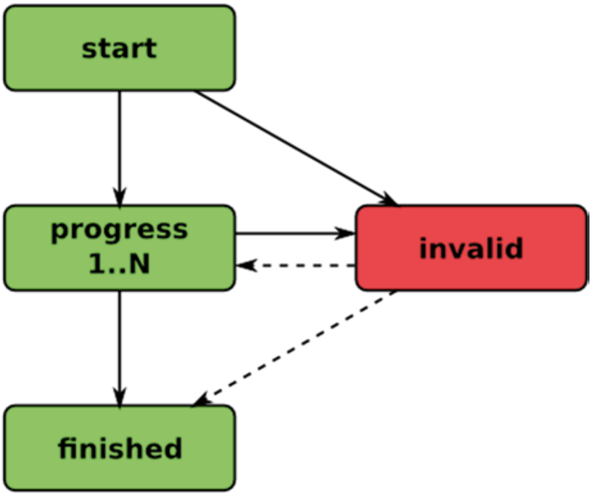


Fig. 6.3 The simplified state machine for an exercise. Each *box* represents a state or a series of states. An exercise starts in the state start and ends with either the invalid state or finished state

The correctness of an exercise is determined by a state machine with various rules (see Fig. 6.3). This state machine is triggered when a patient is either in the starting position or in the ending position of a recorded exercise. Both positions mark the most important pieces of information. The starting point is obviously the beginning of the exercise, but the end position may indicate a fully performed exercise that has not been properly detected. This could happen for a variety of reasons like an abnormal skeleton detection.

The rules of the state machine allow more than one state being active at the same time. This increases the robustness of the detection because smooth movements may not be expected from stroke patients. State transitions allow starting position, monitoring progress, small movements in the wrong direction, temporarily remaining in a fixed position, failing an exercise, and finished exercise.

The progress of an exercise is matched with the recorded exercise. If a recorded exercise consists of N snapshots, the progress is tracked in N steps with 1 being the starting position and N being the end position. Movements in the wrong direction may be possible by trembling. This is caught by considering more than one progress state. Short pauses are covered as well. Failing a number of positions does not necessarily mean for the exercise to fail overall. Reaching the end position can indicate a successfully performed exercise.

The state machine is maintained for all vectors involved in the training. Figure 6.4 shows all body parts of the upper body. The individual state machines for each vector are interlinked to give an estimation of the patient's performance. Either the exercise has been performed or it has been partially performed. In the latter case, the last position in compliance with the training is identified. The percentage of success can be calculated and used to evaluate the performance further.

Additionally, typical movements or gestures are identified to give a direct feedback as the patient may not be aware of the fact that he is doing something wrong. These compensations are monitored separately.

Fig. 6.4 The vectors of the upper body created for exercise evaluation are represented as *arrows*. The *dots* represent the body joints detected by a skeleton detection

6.3.2 Compensations

Compensations are gestures or movements that are done automatically to compensate for a lack of fine motor skills. Avoiding compensations is part of the rehabilitation process of stroke patients.

When detecting compensations one is looking out for some indications. Basis for detecting a compensation in this model of an exercise are the compensations associated with the exercise, the recorded exercise, the behavior of the stroke unaffected side, and a reason why an exercise failed.

Exercises chosen are in most cases already linked to specific types of compensation. Therefore, this can be considered as an important input when trying to detect compensations on the fly. A previously recorded exercise under the supervision of a therapist serves as a basis for any derivations from the intended movements. The supervised recording means the patient's best performance. The behavior of the unaffected side may also indicate compensations when a detection on the affected side fails for some reason. For example, the ipsilateral and contralateral flexion of the torso may be indicated in both sides of the body.

When performing an exercise, like extending an arm, the exercise may fail. By comparing the recorded exercise with the performance, a conclusion could be made on the vector and its direction. All these factors can be brought together in a logical causal context. This is done by using a rich declarative language approach called *Answer Set Programming* (ASP).

The knowledge representation and reasoning system allows for describing a problem in logical and easy way. This permits quick changes without a lot of costs. An optimized universal solving process resolves consequences and constraints until a solution, an answer set, has been found. Additionally, the maximization or minimization of certain aspects allows for a solution tailored towards the needs of a patient.

The complexity of the compensation reasoning has to be matched to the requirement of real-time feedback in the StrokeBack system. The average response time of the underlying reasoning system depends on the number and cross correlation of compensation features. The system used in the StrokeBack project weights up the performance against the complexity of tasks.

The detection of compensations is performed by a declarative programming oriented towards search problems. As an outgrowth of research on the use of non-monotonic reasoning in knowledge representation, it is particularly useful in knowledge-intensive applications [3]. The knowledge base is developed in cooperation with therapists. Background information like typical compensations in an exercise, mean to spot a compensation, and cross-correlations between compensations serve as a base for the reasoning. Compensations are often tied to certain exercises, e.g., the elevation of the scapula can be seen on the stroke affected side when lifting an object with the affected arm. The description of the compensation is also based on the representation model of the body. When comparing the shoulder vector of an elevated scapula with the reference vector of straight shoulders, a difference in the vertical axis is recognized. This deviation is monitored over time and a differentiation between an elevation and a protraction of the shoulder is estimated. All rules are provided with a weight depending on the exercise. For example, when lifting an object straight into the air, a protraction of the scapula may be more likely than a rotation of the body, although both scapula protraction and body rotation have a similar appearance in the representation model. In both cases, the shoulder of the affected side is pushed towards the front. Furthermore, compensations like elevation of the scapula and the lateral flexion towards the unaffected side are occurring together when lifting an object. When detecting interrelated compensations, the accuracy of the compensation diagnosis is increased. Adjusting the weights in consultation with the therapist increases the accuracy further.

The knowledge base and rules developed in cooperation with therapists are merged with the output of the performed exercise. A universe of all possible diagnoses is created. The problem is transformed into a search problem with the goal to find the most accurate compensation diagnosis. This also includes a perfect execution without any kind of compensation. An optimized search algorithm with learning abilities reasons on the underlying data. The search tree is pruned by conflict-driven clause learning (CDCL). See [4] and [5] for more details. The answer set is found by making a decision on the depth-first search. The clauses (*nogoods*) leading to a dead end in the search space are stored and the algorithm jumps back to the last decision level. The learned *nogoods* prevent the search algorithm to making same mistakes again. Clause learning can lead to n learned clauses with n being the number of atoms in a logic program. Rules consist of one or more atoms. The worst case size of learned clauses therefore is $O(n)$. Different decision methods and variations of the algorithm influence the runtime of the search. A real-time compensation detection is therefore feasible.

6.4 The Exercise Design Tool

The general purpose of the exercise design tool is to support physical therapists to design individual exercises for stroke rehabilitation patients. It also acts as an interface to a versatile answer set solving system which permits the real-time evaluation of these exercises. Furthermore, the tool should be easily integrated into the whole StrokeBack system.

In principle, the exercise design tool's graphical user interface is not needed when the tool is fully integrated into an environment. The tool can be configured via TCP socket messages only. But a graphical user interface proved very useful in the prototyping process.

A physical therapist needs a simple to use tool which is nonetheless empowers her or him to design exercises for individual patients. Not only a movement of the upper body should be captured and compared to previously performed exercises, but also it should be able to detect different movements at the same time. The explicit description of a posture which should be avoided may be necessary.

Another aspect of the exercise design tool is the interface to the tools of the Potsdam Answer Set Solving Collection (*Potassco*) [6]. ASP and answer set solving is used to evaluate exercises. Thus, a tight integration is desirable.

Furthermore, the tool should easily integrate into the StrokeBack system. On the contrary, it should work on its own to permit testing the exercise evaluation via ASP. Therefore, at least two means of control may be necessary to implement: a graphical user interface for testing and a library to enable the tool's features to other programs. It is important that the required versatility and flexibility is reflected in the tool's architecture.

This section discusses the tool's key features, hardware and software requirements, design decisions and interfaces. Additionally, a method to make the comparison of movements less difficult is presented in detail. And last but not least, the steps necessary to design an exercise are explained.

The tool's general purpose is to capture and evaluate exercises performed by stroke rehabilitation patients. The tool captures the upper body of a person sitting in front of the depth sensor, e.g., the Microsoft Kinect. The evaluation of the exercise is done using ASP. An answer set solver is called repeatedly with updated data to allow for real-time feedback.

An exercise may consist of one or more movements of the upper body's limbs. Each movement may result in a different output, e.g., the explicit recording of movements which should not be performed by the stroke rehabilitation patient is possible.

The design tool should offer certain key features to fulfill the requirements of a physical therapist as well as the requirements given by the environment or other applications. Thus, the tool should allow displaying the depth sensor image, recording movements performed in front of the depth sensor, selecting one or more movements which should be recognized, saving and loading previously recorded movements, selecting the joints of the upper body which are important for the exercise, selecting the answer set program used to evaluate the exercise, repeatedly calling an answer set solver to display real-time feedback, changing the frequency of depth sensor to increase performance, writing a log file to permit investigation of previously performed exercises, adjusting the preciseness of the exercise evaluation, displaying individualized output for an exercise, stopping the sensor's data stream to save power and cool down sensor, and controlling the depth sensor's tilt motor if necessary.

The identified key features had influence on the design of the graphical user interface as well as the general architecture of the tool.

The fundamental principle of the tool is to provide a versatile interface for physical therapists as well as other applications. Therefore, the tool supports a range of input and control means. The tool allows the use of a graphical interface, start parameters, and also offers a whole interface library which allows the input and output via other applications.

A graphical user interface enables the user use all the features of the tool with simple mouse clicks and keyboard input. Start parameters permit the user to automatize the process of evaluating exercises. The joints chosen for the exercise, the answer set program used for evaluation, and so forth can be configured when starting the program by using the predefined start parameters. With each start of the program, the parameters can be configured to fit the exercise which should be evaluated.

The start parameters can be used to start the design tool without the graphical user interface. In this case, the fully operational design tool will run in the background and can be controlled by another application. In order to do this, a interface library was created. This library supports all functionality of the design tool, e.g., recording a movement, saving and loading movements, and selecting evaluation programs. The interface library can be used to either implement another graphical user interface or to fully incorporate the design tool's features into another application.

The tool can either be restarted for each exercise or run once and configured for each exercise on-the-fly. Having the possibility of running the tool in background over a longer period of time, the necessity to turn off the depth sensor may come in handy to prevent overheating the sensor or consuming too much power. Therefore, the decision was made to include means to turn on and turn off the data stream of the sensor.

The answer set solver is called repeatedly to incorporate incoming data from the depth sensor on-the-fly. Therefore, the incoming data from the depth sensor is transformed to permit a more flexible comparison of movements. The process used to convert the coordinates is described later.

Depth sensors are able to detect more than one person in front of the sensor. In order to simplify the identification of the person who is performing the exercise, the decision was made to work with the person closest to the center of the sensor image. The sensor will have a fixed position. The person in the center of the image is most likely the stroke rehabilitation patient and not an intervening physical therapist or someone else. In the graphical user interface, the person identified for capturing movements is marked with a red dot.

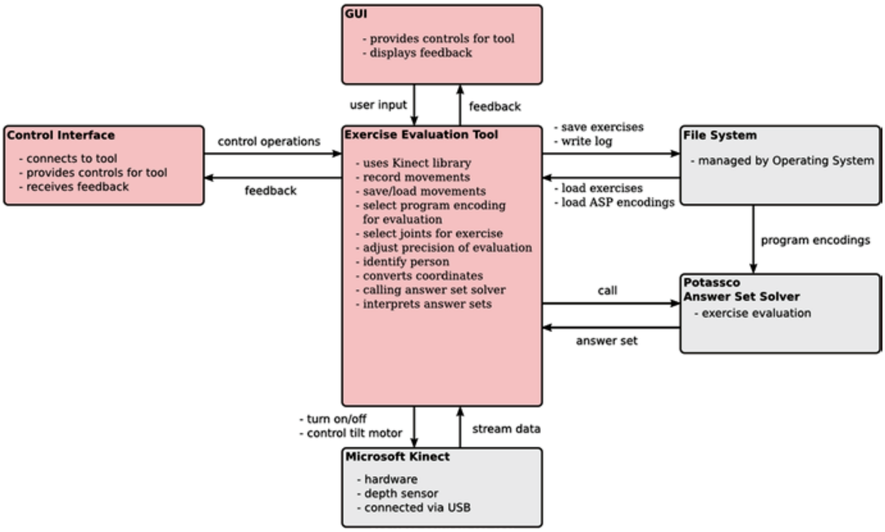


Fig. 6.5 The architecture of the exercise design tool

6.4.1 Architecture

When taking the design decisions and key features into account, the tool's architecture can be planned. The tool's architecture is depicted in Fig. 6.5.

The system uses Microsoft Kinect or rather a Kinect library to control the depth sensor, i.e., Microsoft Kinect. The tool provides the means to record movements, save and load movements, select the programs used for exercise evaluation et cetera. The GUI is the primary input and output method. A control interface which uses the provided interface library can be used as an alternative. This control interface is implemented as a TCP socket in the final prototype. The socket connection is vital for the integration of the exercise design tool into the StrokeBack architecture. The file system which is managed by the Operating System is used to store recorded exercises as well as the program encodings used for exercise evaluation. The program encodings are used by the answer set solver which is called repeatedly to return a live feedback to the tool. This feedback is interpreted by the tool and can be displayed in the graphical user interface or a control interface which uses the already mentioned interface library.

Not shown in the figure is the mean to display messages on the screen which can be displayed over other software like games. The messages can be individualized and are triggered by successful or unsuccessful events, e.g., a successfully performed exercise, a failed exercise, or compensation detected by the software. This functionality was added to allow for fast prototyping. The messages displayed in the overlay can also be transmitted via the TCP socket.

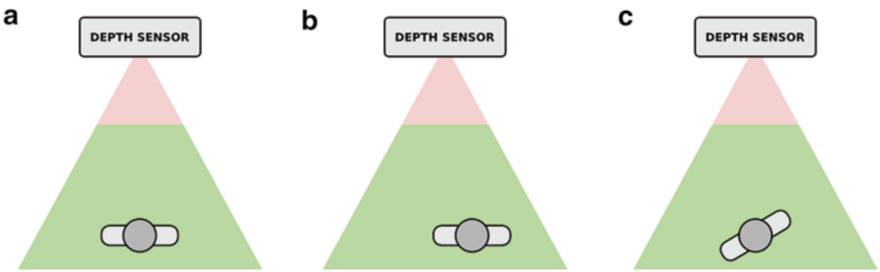
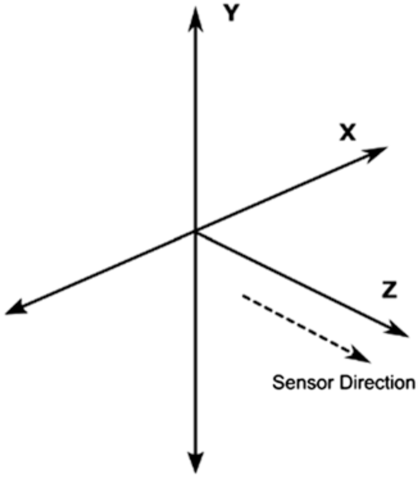


Fig. 6.6 Relative position and angle towards the depth sensor. In (**a**) a person sits in front of the sensor, in (**b**) the person is shifted slightly to the right, and in (**c**) the person's upper body is rotated

Fig. 6.7 The coordinate system of the Microsoft Kinect



6.4.2 *Coordinate Conversion*

In order to easily compare an exercise with a recorded one, coordinates are converted to a unified coordinate system. The conversion allows for the deviation of the patient's absolute position as well as the deviation of the patient's angle towards the depth sensor (compare Fig. 6.6).

The Kinect or a Kinect library respectively delivers a simplified bone structure to represent a person in front of the depth sensor (see Fig. 6.4). The direction of the coordinate system's axes is depicted in Fig. 6.7. The *x*-axis represents the horizontal planer, the *y*-axis represents the vertical plane, and the *z*-axis represents the depth.

A vector reaching from the left to the right shoulder joint is created. This vector is used to calculate the angle φ between this vector v and the *x*-axis of the depth sensor.

$$\varphi = \cos^{-1} \frac{\vec{v} \cdot \overrightarrow{e_1}}{\left\|\vec{v}\right\|}$$

Therefore, unit vector $\overrightarrow{e_1}$ is used.

$$\overrightarrow{e_1} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

Additionally, all body joints are rotated around the *y*-axis. Vector $\vec{v}$ is transformed to the vector $\overrightarrow{v_r}$.

$$\overrightarrow{v_r} = \begin{pmatrix} v_x \cdot \cos\varphi + v_z \cdot \sin\varphi \\ v_y \\ v_x \cdot -\sin\varphi + v_z \cdot \cos\varphi \end{pmatrix}$$

$$\vec{v} = \begin{pmatrix} v_x \\ v_y \\ v_z \end{pmatrix}$$

Furthermore, a vector reaching from the center of the coordinate system to the joint representing the shoulder center is calculated. This vector is subtracted from everybody joint delivered by the Kinect library. This is done to collapse the shoulder center joint and origin of the coordinate system.

6.5 Designing an Exercise

In this section, the steps a therapist has to perform to design a new exercise with the exercise design tool are explained. The same steps could be performed using the commands provided by the interface library. Assume that the stroke rehabilitation patient should perform an exercise with her/his affected left arm. The exercise consists of lifting the arm to a certain degree after the arm had rested on the desktop. The exercise is performed in front of the sensor.

At first, the therapist starts the design tool and checks whether or not the patient is recognized by the depth sensor. Because the patient will take more than 2 s to raise her/his arm, the recording frequency can be lowered to 10 Hz. The therapist also assigns a name to the exercise (see Fig. 6.8). In the StrokeBack system, the name is composed automatically. The therapist does not have to bother about picking a name. Subsequently, the therapist selects the left side to be monitored (see Fig. 6.9). The preparations for the recording are finished with this step.

The physical therapist asks the patient to rest her/his arm on the desktop. The therapist starts the recording by pressing on the button labeled *Start Recording* and gives a sign to the patient to start performing the exercise which was agreed upon. The patient raises the arm under the instructions of the physical therapist.

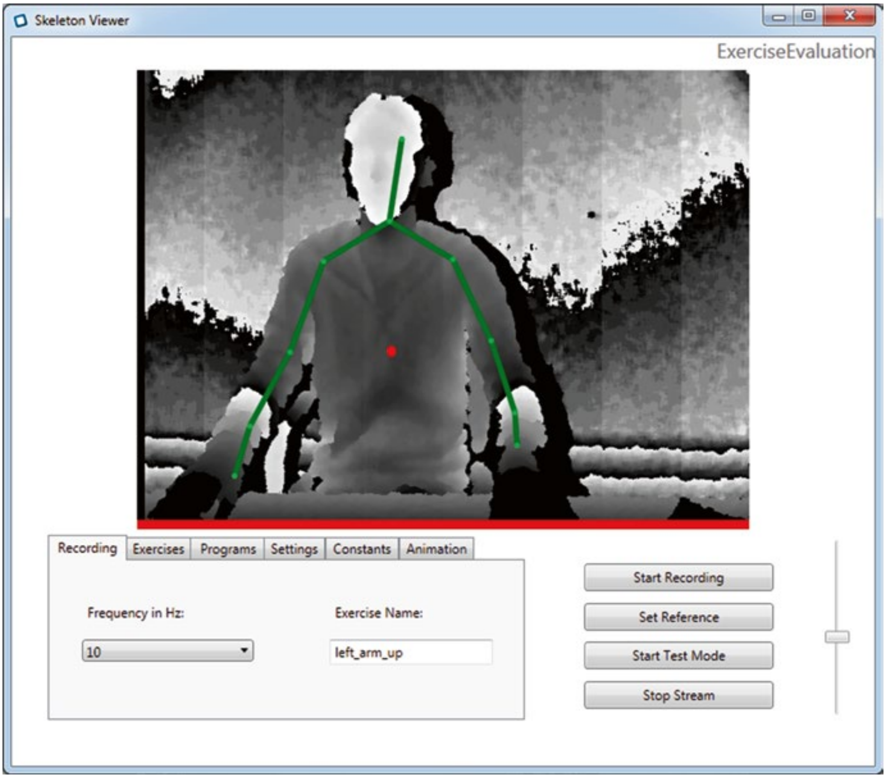


Fig. 6.8 The GUI of the exercise design tool. A skeleton is superposed onto the person in front of Kinect. The *dot* on a torso indicates person being recognized as the one performing the exercise

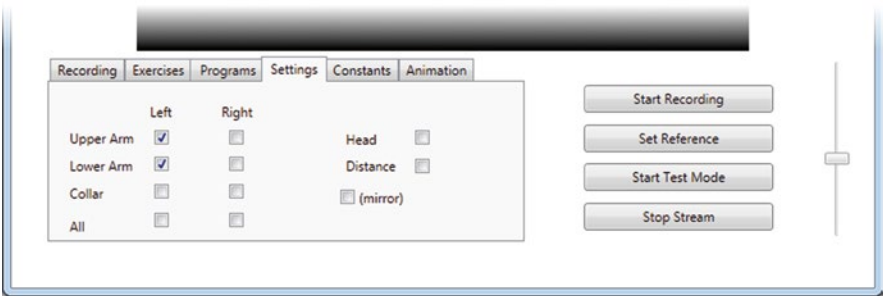


Fig. 6.9 Vectors representing the upper body of a patient can be selected in the GUI

When the patient has reached the desired height, the therapist can stop the recording by pressing the same button. If the movement has not been performed properly, the recording process is repeated until the physical therapist is satisfied with the patient's performance. The exercise has been successfully designed.

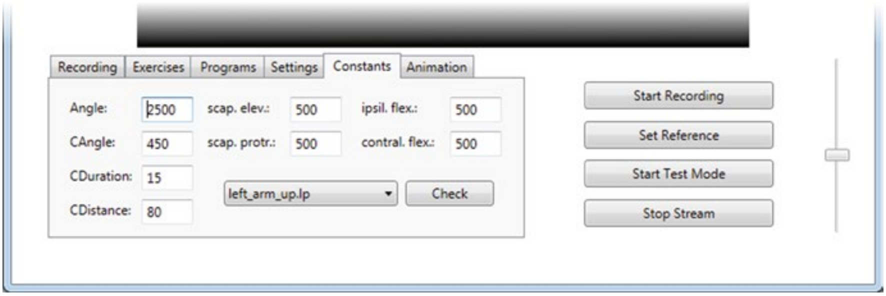


Fig. 6.10 Various settings for exercises and compensation detection in the GUI

The therapist may also check the record by initiating an exercise evaluation by pressing the button labeled *Start Test Mode*. When the movement is successfully recognized, the exercise can be repeated without the supervision of the therapist. If not, the therapist has the possibility to increase the derivation allowed when performing the exercise. There are multiple means to adjust the settings for exercises (see Fig. 6.10).

Two variables can be adjusted to fit an exercise to a patient's condition. The variable *angle* adjusts the allowed derivation from the originally recorded exercise. As the upper body is represented as vectors, the derivation from the recorded exercise can be given as an angle between any two vectors involved in the exercise. An exercise not necessarily fails when the derivation from the original recorded exercises is too high. Some movements made by the patient as well as measurement errors by the sensor should not fail the exercise. Some patients are allowed to vary their movements more than others. Therefore, the therapist can adjust the variable *cDuration*. This variable defines the maximal duration for stronger derivations. This variable is also used when detecting compensation movements.

6.5.1 Adjusting for Compensation

The exercise design tool was developed to also detect compensation movements made by stroke rehabilitation patients. The list of compensations includes contralateral and ipsilateral flexion, scapula protraction, scapula elevation, and the flexion of the torso.

With approaching new technology, other compensations could be added to the list of compensations supported by the prototype in the future.

Assume that a patient is training her/his fine motor skills in front of the Kinect. For each exercise the therapist is able to save a reference of the upper body. This reference represents a near ideal position in which the patient should perform the given exercise. The setup for such an exercise can be automatically configured by the StrokeBack system. In the graphical user interface, this can also be achieved by setting up a name, selecting the involved body vectors, and clicking the button labeled *Set Referenc*e (see Figs. 6.8 and 6.9). The process is very similar to the designing of an exercise. The variables in Fig. 6.10 can be set up for the specific needs and posture of a patient.

Every single type of compensation can be activated or deactivated for an exercise. If a compensation is actively surveyed, the therapist has the option to extend or restrict the movement until a compensation is detected.

The variable *scapula elevation* determines the angle allowed to derivate from the original reference. When the variable is set to *500* and the shoulder is lifted higher than 5°, a compensation may be present. In the same fashion, the variable *scapula protraction* can be used to determine the allowed derivation when pushing the shoulder forward. The variable *ipsilateral flexion* (or *contralateral flexion*) determines the allowed derivation when leaning towards the stroke affected side (or away from the affected side respectively). To measure the flexion of the torso, a little trick is needed. As the Microsoft skeleton detection algorithm only provides unreliable data for the spine (compare Fig. 6.4), the distance between patient and sensor is used as an approximate comparison value. The variable *cDistance* is used to represent the derivation from the original posture in centimeters.

Similar to the use when designing a regular exercise, the variable *cDuration* can be used to give a rough estimate how long a comparison has to show until it is noted or even shown to the patient via a screen message. This message can be appeared over other software like games.

6.5.2 Compensations and ASP

The detection of compensations as well as the evaluation of rehabilitation exercises with the exercise design tool is done with ASP.

ASP is a declarative programming paradigm which is based on the stable model semantics first introduced by [7]. ASP is oriented towards difficult, primarily NP-hard search problems [3] but can be used to solve various problems beyond knowledge representation and reasoning [8, 9].

6.5.2.1 Theoretical Background

$\mathcal{P}$ is a set of *predicate* symbols (e.g., p, q, r), $\mathcal{C}$ is a set of *constant* symbols (e.g., f, g, h), and $\mathcal{V}$ is a set of *variable* symbols (e.g., a, b, c). It is assumed that the sets $\mathcal{P}$, $\mathcal{C}$, and $\mathcal{V}$ are disjoint. The members of $\mathcal{C} \cup \mathcal{V}$ are *terms*. Given a predicate $p \in \mathcal{P}$ of arity n, also denoted as p/n, along with terms $t_1, \cdots, t_n$, $p(t_1,..,t_n)$ is an *atom* over p/n.

A (propositional normal) logic program P over $(\mathcal{P}, \mathcal{C}, \mathcal{V})$ is a finite set of rules of the form

$$p_0 \leftarrow p_1, \cdots, p_m, not\ p_{m+1}, \cdots, not\ p_n$$

where $0 \le m \le n$ and $p_0, p_1, \ldots, p_n$ are atoms. A *literal* is an atom q or its negation *not* q. For a rule r, let $head(r) = p_0$ be the head of r and $body(r) = \{p_1, \ldots, p_m, not\ p_{m+1}, \ldots, not\ p_n\}$ be the body of r. The set of positive body atoms of r is $body(r)^+ = \{p_1, \ldots, p_m\}$ and the set of negative body atoms of r is $body(r)^- = \{p_{m+1}, \ldots, p_n\}$. If $body(r) = \emptyset$, r is also called a *fact*.

A logic program P is called a *positive program* if atoms occur only positively in all bodies, i.e., $body(r)^- = \emptyset$ holds for all rules $r \in P$.

A set $X \in \mathcal{P}$ of atoms is a *model* of a logic program P, if $head(r) \in X$, $body(r)^+ \subsetneq X$, or $body(r)^- \cap X = \emptyset$ holds for every $r \in P$. In ASP, the semantics of P is given by its answer sets [7]. The reduct P^X of P relative to X is defined by $P = \{head(r) \leftarrow body(r)^+ \mid r \in P, body(r)^- \cap X = \emptyset\}$. X is an answer set of P, if X itself is the $\subseteq$-minimal model of P^X. Note that any answer set of P is a model of P as well, while the converse does not hold in general [8].

6.5.2.2 ASP Tools

Getting the answer sets of a normal logic program with variables is usually done in two steps: *grounding* and *solving*. A program that transforms normal logic programs with variables into normal logic programs without variables is called *grounder*. A program that finds the answer sets of such programs is called *solver*.

The Potsdam Answer Set Solving Collection (Potassco) [6] provides among other things both grounder and solver. The grounder is called *gringo*, the solver is called *clasp*. The exercise design tool uses *gringo 4* and *clasp 3* respectively. The output of *gringo* is piped into *clasp* and the answer sets are parsed by the exercise design tool.

6.5.2.3 Encoding

In this section, the encoding of a logic program is discussed. The following logic program is encoded in the *gringo 4* input format and is used to detect compensation movements in stroke rehabilitation patients. Besides the encoding below, the program requires additional facts. The exercise design tool converts the data provided by the Kinect into vectors (compare Fig. 6.4). The data uses the format

$$data(Joint, (X, Y, Z), Time)$$

where *Joint* identifies the single vectors involved in the compensation detection. The vectors which are provided is configured through the exercise design tool. For compensation detection, the vectors *collarleft* and *collarright* are always used. When checking for torso flexion, the vector *distance* is also used. The second term is the vector data with the individual values for each axis *X*, *Y*, and *Z*. The term *Time* identifies the order of the incoming time points. 15 time points sum up to a second. Different joint vectors can have the same value to identify the exact same point in time.

Additionally, a reference for each vector is given by

$$reference\big(Joint,\big(X,Y,Z\big)\big).$$

The reference is used for comparing the current derivation from the ideal posture. The term *Joint* identifies the joint vector, e.g., *distance*. The second term provides the values of the vector.

Other facts are given as well, depending on the compensations selected for detection. Assume that the compensations *ipsilateral flexion*, *scapula elevation*, and *scapula protraction* are to be surveyed. Therefore, the facts

```
lookfor("ipsilateral flexion").
lookfor("scapula elevation").
lookfor("scapula protraction").
```

are added to the logic program. In order to correctly identify the side of the body affected by the stroke, the fact

```
affected(left).
```

or

```
affected(right).
```

are added to the logic program.

The *gringo 4* input format allows the definition of constant symbols. The constant symbols for the exercise are defined as follows.

```
#const ipsilateralflexion = 500.
#const scapulaelevation = 500.
#const scapulaprotraction = 500.
#const cduration = 30.
```

The critical angle for each compensation is set to 5°. When defining the value 30 to the constant *cduration*, the time needed for a compensation to be registered is set to two seconds and the check is set at 15 Hz.

Three auxiliary predicates are used in logic program. Using predicates with a reduced arity reduces the search space for the solver and reduces processor load.

```
reference(Joint,V) :- reference(_,Joint,V).
joint(Joint) :- reference(Joint,_).
time(Time) :- data(_,_,Time).
```

For each joint vector and each time point, the derivation from the ideal posture is calculated. The logic program uses simple functions written in the programming language LUA [10]. The function @*angle*/6 returns the angle between to vectors, the function @*comp*/6 returns an estimate direction to which the shoulder was shifted, e.g., *up*, *down*, *front*, and *upfront*.

```
angle_diff(Joint,Angle,Prog,Time)  :-  data(Joint,(X1,Y1,Z1),
                                       Time),
                                        Joint != distance,
                                        reference(Joint,(X2
                                        ,Y2,Z2)),
                                        Angle   =   @   angle
                                        (X1,Y1,Z1,X2,Y2,Z2),
```

```
Prog = @comp
(X1,Y1,Z1,X2,Y2,Z2),
time(Time).
```

The *torso flexion* is handled different from the other compensation movements. The distance between the reference and the current distance of the torso from the Kinect is calculated by the LUA function @*distance*/2. This is done for every time point if the *torso flexion* is one of the selected compensation movements. When the calculated distance is greater than the constant *cdistance*, it is likely that a compensation is performed by the patient.

```
poss_comp("torso flexion",Time) :- data(distance,(X1,Y1,
                                   Z1),Time),
                                     reference(distance,
                                    (X2,Y2,Z2)),
                                     Dis = @distance
                                    (Z2,Z1),
                                     Dis > cdistance,
                                     lookfor("torso
                                    flexion").
```

All other types of compensation are handled in similar fashion. For each time point it is checked if the previously calculated angle to reference exceeds the corresponding constant set up earlier. This is checked for both sides of the body which may be affected by the stroke and different directions in which the shoulder could be shifted. The shoulder might be pushed upwards to indicate a *scapula elevation* but it also might be pushed slightly towards the front when appearing together with a *scapula protraction*. Different rules cover all possible cases.

```
poss_comp("scapula elevation",Time) :- angle_diff(collar
                                       left,Angle,"up",Time),
                                          Angle >
                                        scapulaelevation,
                                          affected(left),
                                          lookfor("scapula
                                        elevation").

poss_comp("scapula elevation",Time) :- angle_diff(collar
                                       left,Angle,
                                       "upfront",Time),
                                         Angle > scapula
                                       elevation,
                                         affected(left),
                                         lookfor("scapula
                                       elevation").

poss_comp("scapula elevation",Time) :- angle_diff(collarright,
                                    Angle,"up",Time),
                                      Angle > scapula
                                    elevation,
                                      affected(right),
```

```
                                    lookfor("scapula
                                    elevation").

poss_comp("scapula elevation",Time) :- angle_diff(collarright,
                                    Angle,"upfront",Time),
                                      Angle > scapula
                                    elevation,
                                      affected(right),
                                      lookfor("scapula
                                    elevation").

poss_comp("scapula protraction",Time) :- angle_diff(collarleft,
                                    Angle,"front",Time),
                                      Angle > scapula
                                    protraction,
                                      affected(left),
                                      lookfor("scapula
                                    protraction").

poss_comp("scapula protraction",Time) :- angle_diff(collarleft,
                                    Angle,"upfront",Time),
                                      Angle > scapula
                                    protraction,
                                      affected(left),
                                      lookfor("scapula
                                    protraction").

poss_comp("scapula protraction",Time) :- angle_diff(collarright,
                                    Angle,"front",Time),
                                      Angle > scapula
                                    protraction,
                                      affected(right),
                                      lookfor("scapula
                                    protraction").

poss_comp("scapula protraction",Time) :- angle_diff(collarright,
                                    Angle,"upfront",Time),
                                      Angle > scapula
                                    protraction,
                                      affected(right),
                                      lookfor("scapula
                                    protraction").

poss_comp("ipsilateral flexion",Time) :- angle_diff(collarleft,
                                    Angle,"down",Time),
                                      Angle >
                                    ipsilateralflexion,
                                      affected(left),
                                      lookfor("ipsilateral
                                    flexion").
```

```
poss_comp("ipsilateral flexion",Time) :- angle_diff(collarright,
                                          Angle,"down",Time),
                                            Angle > ipsilater
                                          alflexion,
                                            affected(right),
                                            lookfor("ipsilateral
                                          flexion").
poss_comp("contralateral flexion", Time) :- angle_diff(collarright,
                                          Angle,"down",Time),
                                            Angle >
                                          contralateralflexion,
                                            affected(left),
                                            lookfor("contra
                                          lateral flexion").
poss_comp("contralateral flexion", Time) :- angle_diff(collarleft,
                                          Angle,"down",Time),
                                            Angle >
                                          contralateralflexion,
                                            affected(right),
                                            lookfor("contra
                                          lateral flexion").
```

Another auxiliary predicate is used to count the number of consecutive time point where the same type of compensation is registered.

```
poss_comp(Comp,Time,1) :- poss_comp(Comp,Time),
                          not poss_comp(Comp,Time-1),
                          time(Time).
poss_comp(Comp,Time,N+1) :- poss_comp(Comp,Time),
                            poss_comp(Comp,Time-1,N),
                            time(Time).
```

If the number of consecutively detected compensation derivations exceeds the constant *cduration*, the compensation is given as detected.

```
comp(Comp) :- poss_comp(Comp,Time,N),
              time(Time),
              N >= cduration.
```

Predicates names starting with an underscore indicate commands to the exercise design tool. Whenever one or more compensations were detected, the accumulated data is dropped to reduce processor load.

```
  _restart :- comp("scapula elevation").
  _restart :- comp("scapula protraction").
  _restart :- comp("ipsilateral flexion").
  _restart :- comp("contralateral flexion").
  _restart :- comp("torso flexion").
```

The cumulated data is also wiped whenever 8 s have passed without detecting a compensation. This is done to guarantee the real-time processing.

```
  _restart :- time(120).
```

If the fact

```
comp_messages.
```

is added to the logic program, a message can be displayed in an overlay over another software. For each compensation a message can be defined in the predicate *alert*/2. The atom *Message* is then handled by the exercise compensation tool.

```
_message(5,Message) :- comp("scapula elevation"),
                       not comp("scapula protraction"),
                       comp_messages,
                       alert("scapula elevation",Message).
_message(5,Message) :- comp("scapula protraction"),
                       not comp("scapula elevation"),
                       comp_messages,
                       alert("scapula protraction",Message).
_message(5,Message) :- comp("scapula elevation"),
                       comp("scapula protraction"),
                       comp_messages,
                       alert("elevationandprotraction",Message).
_message(5,Message) :- comp("ipsilateral flexion"),
                       comp_messages,
                       alert("ipsilateral flexion",Message).
_message(5,Message) :- comp("contralateral flexion"),
                       comp_messages,
                       alert("contralateral flexion",Message).
_message(5,Message) :- comp("torso flexion"),
                       comp_messages,
                       alert("torso flexion",Message).
```

Below you can find an example of how messages directed towards the patient may look like.

```
alert("torso flexion","Do not bend forward!").
alert("scapula elevation","Lower your shoulder!").
alert("scapula elevation","Do not push shoulder forward!").
alert("elevation and protraction","Lower your shoulder and do not push it forward!").
alert("ipsilateral flexion","Do not lean towards your arm!").
alert("contralateral flexion","Do not bend away from your arm!").
```

Additionally, noninvasive messages can be displayed in the graphical user interface of the exercise design tool. In this case, only the name of the detected compensation is displayed for 2 s. The text is also colored red.

```
_print(2,2,"red","scapula elevation") :- comp("scapula elevation"),
                                         not comp("scapula protraction").
```

```
_print(2,2,"red","scapula protraction") :- comp("scapula pro
                                          traction"), not comp
                                          ("scapula elevation").
_print(2,2,"red","scapula elevation and protraction") :- comp("scapula
                                          elevation"),
                                          comp("scapula
                                          protraction").
_print(2,2,"red","ipsilateral flexion") :- comp("ipsilateral flexion").
_print(2,2,"red","contralateral flexion") :- comp("contralateral
                                          flexion").
_print(2,2,"red","torso flexion") :- comp("torso flexion").
```

In order to have a more direct feedback, the vectors of the skeleton model can be colored red when a *scapula elevation* or *scapula protraction* has been detected.

```
_jointcolor("collarleft","red",2) :- comp("scapula elevation"),
                                     affected(left).
_jointcolor("collarright","red",2) :- comp("scapula elevation"),
                                     affected(right).
_jointcolor("collarleft","red",2) :- comp("scapula protraction"),
                                     affected(left).
_jointcolor("collarright","red",2) :- comp("scapula protraction"),
                                     affected(right).
```

The exercise design tool creates a XML file. This file contains the number of compensations detected for each type. An atom *_xmlelement*/1 increases the count for the given string. This is done for each compensation but could also be used for other purposes.

```
_xmlelement("TorsoFlexion") :- comp("torso flexion").
_xmlelement("ScapulaElevation") :- comp("scapula elevation").
_xmlelement("ScapulaProtraction") :- comp("scapula protraction").
_xmlelement("IpsilateralFlexion") :- comp("ipsilateral flexion").
_xmlelement("ContralateralFlexion") :- n"contralateral flexion").
```

The whole encoding is processed 15 times a second and provides real-time feedback for the exercise design tool.

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Chapter 7
Virtual Reality Gaming with Immersive User Interfaces

Emmanouela Vogiatzaki and Artur Krukowski

Abstract Stroke is one of most common diseases of our modern societies with high socio-economic impact. Hence, rehabilitation approach involving patients in their rehabilitation process while lowering costly involvement of specialised human personnel is needed. This chapter describes a novel approach, offering an integrated rehabilitation training for stroke patients using a serious gaming approach based on a Unity3D virtual reality engine combined with a range of advanced technologies and immersive user interfaces. It puts patients and caretakers in control of the rehabilitation protocols, while leading physicians are enabled to supervise the progress of the rehabilitation via Personal Health Record. Possibility to perform training in a familiar home environment directly improves the effectiveness and compliance in performing personal rehabilitation.

7.1 Introduction

Stroke affects about 2 Million [1] people every year in Europe. For these people the effect of stroke is that they lose certain physical and cognitive abilities at least for a certain period. More than one-third of these patients i.e. more than 670,000 people return to their home with some level of permanent disability leading to a significant reduction of quality of life, which affects not only the patients themselves but also their relatives. This also increases costs of the healthcare services associated with hospitalisation, home services and rehabilitation. Therefore, there is a strong need to improve ambulant care model, in particular, at the home settings, involving the patients into the care pathway, for achieving maximal outcome in terms of clinical as well as quality of life.

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7.2 The Concept

The StrokeBack project addresses both of the indicated problem areas. The goal of the project is the development of a telemedicine system to support ambulant rehabilitation at home settings for the stroke patients with minimal human intervention. With StrokeBack, the patients would be able to perform rehabilitation in their own home where they feel psychologically better than in care centres. In addition, the contact hours with a physiotherapist could be reduced thus leading to a direct reduction of healthcare cost. By ensuring proper execution of physiotherapy trainings in an automated guided way modulated by appropriate clinical knowledge and in supervised way only when necessary, StrokeBack aims to empower and stimulates patients to exercise more while achieving better quality and effectiveness than it would be possible today. This way StrokeBack system is expected to improve rehabilitation speed, while ensuring high quality of life for patients by enabling them to continue rehabilitation in their familiar home environments instead of subjecting them to alien and stressful hospital settings. This offers also means of reducing indirect healthcare cost as well.

The concept of StrokeBack is complemented by a Patient Health Record (PHR) system in which training measurements and vital physiological and personal patient data are stored. Thus, PHR provides all the necessary medical and personal information for the patient that rehabilitation experts might need in order to evaluate the effectiveness and success of the rehabilitation, e.g. to deduce relations between selected exercises and rehabilitation speed of different patients as well as to assess the overall healthiness of the patient. In addition, the PHR can be used to provide the patient with mid-term feedback, e.g. her/his, rehabilitation speed compared to average as well as improvements over last day/weeks, in order to keep patient motivation high.

The StrokeBack project aims at increasing the rehabilitation speed of stroke patients while patients are in their own home. The benefit we expect from our approach is twofold. Most patients feel psychologically better in their own environment than in hospital and rehabilitation speed is improved. Furthermore, we focus on increasing patients' motivation when exercising with tools similar to a gaming console.

The StrokeBack concept puts the patient into the centre of the rehabilitation process. It aims at exploiting the fact the patients feel better at home, that it has been shown that patients train more if the training is combined with attractive training environments [2, 3]. First, the patients learn physical rehabilitation exercises from a therapist at the care centre or in a therapists' practice. Then the patients can exercise at home with the StrokeBack system monitoring their execution and providing a real-time feedback on whether the execution was correct or not. In addition, it records the training results and vital parameters of the patient. This data can be subsequently analysed by the medical experts for assessment of the patient recovery. Furthermore, the patient may also receive midterm feedback on her/his personal recovery process. In order to ensure proper guidance of the patient, the therapist also gets information from the PHR to assess the recovery process enabling him to decide whether other training sequences should be used, which are then introduced to the patient in the practice again.

7.3 Game-Based Rehabilitation

The use of virtual, augmented or mixed-reality environments for training and rehabilitation of post-stroke patients opens an attractive avenue in improving various negative effects occurring because of brain traumas. Those include helping in the recovery of the motor skills, limb-eye coordination, orientation in space, everyday tasks, etc. Training may range from simple goal-directed limb movements aimed at achieving a given goal (e.g. putting a coffee cup on a table), improving lost motor skills (e.g. virtual driving), and others. In order to increase the efficiency of the exercises advanced haptic interfaces are developed, allowing direct body stimulation and use of physical objects within virtual settings, supplementing the visual stimulation.

Immersive environments have quickly been found attractive for remote home-based rehabilitation giving raise to both individual and monitored by therapists remotely. Depending on the type of a physical interface, different types of exercises are possible. Interfaces like Cyber Glove [4] or Rutgers RMII Master [5] allow the transfer of patient's limb movement into the virtual gaming environment. They employ a set of pressure-sensing servos, one per finger, combined with motion sensing. This allows therapists to perform, e.g. range of motion, speed, fractionation (e.g. moving individual fingers) and strength (via pressure-sensing) tasks. Games include two categories: physical exercises (e.g. DigiKey, Power Putty) and functional rehabilitation (e.g. Peg Board or Ball Game) ones. They use computer monitors for visual feedback. Cyber Glove has been used by Rehabilitation Institute of Chicago [2] also for assessing the pattern of finger movements during grasp and movement space determination for diverse stroke conditions. Virtual environments are increasingly used for functional training and simulation of natural environments, e.g. home, work, outdoor. Exercises may range from simple goal-directed movements [6] to learn/train for execution of everyday tasks.

Current generation of post-stroke rehabilitation systems, although exploiting latest immersive technologies tend to proprietary approaches concentrating on a closed range of exercise types, lacking thoroughly addressing the complete set of disabilities and offering a comprehensive set of rehabilitation scenarios. The use of technologies is also very selective and varies from one system to another. Although there are cases of using avatars for more intuitive feedback to the patient, the use of complicated wearable devices makes it tiresome and decreases the effectiveness of the exercise [3]. In our approach we have been exploring novel technologies for body tracing that exploit the rich information gathered by combining wearable sensors with visual feedback systems that are already commercially available such as

Microsoft Kinect [7] or Leap Motion [8] user interfaces and 3D virtual, augmented and mixed-reality visualisation.

The environment we develop aims to provide a full 3D physical and visual feedback through Mixed-Reality interaction and visualisation technologies placing the user inside of the training environment. Considering that detecting muscle activity cannot be done without wearable device support, our partner in the project, IHP GmbH, has been developing a customizable lightweight embedded sensor device allowing short-range wireless transmission of most common parameters including apart from EMG, also other critical medical signs like ECG, Blood Pressure, heart rate, etc. This way the training exercises become much more intuitive in their approach by using exercise templates with feedback showing correctness of performed exercises. Therapists are then able to prescribe a set of the rehabilitation exercises as treatment through the EHR/PHR platform(s) thus offering means of correlating them with changes of patient's condition, thus improving effectiveness of patients' recovery.

7.4 Body Sensing and User Interfaces

In order to enable the tracking the correctness of performed exercises automatically without the constant assistance of the physicians, an automated means of tracking and comparing patient's body movement against correct ones (templates) has to be developed. This is an ongoing part of the work due to the changing requirements from our physicians. Although many methods are in existence, most of them employ elaborate sets of wearable sensors and/or costly visual observations. In our approach we initially intended to employ a proprietary approach using visual-light scanning, but the recent availability of new Kinect, Prime Sense and Leap Motion sensors made us change our approach and use existing IR-LED solutions.

When better accuracy is required that offered by 3D scanners then additional microembedded sensor nodes are employed, e.g. gyros (tilt and position calibration) and inertial/accelerometers (speed changes). Such are readily available for us in both EPOC EEG U/I from Emotiv (used currently as a U/I, though intended to be used in the future for seizure risk alerting) and on Shimmer EMG sensor platform that we use for detecting muscle activity during the exercises. Considering very small sizes of such sensors (less than 5×5 mm each) a development of lightweight wireless energy-autonomous (employing energy harvesting) may be possible.

Muscle activity poses problems for measurement since it has been well known for many years [9] that the EMG reflects effort rather than output and so becomes an unreliable indicator of muscle force as the muscle becomes fatigued. Consequently measurement of force, in addition to the EMG activity, would be a considerable step forward in assessing the effectiveness of rehabilitation strategies and could not only indicate that fatigue is occurring, but also whether the mechanism is central or peripheral in origin [10]. Similarly, conventional surface EMG measurement requires accurate placement of the sensor over the target muscle, which would be inappropriate for a sensor system integrated within a garment for home use. Electrode arrays are, however, now being developed for EMG measurement and signal processing is used to optimise the signal obtained. Several different solutions have been investigated to offer sufficiently reliable, but also economic muscle activity monitoring. Finally, we concluded on using EMG sensors on the 2R sensor platform from Shimmer for system development purposes, while a dedicated solution made by IHP GmbH.

However, EMG is not the only sensor that is needed for home hospitalisation of patients suffering from chronic diseases like stroke. This requires novel approaches to combining building blocks in a body sensor network. Existing commercial systems provide basic information about activity such as speed and direction of movement and postures. Providing precise information about performance, for example relating movement to muscle activity in a given task and detecting deviations from normal, expected patterns or subtle changes associated with recovery, requires a much higher level of sophistication of data acquisition and processing and interpretation. The challenge is therefore to design and develop an integrated multimodal system along with high-level signal processing techniques and optimisation of the data extracted. The Kinect system has potential for use in haptic interfacing [11] and has already been used in some software projects, and Open Source software libraries are available for browsers like Chrome [12] and demonstrations of interfaces to Windows 7 [3] systems have been shown.

The existing techniques for taking measurements on the human body are generally considered to be adequate for the purpose but are often bulky in nature and cumbersome to mount, e.g. electro-goniometers, and they can also be expensive to implement, e.g. VIACON camera system. Their ability to be used in a home environment is therefore very limited. In this context, we have decided to address those deficiencies by extending the state-of-the-art in the areas of:

- Extending the application of existing sensor technologies: For example, we tend to use commercially available MEMS accelerometers with integrated wireless modules to measure joint angles on the upper and lower limbs in order to allow wire-free, low-cost sensor nodes that are optimised in terms of their information content and spatial location.
- Novel sensing methodologies to reduce the number of sensors worn on the human body, while maintaining good information quality. For example, many homes now have at least one games console (e.g. Xbox, Nintendo Wii, etc.) as part of a typical family home entertainment system. With the advent of the Xbox Kinect system, the position and movement of a human will be possible to be monitored using a low-cost camera mounted on the TV set.
- Easy system installation and calibration by non-experts for use in a non-clinical environment, thus making this solution suitable for use at home for the first timer and with support or untrained caretakers and family.
- Transparent verification of correct execution of exercises by patients may be based on data recorded by Body Area Networks (BAN), correlation of prescribed therapies with medical condition thus allows to determine their effectiveness on patient's condition, either it is positive or negative.

7.5 Prototyping

The project has reached 2 years of its lifetime already and the prototyping as well as integration of various technologies have already started. This refers to physiological monitoring with Shimmer sensors, gaming user interfaces as well as the games themselves, focussing on the Unity3D engine. A sub-unit assembly diagram of the 'Patients home training place' is depicted in Fig. 7.1 and shown placed on a patient in Fig. 7.2. The blue and grey rectangles designate respective elements, while green ones are the user interfaces. The PTZ-camera features pan-tilt-zoom. Arrows show the data flow. The description of the user interfaces shown in this diagram follows.

Since home-based rehabilitation may increase the risk of stroke re-occurrence we have decided to include EEG sensor, a 2×7-node Emotiv EPOC EEG, which we use for monitoring of brain signals, looking for 'flashing' activity between the two brain spheres, indicated by participating physiotherapists as a sign of a likely pre-event condition (Fig. 7.3).

This device offers an additional benefit for being used as a supplementary gaming interface, thus shifting patient's perception from its use as a preventive device to enjoying and using for controlling games with the 'power of the mind'. It is not without a merit that Emotiv offers also a Unity3D support for its device, not to mention ongoing development of an even more powerful INSIGHT [13] sensor version.

Currently apart from searching for clues indicating pre-stroke risks and as 'mouse'-like user interface, we use EPOC for establishing a correlation between

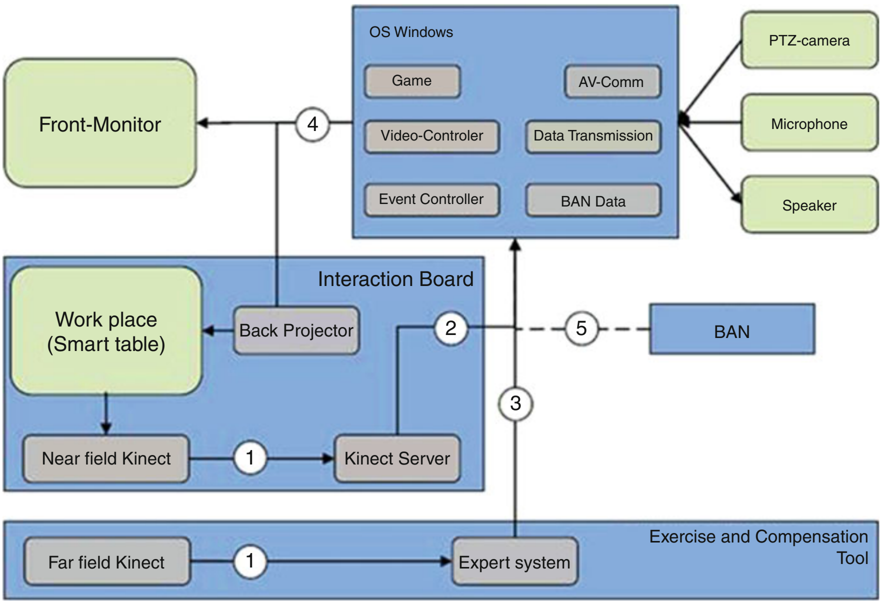

Fig. 7.1 Integration of the overall 'home' system

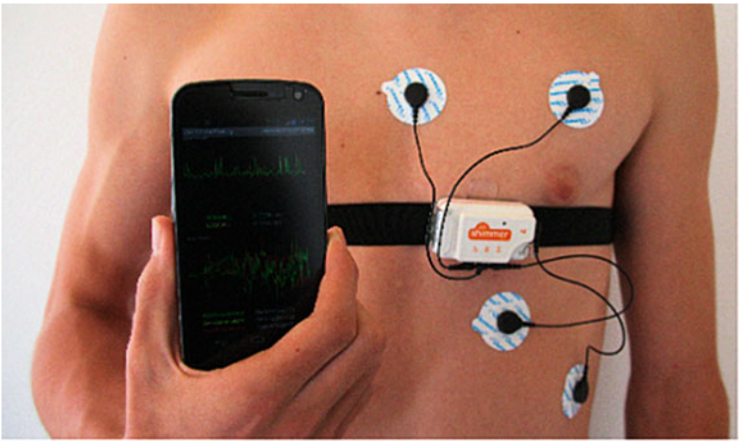

Fig. 7.2 ECG sensing with Shimmer2R

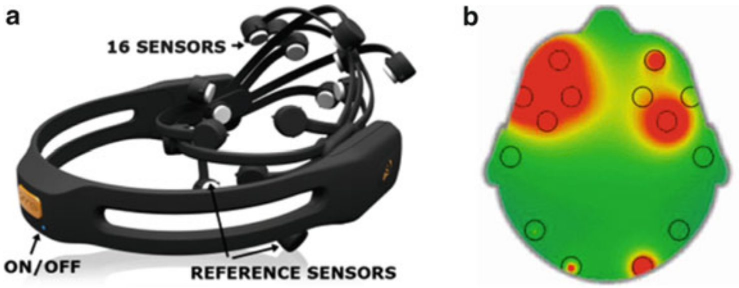

Fig. 7.3 Emotiv EEG (**a**), sample brain activity (**b**)

the mental intention to move a limb and the physical action. By combining with data from EMG sensors we aim to detect cases when patient's brain correctly issues a signal to, e.g. to move an arm, but the patient cannot do it, e.g. due to a broken nerve connection.

7.5.1 'Kinect Server' Implementation

The principal user interface used to control games has been Microsoft Kinect, the Xbox version at first and then the Windows version when it has been first released in early 2012. Its combination of distance sensing with the RGB camera proved perfectly suitable for both full-body exercises (exploring its embedded skeleton recognition) as well as for near-field exercises of upper limbs. However since Kinect has not been designed for short-range scanning of partial bodies, the skeleton tracking could not be used and hence we had to develop our own algorithms that would be able to recognise arms, palms and fingers and distinguish them from the background objects. This has led to the development of the ‘Kinect server’ based on open source algorithms. The first implementation has used Open NI drivers, closed in April 2014 following the acquisition of PrimeSense by Apple [14], offering the opportunity for our software to be built for both MS Windows and Linux platforms.

The ‘Kinect Server’ has been a custom development from RFSAT Ltd in the StrokeBack project to allow remote connectivity to the Microsoft Kinect sensor and subsequently the use of the data from the sensor on a variety of devices, not normally supported natively by the respective SDK from Microsoft. Initial implementation of the Kinect Server has been based on Open NI drivers for Xbox version of the device, which has been later translated to a more general drivers supplied by Microsoft in their Kinect SDK version 1.7 and the subsequent versions.

The principle of its operation is that it is comprised of two components:

- *Server-side*—operating on a software platform supported by the selected Kinect drivers, having a role of obtaining relevant data from the Kinect sensor and making it available in a suitable form via network to connected clients.
- *Client-side*—operating on any platform where WEB browsers with embedded Java Scripts are supported. This means almost any networked device, including tablets and a variety of smartphones, even Smart TVs, and other devices.

The types of information made available to by the server to clients include both RGB and depth map as images as well as the list of detected objects. Customisations include for example such features as the limitations of the visibility (detection) area, thus allowing to reduce clutter from nearby objects, focus on the selected object (e.g. the central or the closest one) and other ones.

Two modes of operation have been anticipated in order to enable its use for rehabilitation training in the project (refer to Fig. 7.4). In case that the persistent network connectivity can be maintained, the server part could operate on the home gateway, the client on a game console while the game server (game repository and management of game results for each user) remotely on the same server that hosts the PHR platform. In such an approach home client would not need to bother about updating games to latest versions or managing results. However, in case that network connectivity may or may not be secured, then the game server would need to be hosted locally on a home gateway, alongside the Kinect Server.

Since server has been implemented as a generic enabler, a supplementary implementation of gesture recognition geared to the Kinect Server has been implemented. In order to achieve wide interoperability on a number of devices and operating systems, an approach using Python script ‘palm_controls’ has been selected with a purpose of detecting specific gestures and mapping them to a custom keystrokes and mouse actions. The list of features and calling syntax is shown below:

palm_controls <server IP> <server PORT> options

Sever IP—network address where Kinect Server is hosted

Server PORT—network port on which the server listens for connections

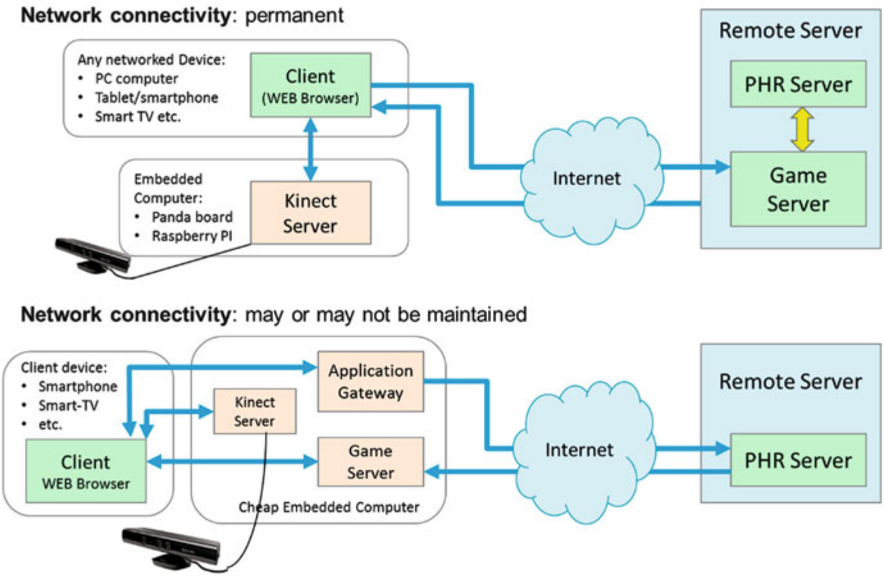

Fig. 7.4 Network operational modes of the 'Kinect Server'

Options:

- '-lHH –rHH –uHH –dHH -sHH'

  Defines keys pressed for left, right, up, down and click actions
  HH is a hexadecimal number from the Microsoft character table:
  http://msdn.microsoft.com/en-us/library/windows/desktop/dd375731(v=vs.85).aspx
  Choosing a zero (0) for a given key disables mapping of the given gesture

- '-x??? –X??? –y??? –Y??? –z??? –Z???'

  This allows the 3D space where objects are detected.
  Parameters define *Xmin*, *Xmax*, *Ymin*, *Ymax*, *Zmin* and *Zmax*, as given below:
  Xmin & Xmax are given in pixels in the range 0–320
  Ymin & Ymax are given in pixels in the range 0–240
  Zmin & Zmax are given in millimeters, refer to a distance from the sensor

7.5.2 Embedded Kinect Server

The limitations of the Kinect in terms of the compatibility with certain Operating Systems, diversity of often-incompatible drivers and restrictiveness to high-end computing platforms have pushed us to investigating alternative ways of interacting

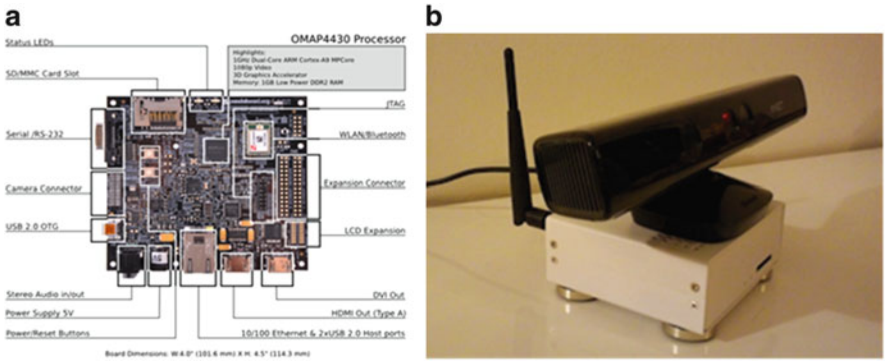

Fig. 7.5 Embedded Kinect server deployment: Panda board (**a**) and physical prototype integrated with the MS Kinect for Windows sensor (**b**)

with Kinect devices. This has led to the attempt to develop an 'Embedded Kinect Server' or EKS. Our idea was to use a microembedded computer like Raspberry PI [15] or similar and allow the client device that was running the game to access data from the EKS via local wireless (or wired) network. Such an approach would allow us to remove the physical connectivity restriction of the Kinect and allow 3D scanning capability from any device as long as it was connected to a network.

Various embedded platforms were investigated: Raspberry PI, eBox 3350 [16], Panda board [17] (Fig. 7.5) and many other ones. Tests have revealed an inherent problem with Kinect physical design that is shared between the Xbox and the subsequent Windows version that is the need to draw high current from USB ports in order to power sensors despite separate power supply still required.

Hardware modifications of the Raspberry PI aimed to increase the current supplied to its USB ports, use of powered external USB hub and other work-around proved all unsuccessful. To date only the Panda Board proved to be the only embedded computer able to maintain the Kinect connectivity and running our EKS. In our tests we have managed to run the Mario Bros game on an Android smartphone and use Kinect wirelessly to control a game with patient's wrists.

7.5.3 Rehabilitation Games Using the 'Kinect Server'

The main features of our implementation offer the capabilities of restricting the visibility window, filtering the background beyond prescribed distance, distinguishing between separate objects, etc. This way we were able to implement the Kinect-based interface where following the requirements of our physiotherapists we replaced the standard keyboard arrows with gestures of the palm (up, down, left, right and open/close to make a click). Such an interface allowed for the first game-based rehabilitation of stroke patients suffering from limited hand control. The tests

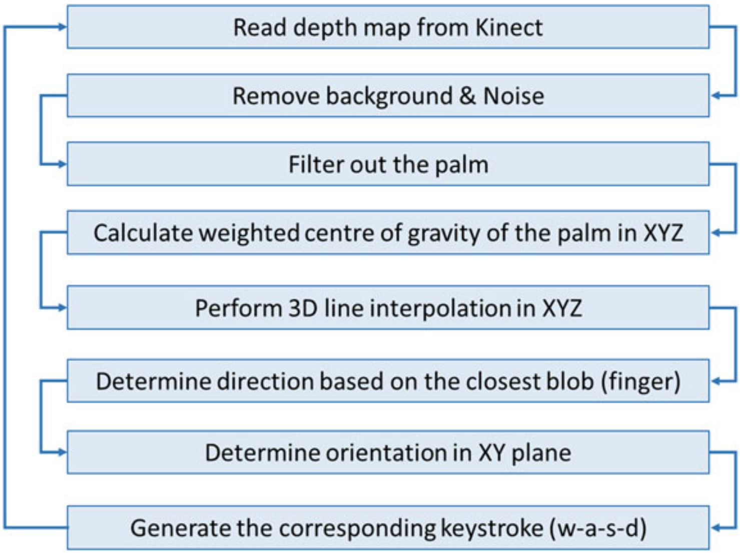

Fig. 7.6 Wrist position detection algorithm

were first made with Mario Bros game where all controls were achieved purely with movements of a single palm. The algorithm for analysing wrist position and generating respective keyboard clicks has been developed initially in Matlab and then ported to PERL for deployment along with the Kinect server on an embedded hardware.

The algorithm is shown in Fig. 7.6. It is based on the idea that assuming that the wrist is placed steadily on a support (requirements from physiotherapists), the patients palm would always have fingers closer to the Kinect than the rest of a hand, this allowing easily to determine the palm position and direction the fingers point. Under such condition, we did not have to pay much attention to Kinect calibration and could avoid fixing the relative position of the hand support with respect to the Kinect device. This allowed us to remove the background simply by disregarding anything more distant than the average palm length centred on the centre of gravity (i.e. centre of the palm itself).

The line was then interpolated through remaining points in 3D, whereby the closest point detected was indicating the tip of the closest finger. The direction of the line was equivalent to the movement of a hand in a given direction allowing us to generate the correct keystroke combination (w-a-s-d for N-W-S-E). Since the accuracy was, better than 1/8 of the circle it allowed us to determine also diagonal movements (double keystrokes, i.e. wd-wa-sd-sa for NW-NE-SE-SW). A predefined time delay was applied corresponding to control detection ‘speed’.

Since classical rehabilitation required the use of physical objects, like cubes of glasses we have implemented subsequently a ‘cube stacking’ game, where patient had to use the physical cubes and place them carefully onto the placeholders

Fig. 7.7 Game using real cubes on a virtual board

displayed on the computer screen positioned flat on the table (later replaced with overhead projection) as shown in Fig. 7.7 where red cubes and placeholders (grey squares) are visible. Here Kinect sensor is placed to scan horizontally at table level, thus allowing to detect XYZ coordinates of the physical cubes. By matching projections with Kinect scan regions allowing detection of correct placement of cubes.

The first level starts with one cube and placeholder parallel to screen edge, then as the game progresses more cubes are used and their requested position could be in any direction. At the end, a score was calculated taking into consideration both the time to place the cubes and the accuracy of placing them over the placeholder. The score was reported in the PHR allowing the physician to track the progress of the patient from one exercise to another. Another variant of the game introduced the possibility of stacking cubes one on top of the other.

An alternative gaming approach to mixing virtual and real objects was a game where patients were requested to throw a paper ball at the virtual circles displayed on the screen as shown in Fig. 7.8. The Kinect sensor synchronised with location of projected object detects physical ball reaching the distance of the wall. Combined with its XY coordinated, this allows to detect the collision.

Such a game allows patients to exercise the whole arm, not just the wrist. Hitting the circle that represented a virtual balloon was rewarded with an animated explosion of the balloon and a respective sound. Such a game proved to be very enjoyable for the patients letting them concentrate on perfecting their movements while forgetting about their motor disabilities, increasing effectiveness of their training.

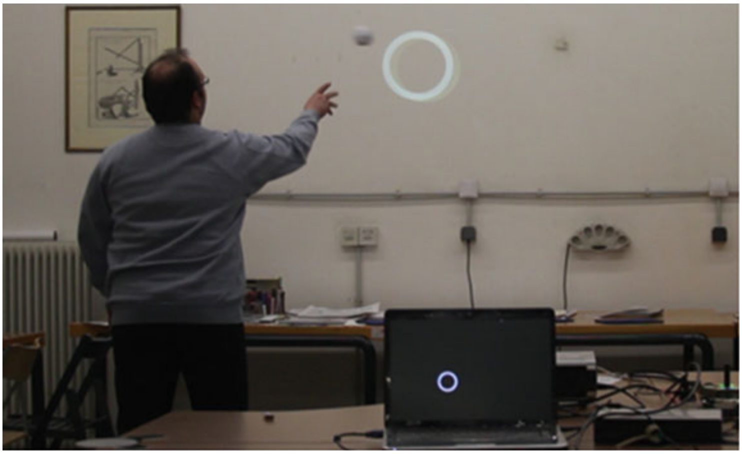

Fig. 7.8 Throwing real paper ball at virtual targets

7.5.4 Full-Body Games with Avateering

Subsequently we have investigated more advanced class of games for stroke patients for full-body exercises. In such a case we have chosen to build such games using 3D engine and employ avateering approach, that is patient's body motion capture and its projection onto a virtual avatar. When we have started our first implementation, the MS Kinect SDK was not available yet and hence we have explored various 'hacks' built by the Kinect developer community. The most applicable to our needs appeared to be ZigFu [18], which was compatible with Open NI drivers and easy to use under Unity3D [19] editor.

It proved easier than using commercial products, e.g. Brekel [20] or Autodesk Motion Builder [21]. A prototype system uses environments ranging from familiar home spaces in photorealistic quality [22] (Fig. 7.9) to generic hospital environments (Fig. 7.10).

Scenes with one and two avatars were implemented. The first one was intended as a base for self-training exercises where instruction would be overlaid over the avatar to indicate the movements that the patient would need to perform in order to pass the exercise. A two-avatar scenario was aimed to offer the side-by-side exercise together with a virtual rehabilitator where patient would need to follow the movements of the 'physician' seeing him/herself at the same time. In both cases, the score would be corresponding to the accuracy of following the expected movements. The two scenarios are being subject to assessment by physiotherapists and the decision as to which one will be used for the final system implementation will be depended on evaluation results.

An important advantage of Unity3D over other 3D gaming engines like Cry Engine 3 or Unreal Engine is the possibility to compile games to run either as stand-alone or under from inside a WEB page. The latter approach makes it easier for integrating

Fig. 7.9 Avateering in a 'home' like environment

Fig. 7.10 Avateering aimed to repeat movements of an instructor in a 'hospital' like virtual environment

games as therapies within the PHR system accessible and controllable via WEB browser. A use of this feature for exercises with a real patient is shown in Fig. 7.11.

The Kinect Server and wrist controls have been integrated into a number of games under Unity3D in order to evaluate the adopted concepts with end users, such as into an 'Infinite Runner' [23], shown in Fig. 7.12. It is an incentive-based game combining rehabilitation with entertainment. High scores (coins collected) correspond to improvement in recovering hand movement capabilities.

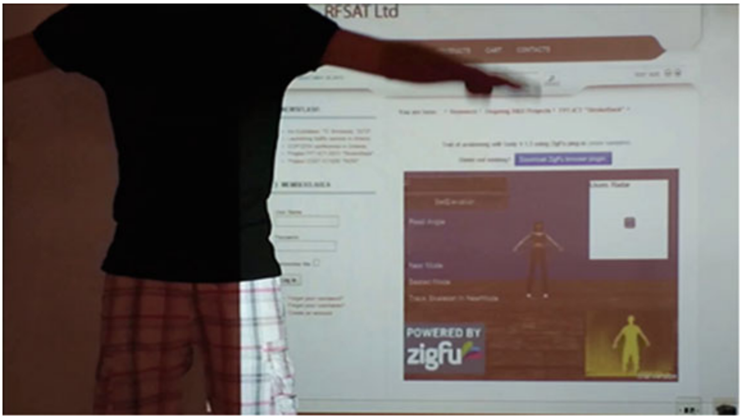

Fig. 7.11 Patient playing online Unity3D game using standard WEB browser

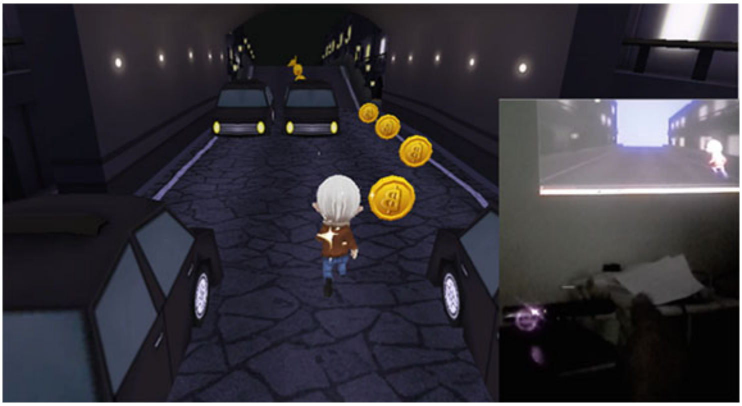

Fig. 7.12 Kinect server used in a wrist-controlled 'Infinite Runner' game

The game uses embedded implementation of the Unity3D plug-in for Kinect Server, thus avoiding intermediary use of the Python gesture-interpretation scripts. The game allows exercising lower left and right limb, implementing movements like left and right swipe, up and down swipes, fist and fingers spread, being translated to respective movements of the character, as well as jump and duck actions.

7.5.5 3D Stereoscopic Visualisation

In order to enhance the realism of the games developed with Unity3D engine a stereoscopic projection was implemented offering a sense of depth on supported 3D displays. The current approach has been based on the 'camera-to-texture' projection feature available in a PRO version of Unity3D.

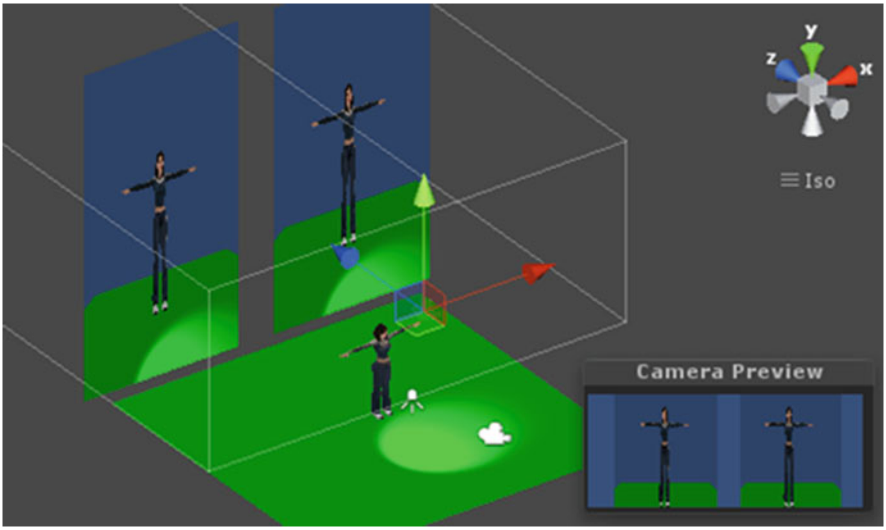

Fig. 7.13 Stereoscopic projection using Unity3D camera-to-texture [24]

It has been based on various published experiments [24, 25]. A dual virtual cameras placed near each other have their images projected onto virtual screens, in turn captured by a single output camera thus creating a side-by-side display (Fig. 7.13). Such an image is then suitable for driving common 3D displays such as of the 3D Smart TV (e.g. Samsung UE46F6400) or 3D projector (e.g. Epson EH-TW5910) with frame-switching 3D glasses. Both of those have been successfully tested with our system. In the future tests we will evaluate also panoramic virtual 3D visors (e.g. Oculus RIFT) and 3D augmented glasses (e.g. VUZIX Star 1200XLD) for virtual and mixed-reality games respectively.

7.5.6 Integration of Leap-Motion User Interface

The latest addition to the portfolio of our user interfaces has been the Leap Motion device. It has proven invaluable for rehabilitation of upper limbs thanks to its superior ability to detect close range distances over the Kinect. Our developments have led us to use features already offered by the Leap Motion SDK and the community applications, e.g. the Touchless for Windows allowing controlling mouse-like control of the Windows applications. This has led us to experiments with standard games used for the rehabilitation of stroke patients like memory board game (as in Fig. 7.14a) and experimenting with operating virtual cubes composing a Stroke word in a virtual 3D space using only your fingers (as in Fig. 7.14b). Both of those have proven very enjoyable for our patients.

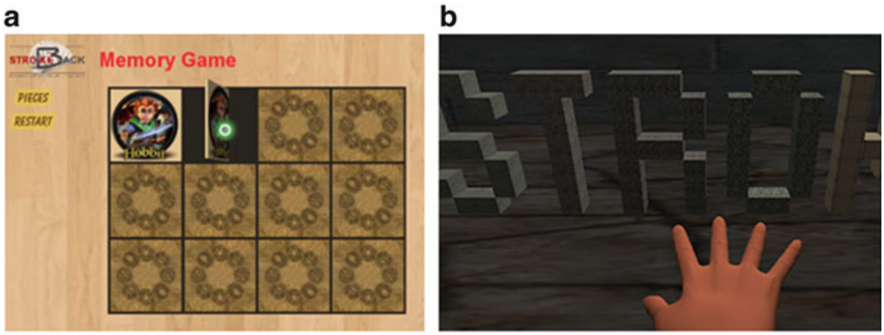

Fig. 7.14 Board games using Leap Motion, Memory (**a**) and Grasping (**b**)

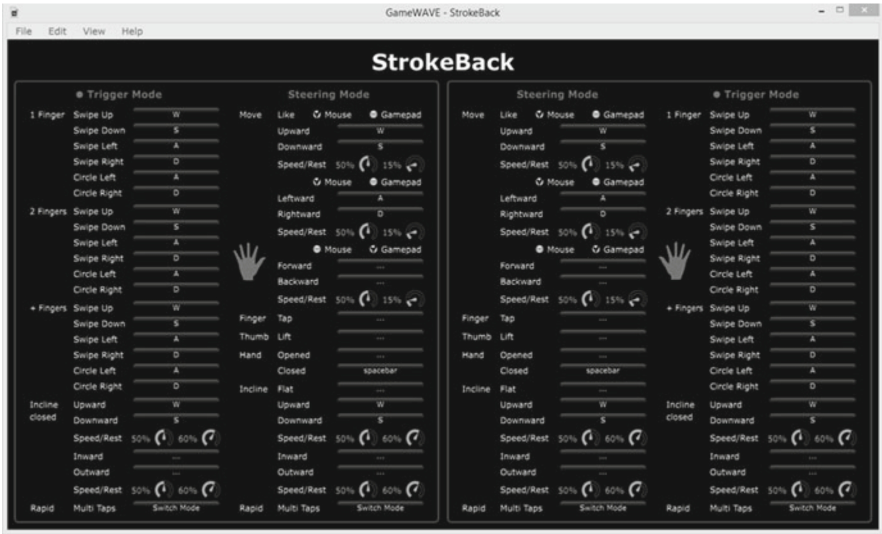

Fig. 7.15 Game WAVE application for Leap Motion [26]

Initial implementation of the games in Fig. 7.15 have used third-party gesture recognition applications, such as Game WAVE for Leap Motion [26], which allowed mapping of pre-defined hand movements to specific keystrokes and mouse movements, thus allowing easy control of any application, including our games. In more recent versions the Unity3D plug-ins from leap Motion have been used, supplemented with custom add-ons aimed to improve the detection of the specific gestures that were important for the selected range of rehabilitation exercises.

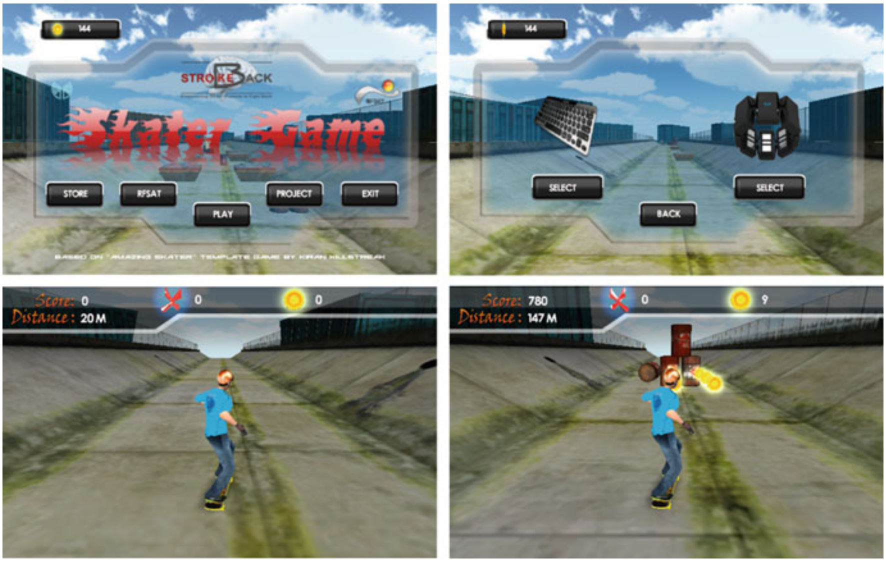

Fig. 7.16 The 'Skater Game' adapted from a template by Ace Games [28]

7.5.7 *Integration of Myo Gesture Control Armband*

The latest of the sensor that are directly applicable for rehabilitation training of stroke suffering users is an electromyographic (EMG) sensor from Thalmic Labs called 'Myo' [27], launched in early 2015. Such a sensor allows the detection of electrical potentials of the muscles on the affected limbs. In this sense it gives two types of benefits. From one side clinicians can have a direct indication whether signals are correctly sent from the brain to the muscles. On the other hand it offers a possibility of being used as a user interface for controlling rehabilitation games. The manufacturer has released a range of support software, including and SD, Unity3D plug-in and an application manager allowing custom mapping of supported gestures to required keystrokes and mouse actions. A direct access to each of the eight (8) EMG sensors is also readily available by the SDK in order to allow developers to view raw signals from muscles and devising own gesture recognition algorithms.

Our rehabilitation system could not refrain from taking advantage of such a useful interface and a game has been built, adapted from the 'Amazing Skater' Unity3D game template from Ace Games [28], presented in Fig. 7.16.

The game can be played using either a keyboard or a Myo sensor. The latter is supported through a Unity3D plug-in, though it can be also operated using custom StrokeBack application profile via Myo Application Manager.

7.6 Summary and Observations

In the frame of the project, most of the technologies have been implemented, including integrated Smart Table as described in Chapter 9, integration with PHR systems allowing management of rehabilitation by physicians as well as a range of user interfaces, not only based on a Kinect sensor. The initial technical validation tests have proven the viability of the design approach adopted.

The suitability of Leap Motion for 'Touch-Screen'-like applications and game development under Unity3D has been confirmed. Following the success of the technical system tests, the clinical trials with real patients are being conducted since September 2014 into early 2015. Primarily the focus is to be made on the motion capture and recording of the real person (therapist) for subsequent use for demonstration of correct exercises by animating his/her avatar as shown earlier in Fig. 7.10.

Furthermore a 3D hand model needs to be developed, rigged and animated in order to allow its use in Unity3D games. Subsequently the overall integration of the gaming system will be performed whereby selection of games and the necessary data exchange mechanism with the PHR system will be developed. The most difficult work will be related to the real-time comparison of avatar movements for providing an accurate scoring of the correctness of exercises, to be achieved in liaison with the physiotherapists.

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Chapter 8
Personal Health Record-based e-Health Services Platform

Ilias Lamprinos, Konstantinos Tsakalos, Michael Chouchoulis, Gioula Giannakopoulou, and Nikolaos Ioannidis

Abstract The aim of this Chapter is to present the basic characteristics of the Personal Health Record Systems (PHR-S) and indicate how the relevant platforms can serve as a basis for developing value added services such as a Care Management service. The basic features of a generic architectural approach for PHR-S are presented as well as the business challenges addressed by the proposed approach. In the context of StrokeBack an ICT-based post-stroke rehabilitation service was implemented. In order to support this service we designed and implemented a set of applications on top of the proposed PHR-S framework. The main features of these applications are also presented in this chapter.

8.1 Personal Health Record Systems

The Personal Health Record System (PHR-S) comprises a controllable, self-contained, flexible, and extendable solution for supporting care management services and for managing associated patient data. According to the HL7 standards development organization, and more specifically the HL7 EHR Work Group [1] the PHR-S is described as a patient centric tool that is controlled for the most part, by the individual. It is available electronically and can be linked to other health information systems. The PHR-S is intended to provide functionality to help an individual maintain a longitudinal view of his or her health history, and may be comprised of information from a plethora of sources. A PHR-S helps the individual to collect vital signs data (including data coming from medical monitoring devices), medication information, care management plans and the like, and can potentially connect to providers, laboratories, pharmacies, nursing homes, hospitals and other institutions, and clinical resources. At its core, the PHR-S provides the ability for

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the individual to capture health history in the form of a health summary, problems, conditions, symptoms, allergies, medications, laboratory and other test results, immunizations, and encounters. Additionally, personal care planning features such as advance directives and care plans can be available. Due to the nature of the collected information, the system must be secure and have appropriate identity and access management capabilities, and use standard nomenclature, coding and data exchange models for consistency and interoperability.

Several commercial and open-source PHR-S are available in the market. For example, Microsoft HealthVault [2] provides an online service to store and maintain health-related information. HealthVault features a thematic search engine, allowing users to search specifically for health-related information. Users can store personal medical records and prescription history, manage records, upload data from medical devices such as blood pressure monitors, and analyse and manage their data. The data can be shared with other health management web sites or directly with medical practitioners. HealthVault also features a desktop client that allows medical data pulled from personal health devices such as heart rate and blood-pressure monitors to be uploaded to the PHR-S. In the open-source domain, Tolven [3] is a characteristic solution focusing on delivering electronic Personal Health Record (ePHR) that enables patients to record and selectively share healthcare information about themselves in a secure manner. Indivo X [4] is another open-source PHR solution. It is promoted as Personally Controlled Health Record (PCHR), a platform that provides the means to create a PHR and also link other PHRs together.

8.2 A Generic Architecture for PHR-S

The proposed PHR-S is based on a modular architecture that enables easy addition or removal of desired functionality. We discriminate between the business domain layer components and the underlying technical framework. The business components reflect the needs of the end users of the specific application domain, while the underlying horizontal layers provide a generic, business agnostic functionality (Fig. 8.1).

Starting from the baseline, the *Middleware Framework* layer offers flexible and loose connection between internal and external components of the PHR-S. The functionality supported by this layer is related to API management, services' access rights management, user interface management, and presentation layer management.

The *Presentation Framework* layer aims at supporting application navigation and visualization in different browsers. The rationale behind the design of the Presentation Framework is to ensure independence of the graphical user interface (GUI) from the business domain layer. It is composed of a set of discrete components, as indicated in Fig. 8.2. For example, the *XSL & XML Handler* offers a flexible GUI and manages the pages' layout, while the *Translation Handler* is responsible for translating XML and XSL to HTML pages.

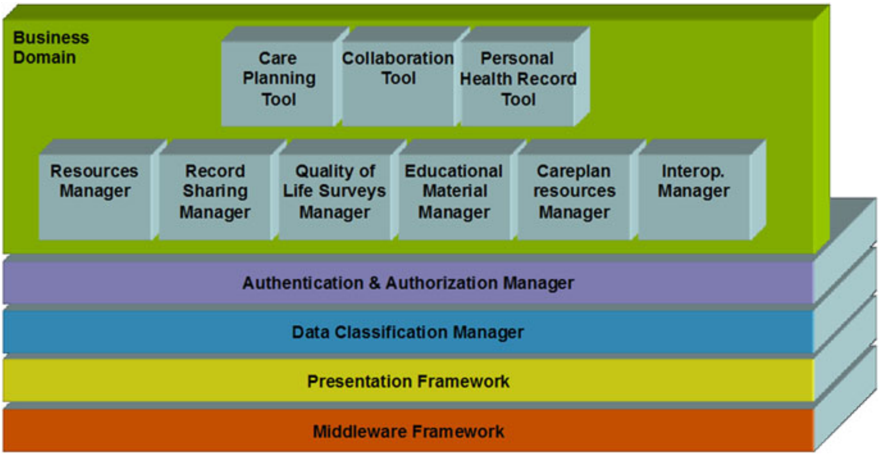

Fig. 8.1 PHR-S platform architecture

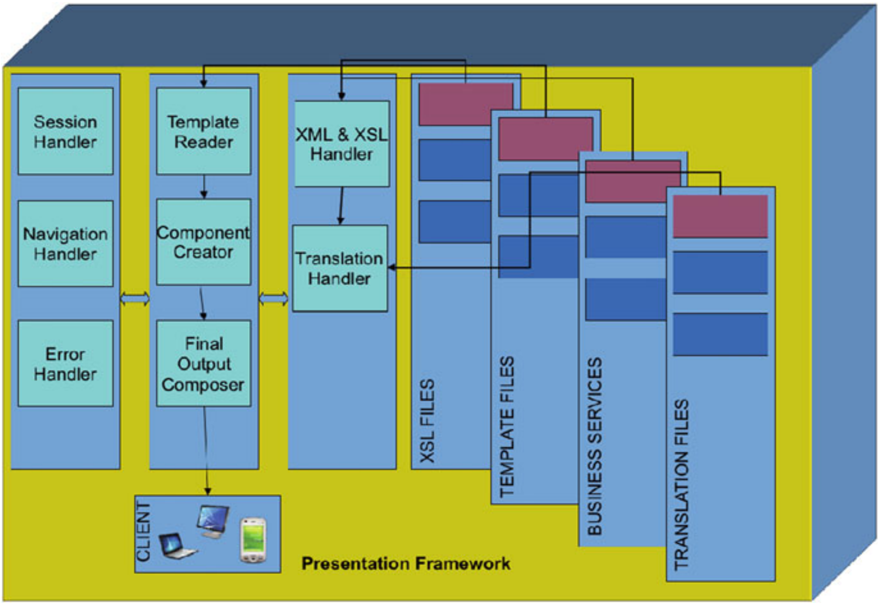

Fig. 8.2 Presentation framework details

The *Data Classification Management* layer provides a configurable and flexible data classification mechanism. It offers functionality related to patient data classification management, classification levels' management, and data access rights' management.

Finally, the *Authentication & Authorization Management* layer provides functionality related to account management, as well as to the definition of authentication and authorization rules (role-based, e.g., admin, clinician, patient).

The *Business Domain* layer includes an expandable set of components that offer domain-specific functionality, such as the *Personal Health Record*, the *Care Planning Tool*, the *Collaboration Tool*, and the *Admin Tool*.

The *Personal Health Record* is an application that facilitates recording of data related to vital signs measurements, visits, surgeries, medications, symptoms, diagnoses (following the International Statistical Classification of Diseases & Related Health Problems standard terminology [6]), patient documents, laboratory tests (orders and results' presentation). The application makes use of the Presentation Framework to offer two flavors of the presentation layer: one for PC web browsers and another for mobile browsers.

The *Care Planning Tool* supports flexible set up of care plans and monitoring of their execution. In particular this component supports: care plan registration; set up of the list of actions that are appropriate for this plan, e.g., vital signs measurements, educational material, quality of life surveys, home visits, physical activity plan, nutrition plan, etc; care plan templates creation; care plan assignment to patient(s); care plan execution monitoring by the medical personnel, and; automatic care plan execution control, followed by appropriate notifications to the patients and the medical personnel.

The *Collaboration Tool* includes functionality related to collaboration between patients and their clinicians, e.g., videoconference, messaging (SMS, e-mail).

Part of the Business Domain layer is also a set of components that support the domain-specific application and services. The *Care Plan Resources Manager* provides functionality related to the configuration of the entities that constitute a care plan, e.g., vital signs collection, quality of life surveys, physical activity and exercises, nutrition, etc. This component is very useful at the configuration of the value added service on top of the PHR-S product as it can be used to reflect the exact management needs of the different diseases (e.g., diabetes, stroke, etc.).

The *Quality of Life Surveys Manager* features functionality to support questionnaires management (questionnaires registration and set up, questionnaires access rights management).

The *Record Sharing Manager* includes functionality that enables patients to share their PHR with other healthcare professionals.

The *Interoperability Manager* includes functionality related to HL7 v3 messaging, as well as generation and consumption of IHE profiles-based information [5]. In particular, the Personal Health Record (XPHR) and the Care Management (CM) profiles are supported.

The *Resources Manager* supports registration and management of equipment that is dispatched to the patients in the course of a care plan (e.g., medical devices, smart phones, etc.). The supported functionality includes equipment registration management; equipment assignment management; and equipment info management.

The *Educational Material Manager* supports the registration and management of educational material related to chronicdiseases management. This material is accessed by the patients in the course of a care plan.

8.3 Business Challenges Addressed by the Proposed Framework

Table 8.1 summarizes the main challenges addressed by the proposed PHR-S framework and the main benefits of the implemented solution.

Table 8.1 Business challenges addressed by the proposed PHR-S framework

Challenge	Implemented Solution	Benefit
Services differentiation	• SOA architecture	Each user is able to use only a predefined subset of services Administrator has the ability to configure the availability of services to users, based on their user role
	• Middleware framework	
	• Authentication and authorization management	
Data classification	• SOA architecture	Users can access different subsets of data, subject to classification
	• Middleware framework	Authorized users can choose a subset of data to be exposed for public or for private usage
	• Data classification management	Administrator can configure the visibility level of data, in accordance with the user role
	• Authentication and authorization management	
Usage flexibility	• SOA architecture	Ability to use common and separate functionality depending on the user role. For example, clinicians of different specialties, paramedical personnel and patients can use the same system
	• Middleware framework	
	• Authentication and authorization management	
GUI flexibility	• XSL, XML handler	The users have the ability to choose a personal style of data and info presentation on screen
GUI personalization	• Navigation handler	Administrator can define different styles of data presentation based on user classification
System interoperability	• Interoperability manager	Ability to communicate with external systems using HL7 standard messages and to exchange information based on IHE profiles (e.g., patient summary, care plan coordination, etc.)

(continued)

Table 8.1 (continued)

Challenge	Implemented Solution	Benefit
Business flexibility	• SOA architecture	A product configurator supports the ability to configure service availability, look & feel, and business layers
	• Middleware framework	The service availability configuration is the result of the cooperation between a service locator, the authorization subsystem, and the presentation framework
	• Services management	The look & feel appearance is the result of the combination of a basic application template and the relative position info of the screen objects. The application template is related to an application ID. The relative position of a screen object is related to the user ID and role
		The Middleware Framework allows for a loose connection between service and components. As a result, the absence of a component, also of a set of services, does not affect the rest of services. Appropriate design and implementation allows deployment without exceptions

8.4 Care Management as a Service on top of a PHR-S

The generic PHR-S framework presented in the previous section forms the technological baseline for developing value added and domain-specific services such as an ICT-based Care Management service. Such a service was implemented in the context of the StrokeBack project in order to support ambulant rehabilitation at home and clinical settings for stroke patients with minimal human intervention (Fig. 8.3).

The implemented solution is composed of:

- An instantiation of the PHR-S described in the previous sections;
- A Care Planning Tool that facilitates clinicians and therapists in the management of the rehabilitation routine followed by their patients (Fig. 8.4). This routine includes a clinical assessment phase, during which the professionals fill in standard questionnaires related to the status of their patients (e.g., Barthel-Index, Stroke Specific Quality of Life and Wolf Motor Function Test questionnaires). They can review past entries and get info about what impact has the rehabilitation intervention in relevant indexes. They can also define specific goals for their patients, in accordance with the International Classification of Functioning, Disability and Health (ICF) [7]. The therapists use the tool to schedule training periods and introduce their suggestions for activities that should be pursued by their patients (e.g., serious games, music-supported therapy). These recommendations are stored in the PHR-S database and transferred to the *Patient Station* (see below) upon request. At a subsequent phase, an overview of the executed

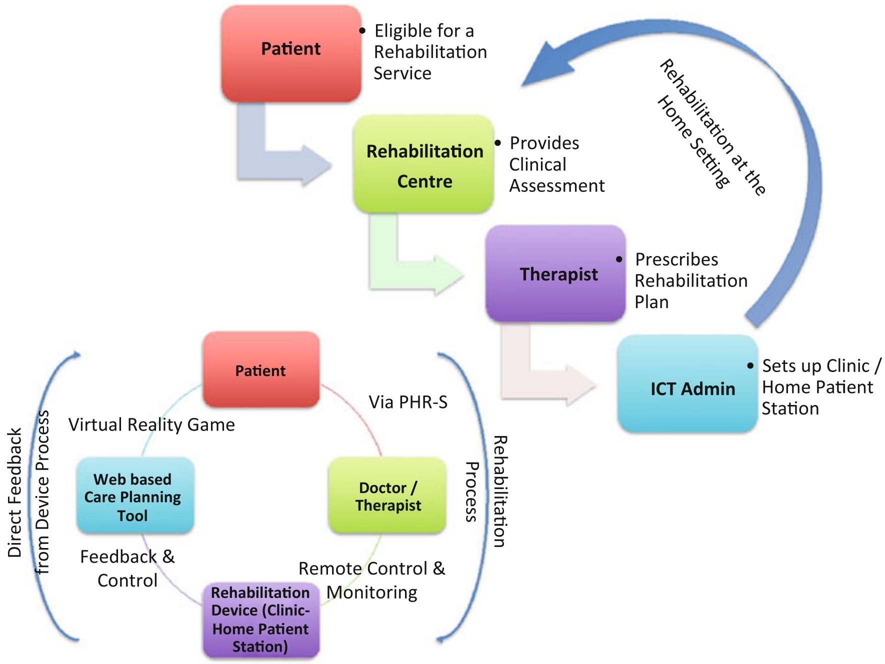

Fig. 8.3 Care management as a service on top of the PHR-S in StrokeBack

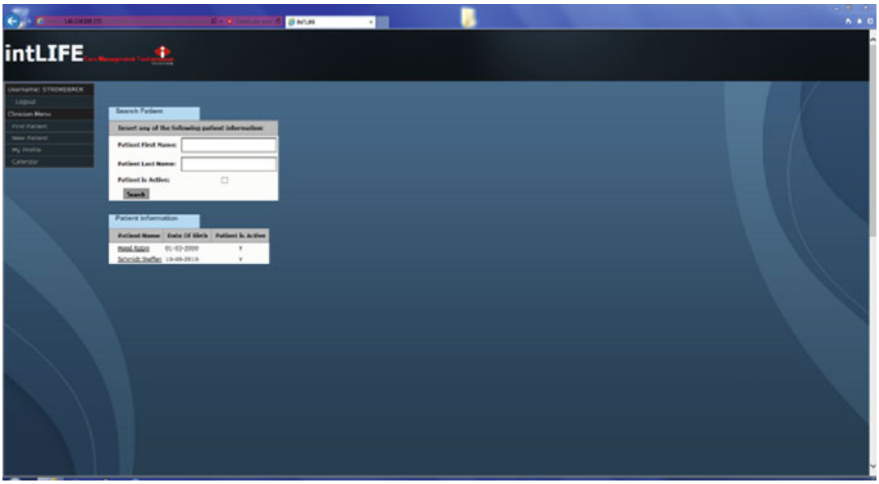

Fig. 8.4 Web interface of the Care Planning Tool

activities is presented to the healthcare professionals. The Care Planning Tool includes all the necessary medical and personal information that rehabilitation experts may need in order to evaluate the effectiveness and success of the rehabilitation process, e.g., to deduce relations between selected exercises and the rehabilitation evolution of different patients as well as to assess the overall healthiness of the patient. In addition, the Care Planning Tool can be used to provide the patient with midterm feedback related to her/his rehabilitation evolution compared to the average as well as to improvements over last day/weeks, in order to keep the motivation of patients high (this tool will be described in detail in this section);

- An object called *Clinic/Home Patient Station* that is used by the patients to interact with rehabilitation applications and services, hosted either by the object itself or by the PHR-S server. The Patient Station is a blend of hardware and software components. The hardware part includes 3D sensors for body activity monitoring, camera for video communication, an interaction board, and a PC that hosts rehabilitation applications and manages communication with the PHR-S. The software part includes an application for the selection and execution of exercises that are part of the Care Plan prescribed by the therapists, audiovideo communication application for real time supervised training, as well as background software services for measurements storage to the PHR-S database and for interaction with the Care Planning Tool. Physically, the Patient Station can be located at the health service provider premises or at the patient's home environment. Further details about this item are presented in Chap. 9.

8.4.1 Web Version of the Care Planning Tool

8.4.1.1 Clinician-Related Functions of the Care Planning Tool

The clinician menu includes a set of items that are relevant to the specific user: *Find Patient*, *New Patient*, *My Profile* and *Calendar*.

Once the authentication process for entering into the Care Planning Tool is successful, the user is provided with the list of patients she is responsible for (i.e., the patients she has registered in the system). The user can also use a search mechanism to narrow down the list of patients presented in the corresponding table. This feature may be particularly interesting when the user deals with an extended list of patients. The search criteria are the name and/or the surname and/or the condition of the patient (being active or not, i.e., a Training Period defined for this specific patient includes the current day). Once the user selects a patient from the table, a new page is presented, with refreshed the left- and right-hand menus: in the left-hand menu, some new items are now visible as part of the Patient Menu (i.e., the *Patient Details*, *Clinical Examination*, *Care Planning Tool*), while in the right-hand column some key details for the selected patient are presented.

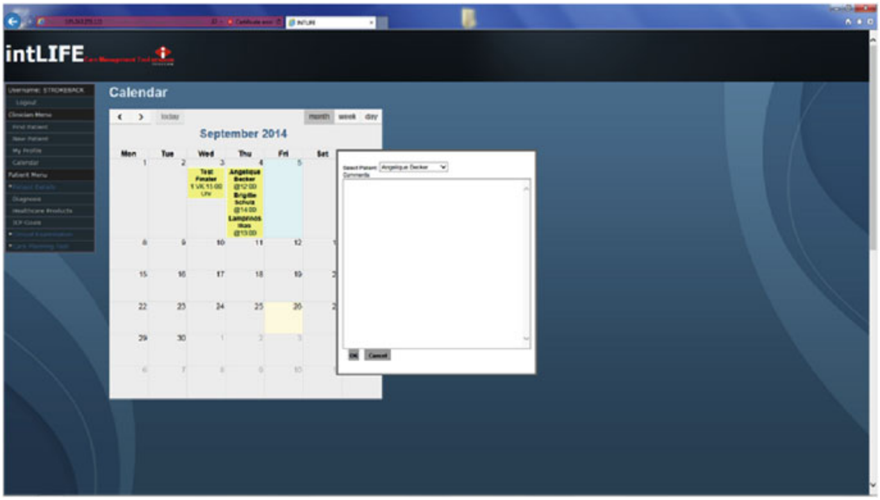

Fig. 8.5 Screenshot of the clinician's calendar page

In the *New Patient* page the user can register a new patient, by editing a set of demographic details, among which the Patient Name, Patient Surname, and the date of birth are compulsory.

In the *My Profile* page the user can change her password and select the desired language of the user interface. In order to change the password the user is requested to fill in the old and the new password. If the information provided in the old password field is not accurate, the user is being informed so. Also in this page the user selects the desired language for the user interface (for the needs of StrokeBack the supported options are the English and the German language).

The user can have an overview of her past and future tasks by choosing the *Calendar* option from the Clinician menu (Fig. 8.5). The calendar can be presented in week, month, and day view. The user can insert a new entry by double clicking within the framework of the desired day. A pop up window appears where the user selects the patient she wishes to fix an appointment for, edits the exact time and inserts further notes. For an already registered appointment, the user can edit the details or delete it.

8.4.1.2 Patient-Related Functions of the Care Planning Tool

The patient-related menu options appear on the left-hand menu column, once the user selects a specific patient. These options include the following: *Patient Details*, *Diagnosis*, *Healthcare Products*, *ICF goals*, *Clinical Examination*, and *Care Planning*.

The Patient Details submenu includes three links: the *Patient Details*, the *Personal Image*, and the *Patient Equipment*. In the Patient Details page, which by default is the page loaded when a user selects a patient from the tabular list of patients mentioned above, the demographic details of the selected patient are presented. The minimum set of information that needs to be filled in includes the Patient Name, the Patient Surname, and the date of birth. The user can modify and update the information presented in this page.

In the Personal Image page the user is provided with a mechanism for uploading an image of the patient that is available locally in her PC or in an external disk attached to it. After uploading an image, the right-hand column of all the patient-related pages is refreshed to present also this image.

In the Patient Equipment page, the user can see the available equipment, either in use (already assigned to a patient) or not. And also the equipment (if any) already assigned to the specific patient. For the needs of StrokeBack, two types of equipment are defined: the Clinic Patient Station and the Home Patient Station. A Clinic Patient Station can be assigned to more than one patient. Contrary, a Home Patient Station can only be assigned to a single patient. If a Patient Station is already assigned to a patient, it is indicated as being *in use*. Particularly for a Home Patient Station, if an item is already assigned to a patient and the user wants to assign it to another subject, then the user has to first unassign the item from the patient to whom is already assigned, in order to be able to assign it to the intended patient. This is not the case for a Clinic Patient Station that is by definition a shared equipment item.

In the Diagnosis page, the user can either insert a new diagnosis for the patient by inserting free text or choose an option from the ICD10 list [6] or the available drop-down list (sorted by medical specialty). The user can also fill in the diagnosis date (it can be different from the current day), the clinician that made the diagnosis, and the status of the diagnosis (selecting among the values *active*, *inactive*, *ongoing*). For previously registered diagnoses, the user can delete an entry or change its status.

In the Healthcare Products page, the user can select the medical aids the patient uses among a large list of products. In case the user has previously inserted a selection of products, those will appear as selected in the screen. There, the user has the option to delete an entry from the list.

In the ICF goals page, the user can fill in the findings with regards to specific items of the ICF questionnaire [7]and view the values of previously submitted questionnaires.

The Clinical Assessment link in the left-hand menu includes the following links to pages: Assessment Questionnaires (with a list of nested options: *Questionnaire BI*, *Questionnaire SSQOL* and *Questionnaire WMFT*), and Assessment Overview. In the Questionnaire BI page (Fig. 8.6) the user fills in the Barthel-Index questions [8]. In the Questionnaire SSQOL page the user fills in the Stroke Specific Quality Of Life scale questions [9]. In the Questionnaire WMFT page the user fills in the Wolf Motor Function Test [10] findings.

While filling on the answers, the user is presented in real time the total score of the questionnaire, based on the already provided answers. For each question, the

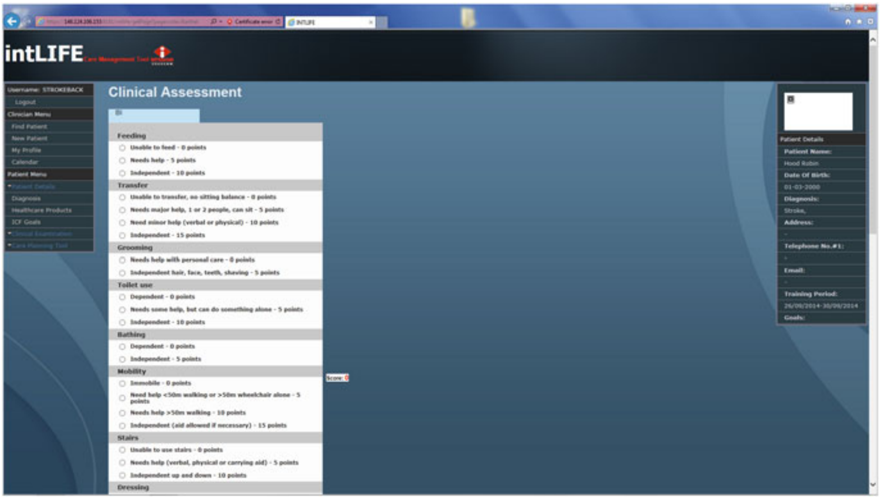

Fig. 8.6 Screenshot of the Barthel-Index questionnaire

user is given a description of its meaning, with a pop up window. For each question, the user is given a summary of the answers provided in previously submitted questionnaires. For each possible answer, the user is given a description of its meaning, with a pop up window.

In the Assessment Overview page, the user first sees a tabular presentation of the already submitted clinical assessment questionnaires, as well as their overall end-score. By pressing the View button for a specific entry in the above-mentioned table, the user is presented the filled-in questionnaire. No option to update the values of these questionnaires is provided.

The Care Planning submenu of the left-hand menu of the pages includes links to the *Training Period Definition* page, the *Training Units Upload* page, and the *Exercises Results* page.

In order to set up a Care Plan it is a prerequisite that the user creates one or more Training Units (TU), using the Training Unit Configurator (a program running locally in her PC). The uploading mechanism is provided via the Training Units Upload link under the Care Planning Tool menu. The user selects a TU file from her PC and uploads it in the server. After doing so, the file name is presented in a table with the available TU files. These files are listed only for the patient for which they were uploaded. The TU files must be in xml format, exactly as saved by the Training Unit Configurator.

In the Training Period Definition page, the user can introduce a new Training Period or overview the already registered training periods. For the introduction of a new Training period, the user has to fill in its name, the number of TUs related to this period, the start and end date, and potentially some further notes. After editing the above info and pressing the submit button, the Training Period is presented in the corresponding table. The software does not allow the user to define overlapping

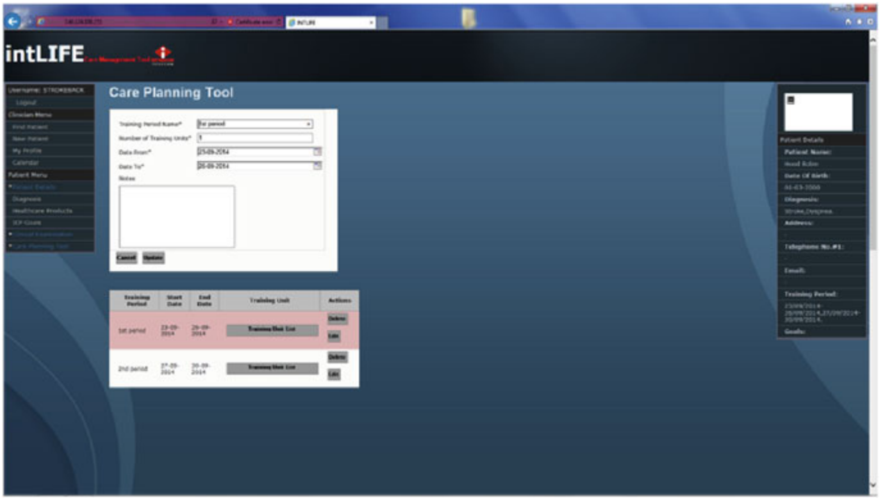

Fig. 8.7 Screenshot of editing the training period details page

Training Periods. Also, when registering a new Training Period, the end date cannot be in the past, compared to the current day.

The user can delete an already registered Training Period, by pressing the Delete button of the specific Training Period in the corresponding Table. The user can re-edit the details of an already registered Training Period (Fig. 8.7).

To do so, the user has to first press the Edit button of the specific Training Period in the Table, update the values of interest for the selected Training Period and press the Update button. Then, from the Table where the Training Periods are listed, the user selects the Training Period entry of interest and presses the "Training Units List" button. In the revealed page the user selects the TU from a drop-down list. Note that, if no TU file was uploaded for the patient, the drop down is empty. After selecting the TU file of interest the user should press the Save button. If more than one TU are defined for a Training Period, then the user has to define one of those TUs as the Current Training Unit. This will be the TU that will be first sent to the Home/Clinic Patient Station to be executed by the patient. Only upon successful exercises results upload of that TU, the next TU will be sent to the Station.

Finally, the user can review the Exercise Results of the exercises executed during a specific Training Period (two examples are shown in Figs. 8.8 and 8.9). If more than one Training Periods are available, the user shall select the Training Period of interest from the corresponding drop-down list. If no data is available for a specific Training Period, an indicative message is presented in the area where normally the graph would be presented. When exercise data is available, the View button appears in the corresponding line of the Training Period.

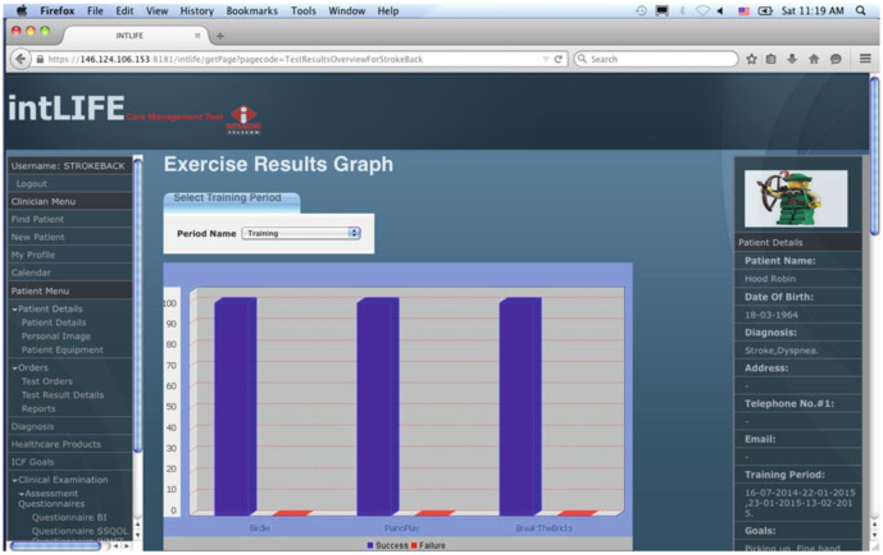

Fig. 8.8 Screenshot of viewing the exercise results graph (example 1)

Fig. 8.9 Screenshot of viewing the exercise results graph (example 2)

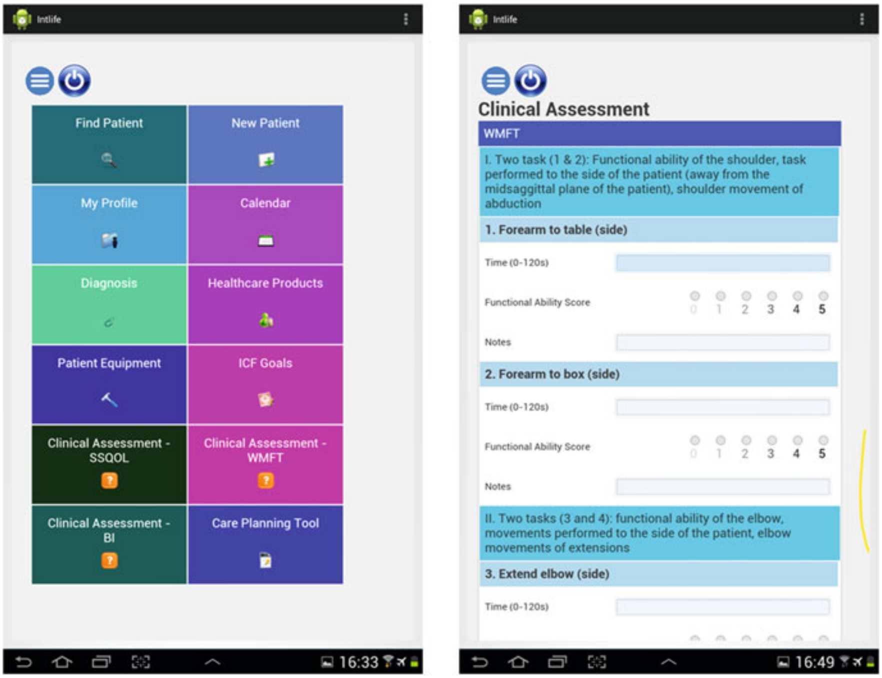

Fig. 8.10 Screenshots of the main menu of the mobile application (*left*) and of the clinical assessment page, i.e., WMFT questionnaire (*right*)

8.4.2 *Mobile Version of the Care Planning Tool*

Most of the functionality of the Care Planning Tool described in the previous section is also offered via a mobile application. This application is compatible with Android devices and is optimized for tablets with mid-sized monitors (7.7″). The application can be found at Google Play app store, by searching with the term "intLIFE Rehab Care Planning" or by following directly the link https://play.google.com/store/apps/details?id=com.intracom.intlifeclient, via the web browser of the mobile device. Some indicative screenshots of the mobile application are presented in Figs. 8.10 and 8.11.

8.4.3 *Web Application for the IT Administrators*

The intended users of the Care Planning Tool described in the previous section are the therapists and clinicians that treat patients during the rehabilitation process. We have also implemented a web application the intended users of which are the IT

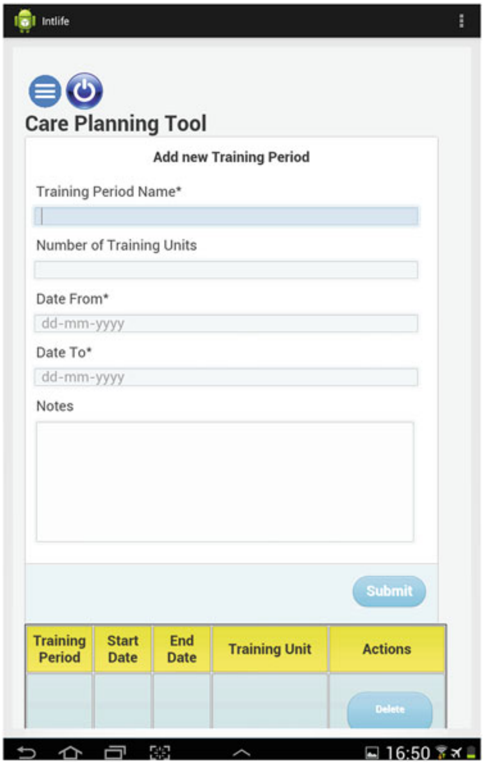

Fig. 8.11 Screenshot of the Care Planning page of the mobile application

administrators of the entity offering the clinical service or of the ICT service provider that supports the clinical service from a technical viewpoint. The main functionality of the web application for the IT administrators is related to the registration of users and assets in the PHR-S database. Only IT administrators can enter in this application, using the credentials that are provided by the Super Administrator, i.e., an entity of the ICT provider. Screenshots of this application are shown in Figs. 8.12 and 8.13.

8.5 Deployment and Validation Framework

For the needs of validating the usability and usefulness of the prototype PHR-S framework and the Care Planning Tool, we conducted a pilot study in Germany. The infrastructure was deployed in Brandenburg Klinik, in the wider area of Berlin [11]. The purpose of the pilot study was to assess whether the implemented framework is *usable* and *useful*, and whether the supported Care Planning Tool facilitates therapists and their patients in the post-stroke rehabilitation service. The outcomes of this study are presented in Chap. 10.

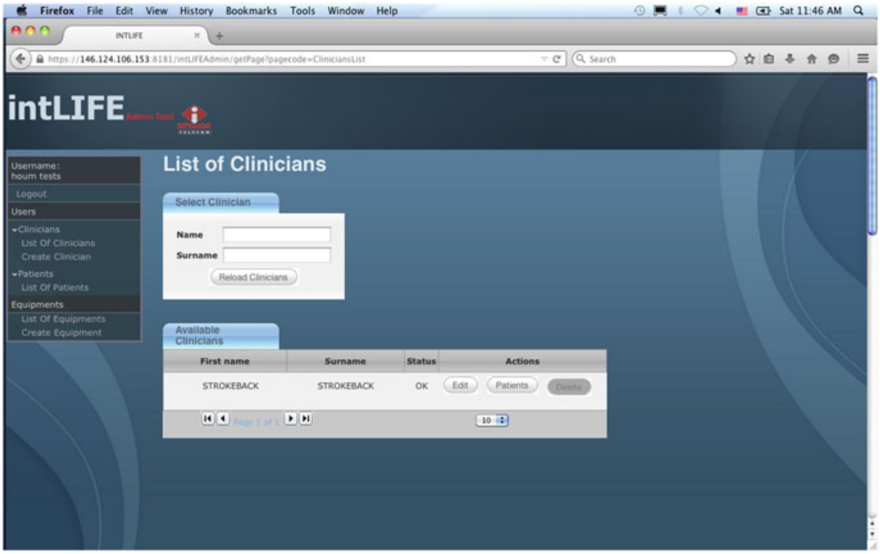

Fig. 8.12 The list of registered users in the PHR-S with the role “Clinician”

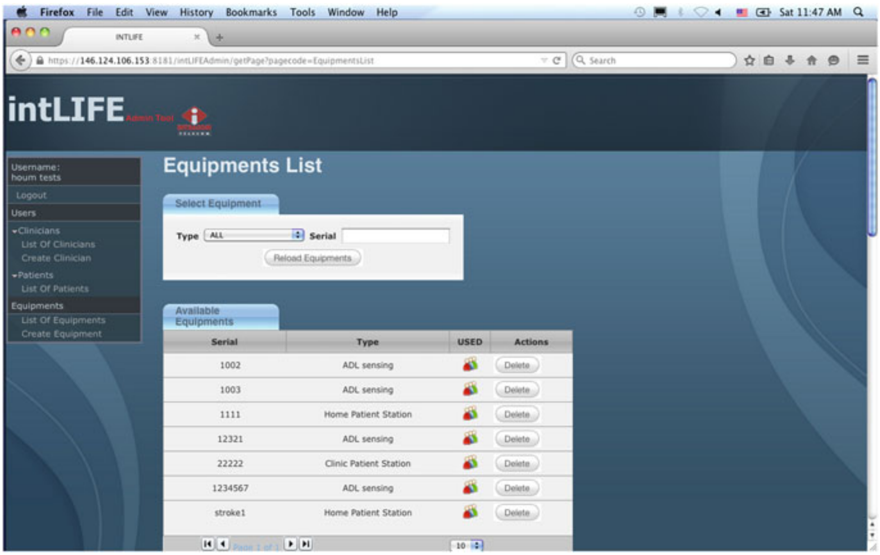

Fig. 8.13 The list of equipment assigned to patients

8.6 Conclusions

In this Chapter we presented our proposal for a generic architecture of PHR-Ss and outlined the business challenges addressed by the proposed approach. The proposed framework served as a basis for designing and implementing a set of applications on top of it, that aim at supporting ICT-based care management services.

These applications were used by therapists in the context of the StrokeBack project and supported them on an ICT-based post-stroke rehabilitation service.

In the near future we plan to test and evaluate the reusability and adaptability of the proposed framework in the support of care management that is focused on different diseases.

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Chapter 9
Prototyping and Business Potential

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Abstract This chapter describes the general look and feel of the StrokeBack system. It concentrates on real-world requirements and previous experiences in telemedicine work and provides the blue print for the StrokeBack system development. The implementation and integration of the overall project solution into a "Smart Table" and "Mobile Station" of MEYTEC is described. In the follow-up aspects related to exploitation of the project results, commercialization and business potential are discussed. It provides the details of the associated market, the profiles of the tentative clients and the opportunities for further post-project exploitation. The same is done for by-products of the project. In addition the reader is provided with details related to regulatory framework regarding medical devices and software and the assessment of the consortium regarding a characterization of exploitable outcomes from this framework.

9.1 System Prototyping

9.1.1 Operational Use Cases

The goal of system development in telemedicine is the user/patient benefit. Corresponding to the software architecture guidelines defined in [1], the user benefit is described in Use Cases (UC). The content of these UC is determined by the

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project description and experiences in former projects concerning medical telerehabilitation [2]. Differences in healthcare systems of partner countries have been considered to design the most suitable system for the StrokeBack project [3–9]. The following sections describe five UC that have been identified to complete the StrokeBack system from user perspective. The list of applicable use cases follows.

9.1.1.1 Clinical Assessment of Patient's Needs (UC 1)

The physician/therapist explores the individual impairments and needs of the physically present patient. She/he agrees with the patient about its expected benefit and outcome of the rehabilitation. The doctor's advice and filling of clinical scores, i.e., Barthel Index (BI) [10] and the Stroke-Specific Quality of Life Scale (SS-QoL), are complemented by execution of test tasks as a subset of the Wolf Motor Function Test (WMFT). This execution of test tasks is tracked by a couple of sensors capable of motion capturing and EMG measurement (if necessary from clinical point of view). Scores of the WMFT are filled manually by the physician/therapist and are determined by the sensing system in parallel.

9.1.1.2 Exercise in Home Environment (UC 2)

The patient executes training sessions at home using the StrokeBack system with and without supervision by the therapist. Supervision may additionally be provided in real time by bidirectional audio-visual communication or by exchange of written messages. Patient may select the exercise to do from an offered set of exercises. The difficulty may be adjusted by the patient in a given range or set by the therapist.

9.1.1.3 Capturing Activities of Daily Living (UC 3)

Patient's daily live activities are tracked by a Body Area Network (BAN) worn throughout the day. All data are logged and transferred in certain periods to the home base station where data are processed to determine daily activity statistics. Thereafter, these statistics are stored in patient's Personal Health Record (PHR). The patient needs a BAN and a comfortable way to attach it for daily use.

9.1.1.4 Remote Care (UC 4)

This is a top level UC that enables the therapist to remotely supervise and control patient's rehabilitation status and schedule. This is done via access to the patients PHR and encloses the following activities, where the therapists can:

- Schedule training sessions for the selected patient
- Analyze results of past training sessions based on final statistics about exercises

- Advice patient in real time during the training session via audio-visual link
- Advise the patient by written messages (e.g., e-mails)
- Inform the physician about clinical relevant changes of patient's state

9.1.1.5 Administration of the StrokeBack System (UC 5)

This UC addresses main system administration and maintenance of the StrokeBack system in the clinic and at home of the patient. In this context it may be advantageous to assign a technical and a medical administrator.

- The technical administrator enrolls the devices to the patient, maintains the devices in the homely environment and regularly performs database backups.
- The medical administrator admits medical professionals into the team of neurologists being responsible for medical rehabilitation after stroke in accordance to guilty rules provided by medical societies. The medical administrator admits approved therapists in rehabilitation practices.

9.1.2 Components

Components are logical units of the StrokeBack system. They may refer to software and/or hardware components and subsystems.

The components reflect what is needed to perform the use cases. The following main components have been derived from the use cases, see also Fig. 9.1:

- *Patient's Home Station* (*PHS*)—controls patient exercises in her/his home environment. It is the main data sink for the BAN and central processing unit at home. It provides connectivity to the PHR and audio-visual interaction between patient and therapist or clinician during training sessions.
- *Patient's Interaction Board* (*IAB*)—enables the patient to control the Home Station PHS and to perform exercises. It fits the movement impairment of the patient. PHS and IAB create a training place in patient's living room.
- *Personal Health Record* (*PHR*)—stores persistent data of entire processes in StrokeBack system at a central location, e.g., a web server. It can further be accessed remotely by the therapist for rehabilitation management.
- *Clinician's interface* (*CIF*)—offers to monitor the rehabilitation process and to access data for the Clinician. It is bound to the PHR as web interface and thereby accessible by any networked device, e.g., personal computers or tablet.
- *Therapist's Workplace* (*TWP*)—is installed in the clinic or therapists practice. It offers to schedule patient's exercises and provide real-time supervision of the patient by the therapist and furthermore any kind of off line advisement, messaging and connection to the PHR.
- *Exercise and Compensation Tool* (*ECT*)—performs an automatic evaluation of patients movement during training sessions. It monitors and evaluates training sessions automatically and provides feedback to patients without a therapist.

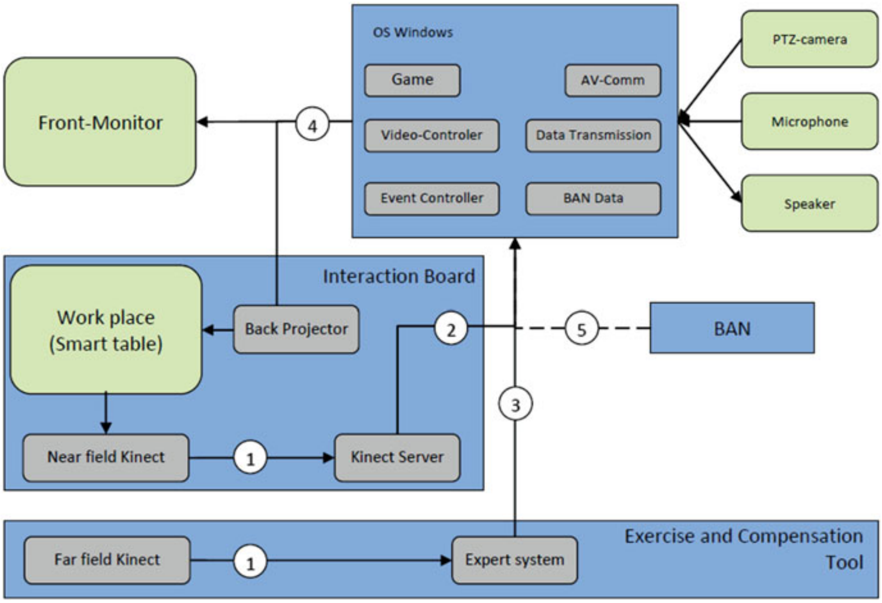

Fig. 9.1 System components (*blue*) and interactions between them: (*1*) wide area data exchange, (*2*) bidirectional audio-visual connection in real time, (*3*) small distance wired or wireless connection, (*4*) visual feedback, and (*5*) wireless BAN sensors

- *Body Area Network* (*BAN*)—captures motion data of the patient without any local restriction and is suited for time periods outside the training sessions. It measures the transfer of movement skills from trainings session to daily life.

A detailed description of these components is given in the next subsections.

9.1.2.1 Patient's Home Station

The PHS is located in the patient's living room as part of her/his training place. To control the patient's exercises in home environment, it needs multimedia output channels as speaker for audio signals and a screen for video signals. Both channels are used to give the patient three different stimuli: (a) a number of pointers how to execute correctly the exercise, (b) the information about the exercise and its options and (c) experience of motivation by playful tasks. The PHS gets multimodal feedback from the patient as the speech, the body gesture and the hand movements handling the training objects and while executing the exercises. Speech and body gesture are captured by the component itself while further inputs are given by the components IAB, ECT, and BAN. The PHS contains the following subsystems: a computer, front screen, microphone and speaker, controllable camera (with pan and tilt), and the network interface.

9.1.2.2 Interaction Board

This component is also located in the patient's living room as part of her/his training place. The unit "Interaction Board" is a cluster of subsystems providing the patient's interface for controlling the entire system. Furthermore, there is a display functionality to support the interaction. It is designed as universal input device for impaired persons. The patient should be enabled to handle the system in different modes. Those are the modes "Exercise," "Session preparation" and "Communication." For reasons of early and fast ability to work of the "Interaction Board" it may be delivered in different versions:

Version 1: The unit "Interaction Board" consists of the elements "Back Projector," "Near-field Kinect" and "Kinect-Server." The solution offers the maximum of adaptability, scalability, and functionality.
Version 2: The unit "Interaction Board" is emulated by a regular touch screen located horizontally as one unit and the "Near-field Kinect" subsystem.
Version 3: The unit "Interaction Board" is emulated by a tablet PC.

Game handling is managed by the "Interaction Board" unit (providing graphical content plus touch event) via Kinect-Server to "Event Controller" in main computer.

The "Event Controller" provides the interface between the HID (Human interface device, i.e., mouse or keyboard) and the game. The "Event Controller" would transform any Ethernet datagram into HID-event. The games could be tested temporarily by mouse or keyboard. The data flow in the Home station includes:

1. Raw data from element "Near-field Kinect" and "Far-field Kinect" to be processed by the Kinect-Server for the Interaction Board or by the OpenNI Framework and Microsoft Kinect SDK for calculating "skeleton stream" data for the ECT.
2. Capture of objects, fingers, etc., by the "Near-field Kinect" unit and transmission to the main computer with a rate of 50 per second via IP datagrams. They ensure the response of game logic to movements.
3. Messages sent from "Expert system" via IP datagram enable the system to display messages to the patient generated by the artificial advisor system. Furthermore 3D coordinates and orientation data of body joints with a rate of 50 frames per second are transferred for calculating a vector-based, 3D representation model of the patient's upper body.
4. Video data to screen (VGA or HDMI). It is controlled by the main application displaying PHR-content, Game-content, or management content in the work place and/or the front monitor.
5. Temporary connected BAN transfers the raw or pre-classified sensor data from BAN nodes for the evaluation of daily living behavior to the subunit "Main computer" for pre-processing and uploads to PHR.

9.1.2.3 Personal Health Record

The PHR stores all patient-related data necessary to manage an entire rehabilitation process after stroke. The following components exchange data with the component PHR: Clinician Interface, Therapist Work Place, and Patient Home Station. No clinical or personal data is stored anywhere else, but the PHR with firm data security.

9.1.2.4 Clinician's Interface

The CIF consists of a regular PC with web cam and head phone and Internet connectivity. The physician communicates with the PHR and with the devices during clinical assessment.

9.1.2.5 Therapist's Workplace

The therapist's station consists of a regular PC with web cam and head phone and Internet connectivity for access to the PHR. The therapist uses specialized software to communicate with the patient for remote supervision sessions.

9.1.2.6 Exercise and Compensation Tool

The exercise evaluation tool provides automatic real-time supervision of rehabilitation exercises. It allows to record and monitor individual exercises to evaluate the correctness of exercises and compensational movements made during the training sessions. It will be individually trained/configured by the therapists for certain patients to fit the individual clinical requirements.

This tool decouples the therapist from time consuming observation of patient's exercise and empowers the patient to train alone and individually in preferred way and time. It generates messages for the component "Patient's Home Station." It is software processing skeleton data from Kinect to evaluate execution of exercises. Generated feedback messages should be simple and plausible. They may be spoken via speakers and/or written on the main video screen.

9.1.2.7 Body Area Network

The BAN consists of wearable sensors with data storage facility and a wireless receiver. The BAN sensors can be configured to proper data acquisition rate. The prototype of a very small and lightweight BAN node is shown in Fig. 9.2.

Each sensor processes and stores sensor data in real-time and may perform data compression to reduce data storage requirements. Data will be gathered by the BAN over a fixed period depending on estimated battery life or patient's needs. Recorded

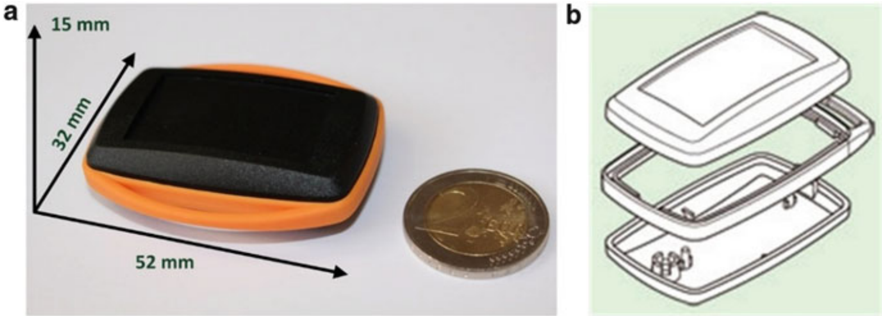

Fig. 9.2 Photo from sensor node case in comparison to a 2-Euro coin (**a**) and a schematic view of the case (**b**) taken from www.okw.com

data of each session will be transferred to a PC (PHS or TWP) while charging batteries, e.g., in a docking station. Sensor data will be analyzed and classified to determine characteristic patterns that are associated with particular movements to generate movement statistics on daily basis. The BAN captures motion data during daily life of a patient. It is used to document transfer of motion abilities regained in training sessions. It logs data and transmits it to the PHS in regular intervals, where it is analyzed before results are stored in the PHR. It should work nearly invisible and must not hinder the patient in her/his daily life activities.

9.2 Design of the Prototype System

This section describes preliminary implementation of the components in hard- and software. The patient's training place at home is composed by the components "Patient's Home Station," "Interaction Board" and the "Exercise and Compensation Tool." The design considers the situation in patient's living room. For technical reasons the mentioned components are needed and should be positioned inside the living room. However, they should not hinder the patient and its relatives and should not occupy more room than absolutely necessary. Bear in mind also that equipment might be rented by the patient, i.e., it may be transported from one patient to another. The identified requirements resulted in assembling all components on one work table trolley. This means that:

- All the components are available on the work place of the patient
- Existing furniture's not need to be occupied
- Required volume of equipment is reduced to a minimum
- Work place can be easily moved to a different room of the patients home
- Equipment installation and maintenance may be offered by service providers

9.2.1 Work Table Trolley

9.2.1.1 Schematic View

The patient sits in the chair (or wheelchair) at the work table trolley. Chair and trolley can be adapted to the needs of the individual patient. His/her body posture should be optimal for monitoring by sensors and/or camera. The table trolley must be equipped with immobilization brakes and the option to adjust the table height, preferably during installation phase. Adjustment to table height can be done using dowels steps. Table design must prevent it from falling. Its size should fit to the free place in a regular living room. As a first approach, the size of 800×1000 mm is fixed. The depth of 800 mm is needed for positioning of vertical computer screen. The width of 1000 mm is needed for positioning of the near-field motion tracker.

The motion tracking of hands and training objects must be available to (1) support exercises, (2) to evaluate movements during exercises and (3) to provide a comfortable Human—Machine Interface (HMI) for the patient. The design of comfortable HMI for the patient considers his/her impairments controlling the "Patient's training place" by movements. Such functionality is provided by the unit "Motion Tracker" represented in the first approach by the commercial product "Kinect," used in near-field mode, and the "Kinect-Server."

The "Kinect-Server" subsystem reduces the data stream sent by the commercial product "Kinect" to few essential messages and skeleton ankle positions. The output of the unit "Motion Tracker" is formatted specifically, so that a transmission to the component "Patient's Home Station" is feasible. It is intended proposing a communication standard between training devices and the PHS in the framework of homely rehabilitation equipment. The mentioned concept considers optionally developing further kinds of interaction boards or training devices in the future, which then may communicate via that interface with the PHS as well.

Patients interact with the "Patient's Home Station" via three different user interfaces: a video screen, a graphical display of the "Interaction Board" and audio (microphone and speakers). The main video screen displays information regarding a choice of exercises, the configuration of exercises such as level of difficulty, the type of sounds, and other adjustments preparing the exercise. During live communication, the face of therapist or physician may be displayed on the main screen. The live communication can be combined with exercises motivating the patient and suggestions by therapist in parallel. Both tasks of remote care are essentially to keep the motivation of the patient high and to avoid wrong movement learning.

During training, the state of exercises and scores are displayed. Content of exercises and the graphical representation of tasks can also be displayed on the interaction board. Graphical information must not be presented on both channels in parallel to avoid too complex tasks and irritation while concentrating on both screens. At the end, the kind of exercise practically identifies where the main content is displayed: Exercises for hand rehabilitation and tasks with real training objects will be displayed on the interaction board. Exercises with virtual reality involving whole upper body parts will display their content on the main screen. The speaker outputs the speech in live communication with the advisor and the sound of exercises, i.e., music or spoken commands.

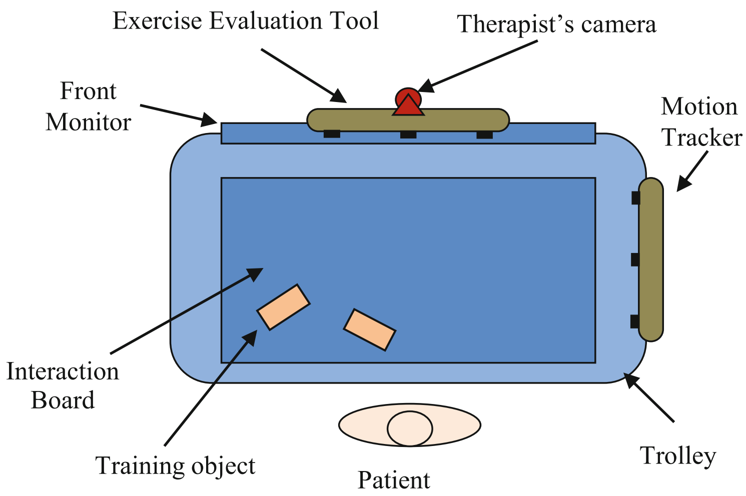

Fig. 9.3 Schematic drawing of the "patient's training place"

The "Patient's Home Station" (shown in Fig. 9.3) receives information about the patient from four different sources: microphone, pan tilt zoom camera, body motion from far-field Kinect sensor, while and limb motion and object capture from the near-field Kinect.

The microphone is used for the live communication with therapist or physician. The PTZ camera can be used to observe movements of the patient during live communication sessions. The live communication between patient and therapist currently is a key issue in state-of-the-art remote care [2]. In the mentioned project the live communication encloses suggestions of the therapist immediately whilst the exercise is performed by the patient.

However, such approach requires more or less equal time of therapists as in real visit. Overcoming such drawback, the component "Exercise and Compensation Tool" is added. This unit automatically evaluates current movements and exercises to signal changes or failures to improve patient performance similar to real trainings with therapists. This feedback is based on capturing motion of the entire upper part of the body. The unit contains "Far-Field Kinect" and "Expert System" units. The latter one generates feedback for the patient based on motion capture and transmits feedback messages from the component "ECT" to the "Patient's Home Station" unit, where these are put out via speakers.

9.2.1.2 Implementation

The look and feel of the "Patient's training place" is shown in Fig. 9.4 from the perspective of the work table and showing the patient's training place in Fig. 9.5.

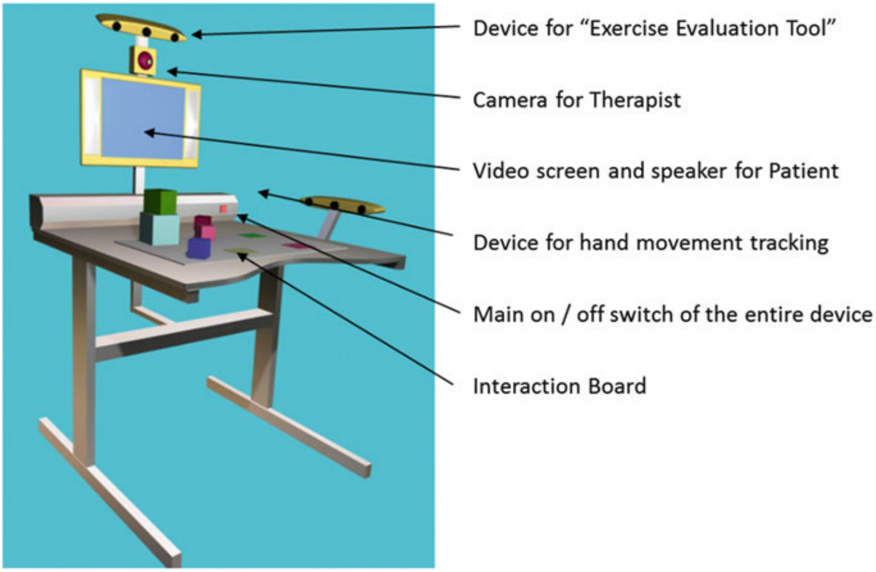

Fig. 9.4 Schematic drawing of the design of the patient's training place

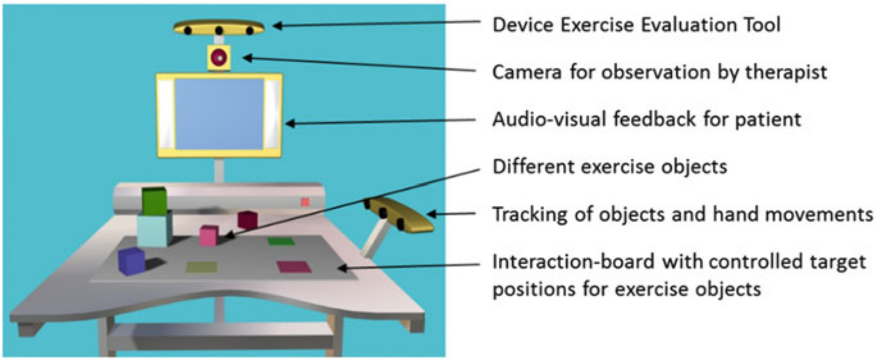

Fig. 9.5 Preliminary design of patient's training place, patient's view

The main issue of medical rehabilitation after stroke is the huge extend of training to regain movement capabilities of the patient. More than 40,000 repetitions of meaningful movements are necessary to percept a success as patient. To encourage the patient continuing the training, a complex form of motivation management is indispensable. The StrokeBack system uses three methods for increasing patients' motivation:

1. Personal contact between patient and therapist
2. Feedback in real time
3. Connection of gaming and learning

The personal contact between patient and therapist is quite common in the setting of occupational therapy. The tele-rehabilitation replaces the physical contact with audio-visual experience of a joint talk. However, it is a talk about the currently performed physical activity. Simultaneous activities, talking and moving, enlarge the effect of the conversation in the sense of unconscious learning.

Since the patient must keep on training regularly to improve the motion capabilities, the exercises have to be interesting and motivating. To meet such goal, the “Patient’s training place” should allow presenting different exercises in different outfit with different training objects or training devices.

The feedback for the patient has to be presented in real time through different channels. There is the graphic presentation, the output of music, and the linguistic or written presentation of messages and the evaluation of the performance by scores. Three types of scores are used to:

1. Motivate the patient
2. Substantiate the individual progress for patient’s health record
3. Prove differences between therapy approaches for scientific evaluation

The scores of type (1) should be comprehendible for the patient. The scores of type (2) and (3) should possess a clinical meaning. The design and formulation of appropriate scores is a continuing task during the project work. The process considers knowledge from rehabilitation medicine, from motivational theories in psychology and from statistics.

There are a set of biomechanical and functional parameters serving as the start point for further development. The aspects of sensitivity and selectivity play a big role selecting or creating the scores. From technical point of view, a hierarchical organization of scores offers all opportunities to improve the scores at any time.

9.2.2 Patient’s Interface “Interaction Board”

The “Interaction Board” used by patients is shown in Fig. 9.6 with “Video screen” at the top and the emulation of the “smart table” below.

Its user interfaces may be implemented in different versions, such as:

Version A: The “Interaction Board” consists of “Glass plate,” “Motion Tracker,” “Kinect-Server,” “Video Controller,” “Back Projector” and “WLAN” units. This solution offers maximum adaptability, scalability, and best range of functionalities.

Version B: The “Interaction Board” is emulated by a regular touch screen located horizontally as one unit and a mini-PC containing “Touch screen,” “Video Controller,” “Touch Controller” and “WLAN.”

Both versions support the feasibility and the early opportunity to test the system. Both versions offer best compromise between the scalability of the solution and its costs. They also do not require much space and can be considered as a mare extension of the regular living room of the patient’s home.

Fig. 9.6 Prototype implementation of the “interaction board”

From implementation point of view both versions offer different set of capabilities:

Version A: The “Interactions Board” consists of a glass plate as half transparent back projection screen, a mini projector with controller and the unit “Motion Tracker.” The visual content is received by the unit “WLAN” and sent to the mini projector via the video controller. The projection is executed from below against the glass plate serving as work area for the patient. The training objects are located on the glass plate where the exercise is executed. The unit “Motion Tracker” is located above the glass plate on the right or left side and must not hinder the exercises of the patient. The unit “Motion Tracker” creates a volume model of the hand and the training objects and identifies collisions between the hands and objects as well as the glass plate. The collisions are messaged as touch-events to the component “Patient’s Home Station.” Currently the functionalities of the “Motion Tracker” are offered by the modified commercial “Kinect-Server.”

Version B: The “Interaction Board” is assembled by a regular touch screen located horizontally as one unit and a mini-PC containing the “Video Controller,” “Touch Controller” and “WLAN.” Instead of the 3D coordinates of hand and training objects, only the horizontal position is available. The assembly is cheaper than the version A and needs less space. The current realization of such assembly needs the width 530 mm, the depth of 420 mm and the height of 50 mm, see lower part of Fig. 9.5.

9.2.3 Patient’s Home Station

The “Patient’s home station” controls the interaction between the patient and the StrokeBack system. Graphical symbols displayed on video screens, the front screen, and the interaction Board are main parts of the user interface. The exact distribution of visual content among “Video-Screen” and the “Interaction Board” depends on the actual task. The following tasks are supported:

1. **Selection of exercises**: a list of supposed exercises is displayed on front screen. The Interaction board displays the control to select the wished items and tasks.
2. **Configuration**: allows choosing a level of difficulty, type of sounds and setting related to live communication with the therapist. The Interaction board displays a list of supposed items and provides controls to select the wished item.
3. **Execution of training**: two types are considered, using virtual and real objects:
   (a) *Virtual objects*: objects are displayed on the front screen. The interaction board displays instructions and controls to adjust the exercise course.
   (b) *Real objects*: current state and scores are displayed on the front screen. The graphical illustration of tasks is displayed on the interaction board.
4. **Live communication**: Enables execution of bidirectional audio-visual live communication with therapist or physician.

The “Patient’s home station” controls the audio output for the patient, which comes from exercises as messages, songs, sounds, or directly from live communication. Furthermore the unit “Patient’s home station” controls the data exchange with the components “BAN” and “PHR.”

9.2.4 Therapist’s Workplace

The work place of therapist is designed to support the use cases in its entire granularity. As hardware component a multimedia PC with internet connectivity is thought to be sufficient. The software was designed as a local application integrating browser capabilities. It includes an administration console implemented as a WEB page, embedded into a PHR server.

The “selection of Patient” page of the PHR embedded into a therapist’s view is shown in Fig. 9.7, while Fig. 9.8 shows the live video of a patient doing the exercise. The live video of the Therapist appears on the left of the windows. The buttons enable therapists to select different tasks.

Fig. 9.7 Therapist’s view to the page “selection of patient” of PHR

Fig. 9.8 Therapist’s view while the patient executes exercises

The therapist can observe how patients executes their exercise and to comment immediately on any wrong movements. He can also see a statistics of exercises performed (Fig. 9.9) and/or see live videos with all patients together (Fig. 9.10).

Fig. 9.9 Therapist's view during exercises: showing scores (*left*)

Fig. 9.10 Therapist may advice different patients at once

9.2.5 Work Place for Clinical Assessment

The workplace used for a clinical assessment is built from a laminated surface with marked distances for the placements of objects (refer to a schematic in Fig. 9.11).

In addition, a couple of objects, such as checkers, cards, an ordinary lock, etc., are needed to execute different tasks. Photos of the surface are given in Fig. 9.12.

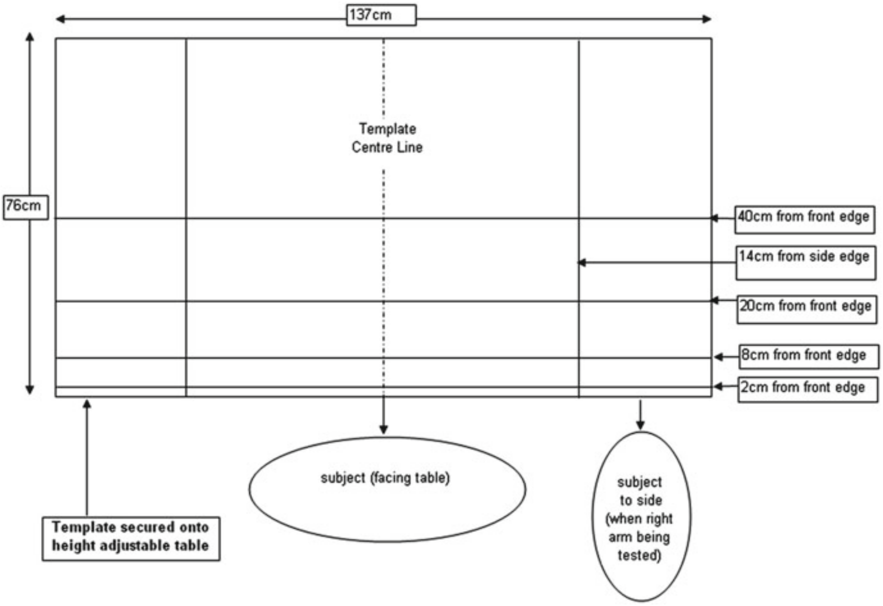

Fig. 9.11 Schematic view of WMFT surface

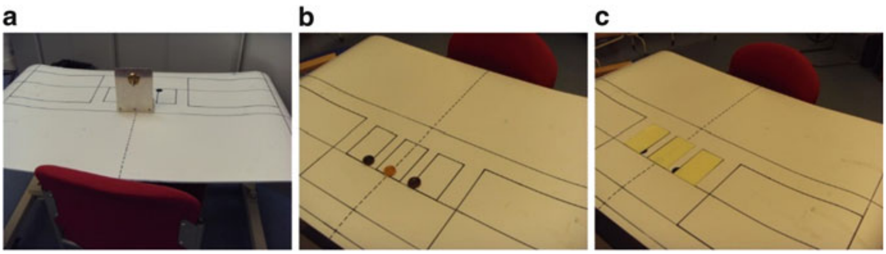

Fig. 9.12 Photos from laminated surface used for WMFT test task, e.g., using a key lock (**a**), checkers (**b**), or cards (**c**)

9.2.6 Data Flow

The main components and their data exchange scheme are given in Fig. 9.13. Rectangles represent components, arrows show data paths, circles indicate references to the description of the data content, detailed in Table 9.1.

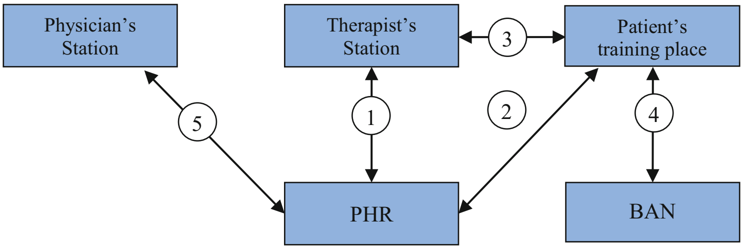

Fig. 9.13 Data flow between main components of system "StrokeBack"

Table 9.1 Overview of main paths for data exchange

Path no.	Source	Unit	Purpose	Use case
1	Therapist station	PHR	Transmits therapist's ID Selects the patient Starts a session as a therapist Gets information about the patient Composes and schedules training Reads earlier training sessions	1
2	Patient training	PHR	Starts the session as a patient Receives info about exercises (games) BAN data about earlier daily activities	4
3	Patient training	Therapist station	Starts a session with supervision Transmits bidirectional live link Sends messages controlling exercises Sends current exercise performance data	2
4	BAN	Patients training	Sends data about past daily activities Transferring data to PHR	3
5	Physician station	PHR	Sends physician's credentials Selects a patient Starts a session as a physician Gets information about a patient Transmits evaluation results	1

9.2.6.1 Data Flow Between "Therapist's Station" and the PHR

To get access to the PHR, the therapist's credentials are transmitted in an authentication process. This initiates a session for the therapist. The therapist will then select a patient and study the actual and recent training results to determine the patient's current needs. Based on protocols from passed training sessions, the therapist may compose and schedule future training sessions of the selected patient.

9.2.6.2 Data Flow Between "Patient's Training Place" and PHR

The patient logs into the PHR to start a training session and receives information about his/her training schedule, exercises, scores, results, and messages if available.

9.2.6.3 Data Flow Between "Patients Training Place" and "Therapist Station"

This data exchange is initiated via the PHR to start a scheduled training session with supervision. It transmits bidirectional audio–video streams and transfers messages and scores to modify the exercise level and analyze exercise performance.

9.2.6.4 Data Flow Between BAN and "Patients Training Place"

The BAN transmits motion data that is analyzed to determine statistics of passed daily activities. Respective results are stored in the PHR automatically. The patient does not need to initiate this process. All data exchanges are managed autonomously by the BAN and PHS without being triggered by the patient.

9.2.6.5 Data Flow Between "Physician's Station" and PHR

This is similar to the data exchange between the "Therapist's station" and the PHR. It transmits the physicians ID, allows selecting a patient, study training protocols, starting sessions, and uploading evaluation results.

9.2.6.6 Data Flow Within the "Patients Training Place"

This paragraph describes the data flows between the main components in the patient's home station that is depicted in Fig. 9.14. There, blue and gray rectangles specify subsystems and their respective elements whereas green rectangles

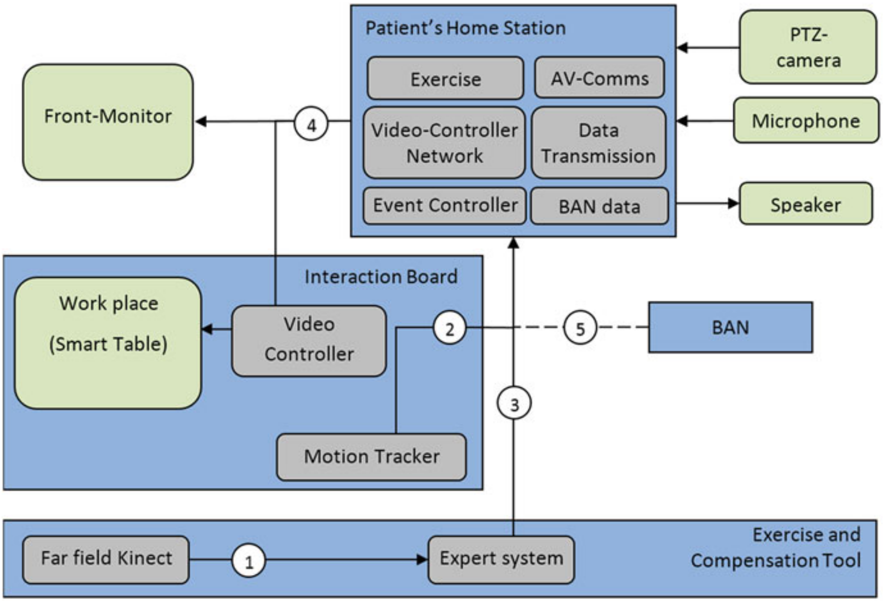

Fig. 9.14 Data flow in patient's training place

determine user interface elements. The arrows represented directed data flow. The numbered arrows in Fig. 9.14 correspond to the following data flows:

1. Raw data from elements "Near-field Kinect" and "Far-field Kinect" to be processed by the Kinect-Server for the Interaction Board or by the Open NI Framework and Microsoft Kinect SDK for calculating "skeleton stream" data for the ECT.
2. Coordinates of objects, finger and hand movements from unit "Near-field Kinect" to main computer with a rate of 50 items per second. These data is required to analyze movements and calculate input for the game logic.
3. 3D coordinates and orientation data of body joints with a rate of 50 frames per second are transferred for calculating a vector-based, 3D representation model of the patient's upper body. It is used to control correct execution of exercises and determine compensational movements.
4. Video data to screen (VGA or HDMI). It is controlled by the main application displaying PHR-content, Game-content, or management content on the interaction board and the front monitor.
5. BAN nodes transfer raw or pre-classified sensor data for the evaluation of ADL behavior to the "Main computer" for processing and the upload to the PHR.

9.2.7 Detailed Use Cases and Actions

There are characteristic sequences of actions for all mentioned users. Every single action refers to a "use case" with regard to software development. There exist interdependencies between actions of users, i.e., an action of one user may be required before other users may continue their actions. To keep it simple, the isolated sequences of main actions are presented only. Any action may be disassembled into more fine-grained activity steps described in the following paragraphs. The following activity steps could be identified in a more granulated manner:

- **Initial assessment in clinical environment**
  - Execution of test tasks
  - Motion capturing
  - EMG Measurement
- **Execution of training sessions at home**
  - Patient switches on the training device.
  - Patient starts a "Tele-rehabilitation"-session using the interaction board.
  - The patient may select between "autonomous training," i.e., without real-time connection to the therapist, or "with supervision." In case of no supervised training is scheduled or there is no connection to internet, the "autonomous training" mode is selected automatically.
  - The patient selects an exercise and starts it. She/He may consider former training scores and adjust the difficulty level. Some exercises may be accompanied by user-selectable music. All actions follow a set of permissions that have been configured by the therapist before.
  - The patient executes the exercise in the autonomous modes. The PHS monitors and analyses the execution of tasks and exercises and generates respective feedback. Training results and scores are then sent to the PHR.
  - The patient executes the exercise with live-supervision by the therapist. She/He is observed by the therapist, may see the therapist on the screen via bidirectional video communication and may receive real-time guidance.
  - The patient can see the exercise evaluation and score after finishing it.

9.2.8 Detailed Actions of a Therapist Within Use Case 4: "Remote Care"

The following actions are performed by the therapist:

- **Action 1**: Schedule training for a patient
  - Study the patients' health record
  - Compose training schedule by selection of predefined exercises

  - Configure exercises and difficulty levels
  - Schedule meeting dates and supervised training sessions with the patient

- **Action 2**: Real-time supervision
  - Observe the patient
  - Support the patient via verbal comments
  - Demonstrate intended movements and exercises via video link
  - Adjust the exercise level to the actual shape and mood of the patient

- **Action 3**: Training Evaluation
  - Evaluate the training sessions
  - Check the scores
  - Comment on sessions and storage of reports

- **Action 4**: Remote consultation
  - Respond to alerts or training results

9.2.9 Sequencing of Actions

An UML sequence diagrams for the training session according to [11] is shown in Fig. 9.15.

9.3 Final Implementation

The StrokeBack system addressed two primary types of users i.e., patients and therapists or care persons respectively. It is quite obvious that both user types must not be confronted with any technical duties and tasks. Therefore the system had to be self-explanatory and self-calibrating up to certain level, e.g., a fixed training place should be able to recalibrate or reconfigure autonomously with minimal intervention of the users.

From the patient's point of view, the usability of hardware components of the StrokeBack system, especially when used at home without on-site therapists, is the most crucial point to be sorted out. Currently, the most challenging tasks will be: How to enable ease of use when sensors need to be attached to the body by the patient herself? How to determine, or make sure respectively, that the sensors will be at the right positions? Different ideas have been discussed already. For example, a wrist band such as used for wristwatches should be a proper means to attach sensors to the wrist of the arm under monitoring. However, means that aren't easy to handle for the patient, or that need assistance from a care person, are to be avoided wherever applicable. Here, the consortium will rely on hands-on knowledge gathered in previous projects. Necessary approaches were agreed as soon as first

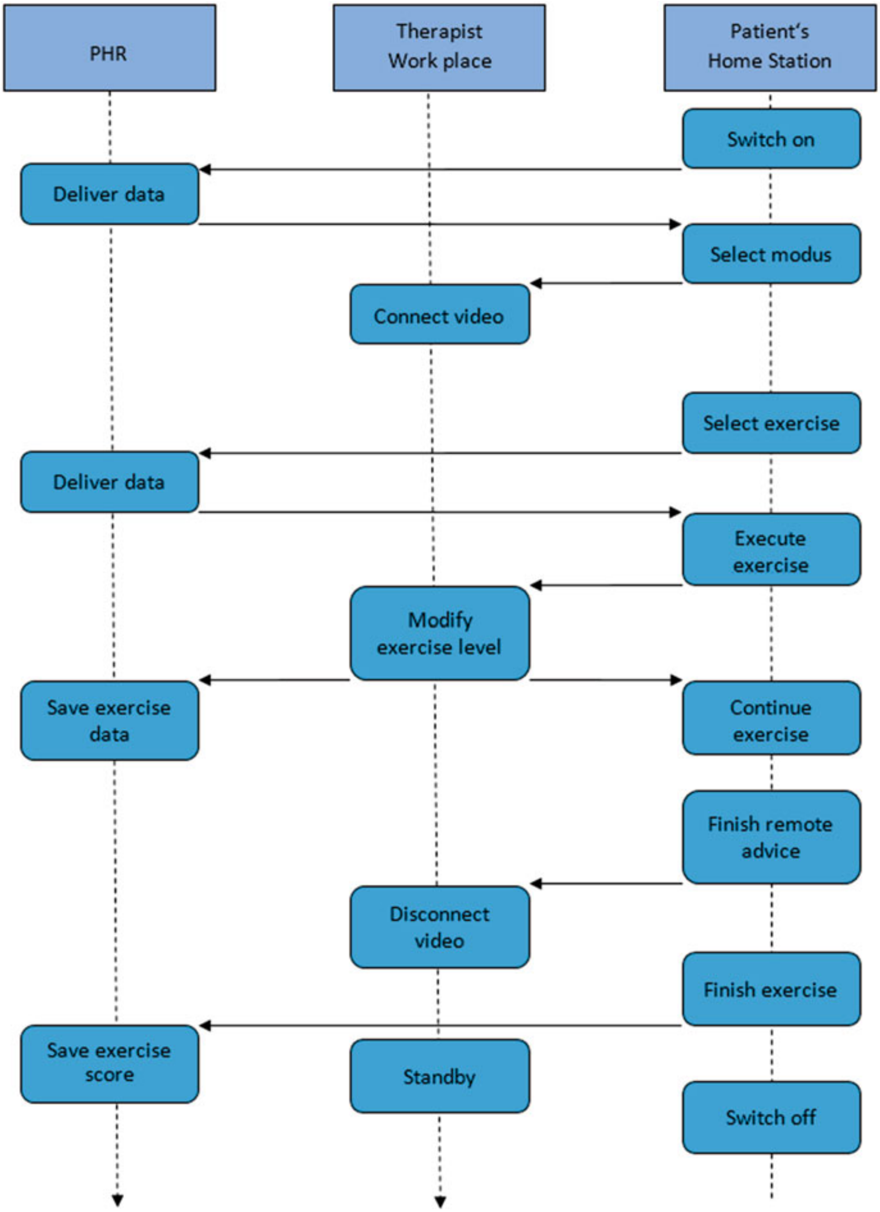

Fig. 9.15 Sequence diagram for three components of the StrokeBack system

technical experiments allowed a detailed analysis of a technical architecture and components used. A close work with therapists in early experimental phases allowed to determine proper and smooth ways of integrating devices in patients' daily routines.

Furthermore, designs of user interfaces regarding the look and feel of the system and the graphical representation have been discussed. Currently, the system provides a touch screen display with a simple GUI for patients composed of large, color-coded icons. The four sections are represented to patients with big buttons:

- **Exercises/Training**—The patient should use this section to initiate and select training sessions and exercises. It will feature a graphical representation of the rehabilitation plan that is to be configured by the therapist. It will most probably allow configuring training sessions on daily basis with an integrated calendar function. This enables to integrate reminder messages and audio-visual reminder functions as well.
- **Feedback**—In this section the patient can have a look at previous training sessions, results, high scores in games, and rehabilitation progress.
- **Messages**—This enables the therapist to send messages to the patient. Messages can be sent by the therapist only to provide feedback and encouragement for example. It is explicitly planned as one way communication. It will not allow patients to communicate actively with the therapist to avoid a mass of unnecessary and not manageable messages.
- **Video Session**—We will optionally integrate means for audio-visually guided training sessions in the system. These are to be configured and used on behalf of the therapist only. Experiences from previous projects have shown that many patients desire such functionality.

In general, any data given to the patient should be high-level data with minimal details and should preferably be presented in graphical and/or audio-visual way. Similarly, data accessible by the therapist should also be simple data but on a more detailed basis. Therapists will have access to timesheets, training results, and rehabilitation progress in more detail, e.g., being able to figure out number and quality of single exercises. However, end users will neither gain access to raw sensor data nor to interim values or algorithms. The main design rule is: Keep it simple!

The technical design guidelines based on experiences from previous projects, various system approaches, and use cases have been reviewed and assessed for drafting the StrokeBack architecture.

9.3.1 Evaluation of the Overall Design

The first drafts of the architecture and requirements, allowed for use cases and lists of components required for each use case to be selected. Furthermore, aspects of look and feel of the StrokeBack system and its integration into patient's home and life have been incorporated into the design. As a result of further investigations regarding minimum distances between patient and the Kinect cameras, a prototype of the patient home station has been produced. This has been used as initial reference system for parallel developments of all subsystems.

Several instances of serious games have been tested and improved according to the feedback from therapists and patients. The same holds true for development of the PHR interfaces, the Exercise and Compensation Analyse (ECA) tool from UP and the user interface of the patient station. With respect to the events specified for controlling the rehab games, the event capturing algorithms has been developed using a near-field Kinect focussing on wrist movements and palm opening/closing as these have been identified by the physicians as key objectives for successful rehabilitation of the post-stroke patient (refer to Chap. 7).

While integrating both main Kinect-based subsystems ECA tool and wrist movement capturing, the performance of the near-field Kinect system decreases significantly when both Kinects are used in parallel. Hence, we need to merge both implementations to work with one Kinect only if possible. Therefore the patient home station will integrate one Kinect device only.

Finally, the empirical evaluation of the assembled Patient Station and its respective workflow commenced with the design of the patient station with a vertical and a horizontal screen. A training cycle is offered to the patient as shown in Table 9.2.

Since the first prototype of the mobile patient station was quite large and heavy, thus a second much smaller variant has been designed. Photos of both variants are shown in Figs. 9.16 and 9.17, respectively. The first prototype is based on the design of the stationary device in the clinic, while the second one adds few technical improvements. In particular, near-field Kinect was removed with a leap motion sensor taking over monitoring/recognition of hand movements. This allowed to get rid of the second computer inside the horizontal part of the device lying on the desk. In total, the size of the mobile station has been reduced by 30–40 % and the weight reduced by 50 % as well. Please note that the sizes of the displays used in both variants are equal, as this might not be distinguishable in the figures.

9.3.2 Specification and Implementation of Selected Rehabilitation Trainings

The functionality of exercise monitoring tool has enabled the monitoring of the whole upper body of a person instead of single limbs only. Instead of calculating position of body joints and angles between adjacent body parts, the evaluation tool can calculate complete 3D vectors of each body part including length and direction of those. This enables a much more precise modelling of the upper body. A tool for real-time supervision of simple, non-complex exercises is already available. It allows to record and monitor individual but simple exercises. This tool has been re-implemented for usage on window platforms, which has been chosen as the basic programming environment for the StrokeBack system. It has been further extended to support parallel multi-exercise monitoring of previously recorded exercises.

Table 9.2 Typical training cycle at patient home station

Step	Description	Vertical monitor	Horizontal monitor
1	Switching the Rehab Table on using the main switch	Welcome screen and a list of patients registered on the Rehab Table (clinical device only)	Welcome screen and the list of patients registered on this Rehab Table (clinic device only) plus the button “Start”
2	After touching the “Start” button on the horizontal monitor	Welcome screen remains	Four buttons of main menu: “Exercise”, “Feedback”, “Help”, “Video-Session”
3	After touching “Exercise” button on the horizontal monitor	The text “Select an exercise”	Buttons to select the exercise depending on the configured training unit
4	Select an exercise on the horizontal monitor → exercise is launched	Exercise content (game)	Control keys of the selected exercise (if necessary) + “Quit” and “Help” buttons
5	Exercise stopped by pressing the “Quit” button on the horizontal monitor		
6	Start of video link with the therapist by touching “Video-Session” button on the horizontal screen	Smaller image from the local camera left above and a larger image from the remote video camera right sites	Four buttons of main menus: “Exercise”, “Feedback”, “Help”, “Video-Session”
7	Request feedback: by touching the “Feedback” button on the horizontal monitor	Feedback in graphical form	Button “Back/Quit”
8	Request help: by touching the “Help” button on the horizontal monitor	Textual advise, video, or no change (depends on previous content)	Textual advice and the button “Messages”
9	How to switch off the rehab table completely?		All interfaces enclose a “Finish” button at all time

In addition to the modelling and evaluation of correct execution of therapeutic exercises, a tool to detect unwanted or not-allowed movements during training sessions, called compensational movements, is developed. This is especially desirable from the therapeutical point of view. In a real-life training session, normally the therapist pays attention to unintentional movements and corrects those, e.g., leaning forward or movement of the shoulder. In StrokeBack, the monitoring systems should do this automatically. Hence, we investigated a library of compensational movements that need to be monitored during normal execution of exercises. Therefore we have worked out an overview of compensational movements that commonly appear during training with stroke affected patients. A first version of this tool that detects compensational shoulder movements. In the very end, both tools would be merged into one tool, called Exercise and Compensation Analyse.

Fig. 9.16 First prototype of mobile patient station for home use

Fig. 9.17 Second prototype of mobile patient station for home use

Advanced training means based on the interaction board and near-field use of the Kinect camera have been discussed. It deals with fine-granular tracking of hand movements and gesture recognition for a single hand. In particular, to clench a fist, to open and close the hand as well as extension/flexion of the wrist should be observed. This setting will be investigated as an extended rehabilitation tool. Please note, none of the currently available Service Development Kits (SDKs) for the Kinect camera allows for fine-grained tracking of hand movements or finger tracking in general. Such a tool is currently still under development. The wrist movement monitoring tool based on near-field use of the Kinect for Xbox is ready for use. A respective application using the Kinect for Windows device and the standard SDK is under development.

To keep the motivation of the patient high while exercising, the exercises are to be combined with small games. A respective list of several potential games has been described in Chap. 5. All games have been iteratively reviewed by the medical partners in view of usability for stroke patient and potential therapeutic impact of expected control means (movements/exercises to control the game) in correlation to rehabilitation outcome. The gaming engine will be loosely coupled to different exercises, which means the controlling movements can be individually set to the patient's therapeutic needs. Prototypes of four games are ready to be tested. After testing and selection by the therapists, we focus future implementations on the following games (refer to Chap. 5):

- "*Break the Bricks*"—classical game where the user aims to hit a ball against the brick wall to breakthrough and proceed onto the next level by removing all while controlling a board to prevent the ball from falling down.
- "*Birdie game*"—a bird is controlled to fly around the obstacles.
- "*Gardener game*"—the user waters plants to prevent them from drying out.

These games can be parameterised by configuration files, where speed, input accuracy, etc., can be defined according to the needs of single patients. In addition, level editors and manuals have been implemented. The implementation of instrumented object for home therapy use has been refined by the therapists and those responsible for implementing the sensor-equipped die and a multi-function board. Furthermore, integration of a programmable keyboard for application of music supported therapy has been done.

9.3.3 Integration, Test, and Evaluation

The evaluation of the StrokeBack system allowed to ensure high acceptance of the results by end users. In order to achieve this we follow an iterative approach. In very early stages we use the Tandem stack available at IHP or the FeuerWehr sensor node developed at IHP to do experiments for evaluating the feasibility of approaches under consideration in other work packages. Here we think of evaluating technical parameters such as processing speed accuracy. In addition we involved experts in the field (sub-contractors, e.g., physical therapists with working experience in stationary and ambulant rehabilitation) and patients to get early feedback on the acceptance, e.g., of graphical look and feel of applications under development. Later on when the final system is ready we aim to do experiments with the fully integrated system together with sub-contractor and patients. Early designed workstation is located at therapists and at patients living room to enable project partners to perform real live tests.

The project partners have agreed on a common procedure and time schedule for development and closely coupled early tests of game ideas and exercises in parallel. BBK has led and assisted in the technical development, thanks to their medical and therapeutic knowledge. The key issue here is to balance the technical feasibilities and medical requirements to develop a reasonable system for individual needs of people suffering from stroke. During the project lifetime, the StrokeBack team investigated the following components:

- Developed an "**Exercise and Compensation Analyse**" tool that uses the skeleton data for the whole upper body, which has been provided using a far-field Kinect (distance to patient is approximately around 120 cm). The first implementation has been demonstrated in September 2013.
- Developed an "**interaction board**" that applies a near-field Kinect (distance to object is about 40–60 cm in average) to monitor hand and finger movements as well as the manipulation of objects for rehabilitation purposes. The hand and finger movement recognition is running on a Kinect for Xbox. The tracking of object via Kinect was suspended due to expected limitation in sensing features and sensing area. Instead, sensor-equipped objects that can wirelessly communicate were developed (refer to Chap. 3).
- Designed and implemented several small games that are loosely coupled to the training components (refer to Chaps. 5 and 7). Those allow for controlling the games equally with training tasks (exercises) that can be chosen individually according to the patient's needs. Three games were fully implemented and have been integrated into the table.
- Developed a mobile BAN sensor system (refer to Chap. 3) that automatically collects and classifies sensor data to analyze ADL during the day while assuring mandatory security and privacy issues.

A description of the WMFT test procedures, descriptions, and manuals of assessment principles and scores as well as complete exercise evaluation sheets are available. These have already been used for the patient trials in March 2013. An initial sensor set-up of Shimmer sensing devices have further been used in regular tests with patients at BBK. This setting was technically supported by IHP and SOTON. The reason behind this is the fact that a patient usually stays in the rehabilitation clinic at BBK for 3–4 weeks only. To gather realistic sensor data for development and refinement of movement detection algorithms, BBK has integrated several test movements into the regular therapy schedule, i.e., same patients have carried out the same exercises on weekly basis. Thereby we have collected reliable data about feasibility and accuracy of developed algorithms and more important, we have investigated whether a progress in rehabilitation could be measured with technical means. To compare technical outcome to clinical assessment means, therapists have made a record of the protocol rehabilitation progress in parallel.

According to the feedback from medical partners, the patient station and the sensor system only could be accepted for trials if both parts provided the minimum safety CE marks. Therefore MEYTEC as the partner responsible for overall system integration, investigated all CE requirements for the patient station and IHP for the BAN. As the BAN is a wireless radio system, it had to be further proofed to meet the maximum safety value of electromagnetic tolerance. For IHP as a research partner this meant to have the sensor system tested by a certified sub-contractor.

The wrist detection engine has been improved to deliver more accurate and reliable gesture recognition. In addition, it is now more robust against influences from the compensation detection tool using the second (far-field) Kinect. The wrist detection tools can now be more accurately configured to the patients sitting position at the table and provides better detection results even if the patient does not exactly adhere to the training position. The latter one might be the most difficult problem at the very end, especially for patients with severely limited mobility of the upper limbs or the hand respectively. For better usability, several improvements have been made such as manuals and instruction videos for the games and the other exercises.

The EET tool has been improved and tested in several instances for application of more fine-grained configuration means. Also a GUI for more visual feedback is now available. The new features are running properly, but however require to have detailed knowledge about its behavior and influence of several different parameters that can be set for configuration. Indeed, detailed configuration for various patients and upper limbs movement recognition can be configured. Hence the EET tool demonstrated its functionality, but might not be useful in common practice due to configuration process that is too complex for therapists or non-technical personnel.

The ADL-detection engine using the BAN is available as stand-alone unit for live detection of ADL activities. The application has been improved so that the sensor worn at the wrist is automatically activated and collects data autonomously during the day. For demonstration purposes a GUI has been implemented displaying gathered data and detection results. Likewise the sensor-equipped cube is available for therapy means. It automatically connects to the patient station and sends orientation data during training. Respective software with a GUI has been implemented.

The most severe problems have arisen due to instability and size of the mobile prototype as well as unsynchronised communication between the patient station and the PHR. The interplay between the different components of all partners has been changed many times. Hence the integration of the software components and especially exchange of training plans, configurations and training results between the patient station and the PHR is prone to failures.

9.4 Business Perspective

9.4.1 Product Definition

The core exploitable outcome of the StrokeBack project is a telemedicine system which supports ambulant rehabilitation at home settings for stroke patients with minimal human intervention (Fig. 9.18).

This system is composed of:

- An object called "Rehab Table" that will be used by the patients in their home environment to interact with the rehabilitation applications and services, hosted either by the object itself or by a server, is physically located at the clinical service provider premises. The Rehab Table is a blend of hardware and software components. The hardware part of the Rehab Table is shown in Fig. 9.19. It includes two 3D sensors for body activity monitoring, camera for video communication, interaction board, PC that hosts rehabilitation applications and manages communications. The software part includes application for the selection and execution of exercises—using virtual and actual objects—that are part of the Care Plan prescribed by the attending physician, audio–video communication application for real-time supervised training, as well as background software services for integration with the PHR database for measurements storage and the Care Management application for care plan details synchronization.

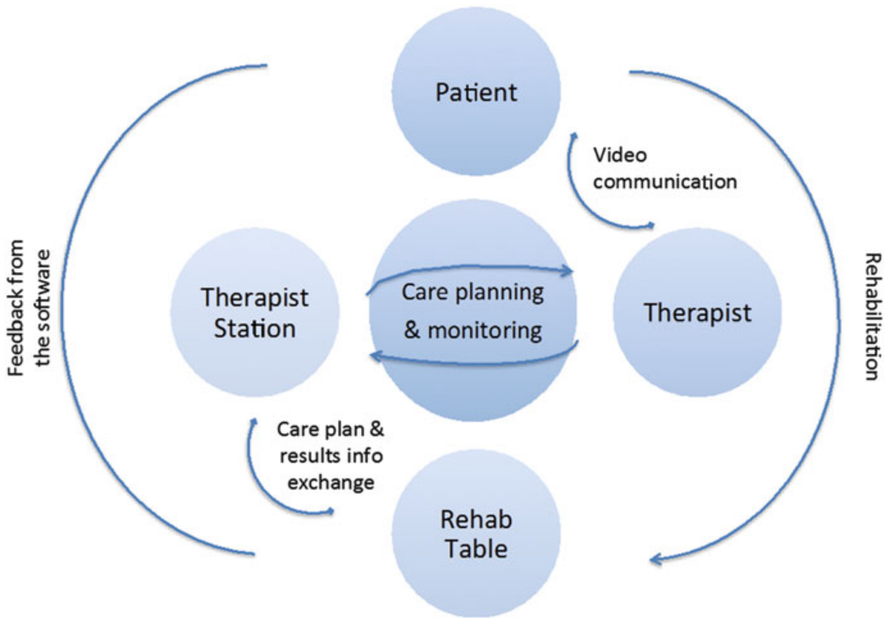

Fig. 9.18 StrokeBack system concept

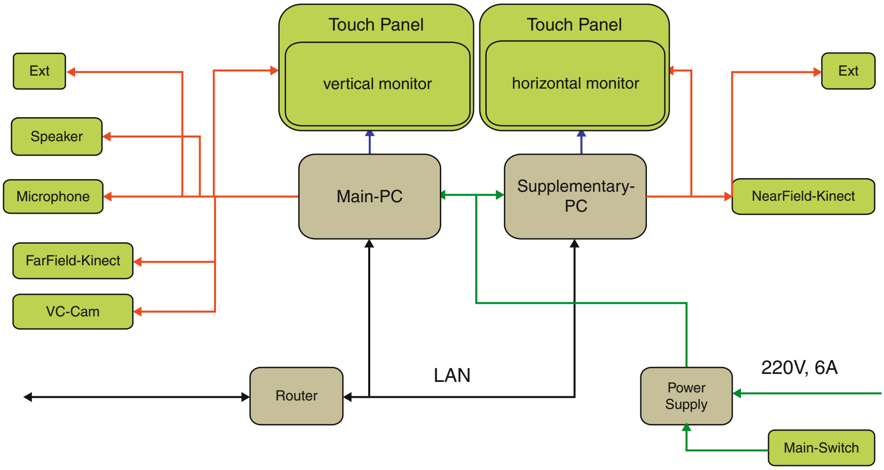

Fig. 9.19 Schematic of the hardware of the Rehab Table

- A web-based Care Management application to be used by the clinicians during the clinical assessment phase and by the clinicians and therapists during care planning, overview, and results assessment phases.
- A PHR System, including a database for persistent storage of the care plan details (prescribed and executed plan, measurements, evaluation reports), and a web application for the patient for accessing her PHR.

9.4.2 *Market Analysis*

There are many different customer paths that StrokeBack could attempt to go to market with, but one market that clearly is important is that of at-home rehabilitation care (tele-rehabilitation). With this said, and although at-home market incorporates the end user, it is important to understand that, before attempting to penetrate that market, the clinical segment should be the initial market to be targeted. For this market, some relevant details are provided in following paragraphs.

In the USA, according to Hoovers' market report on Rehabilitation Therapy Services [12], the rehabilitation therapy industry consists of about 30,000 establishments with combined annual revenue of approximately $20 billion. The industry is highly fragmented, with the top 50 companies accounting for less than 25 % of total revenue. More specifically, the outpatient rehabilitation industry accounts for nearly $5 billion of Medicare spending. This figure has been rising steadily, and has more than doubled since 2000 when annual rehabilitation expenditures were $2.1 billion. The three primary classifications within outpatient rehabilitation are: physical therapy, i.e., diagnosis and treatment of physical impairments, functional limitations, disabilities, or changes in physical function and health status; occupational therapy, i.e., treatment to improve or restore functions that have been impaired (or permanently lost or reduced) because of illness or injury, to improve the individual's ability to perform tasks required for independent functioning; and speech language pathology—diagnosis and treatment of speech and language disorders that result in communication disabilities or problems with swallowing. Of the three outpatient rehabilitation classifications, physical therapy expenditures far outweigh spending in the other areas, accounting for nearly three quarters of all outpatient rehabilitation spending (Fig. 9.20).

Regarding European market, Frost & Sullivan (F&S) published an exhaustive analysis of European Remote Patient Monitoring (RPM) market in June 2008, in which StrokeBack is framed up. Some results of this work are presented into the publicly available report [13]. F&S has found that the European RPM market earned revenues of US $175 million in 2007 and estimates this to reach $400 million by 2014. More specifically, RPM in Europe in 2009 was dominated by UK with 25 % market share and Germany with 21 %. Other prominent markets include France, Italy, and Benelux. The scenario is likely to remain the same throughout the forecast period, with no major change in each country's market share in the region. F&S identifies two distinctive segments into the European market:

- ***Equipment vendors***: Companies that manufacture/integrate/sell RPM products as part of vertical products for continuous patient monitoring.
- ***Service providers***: These follow a more flexible approach, connecting patients and healthcare services to improve aid and decision-making. Technological infrastructure is just the means for providing their service. In that sense, service providers do not invest on technology development, but mix and match end users' needs with available ICT solutions.

StrokeBack delivers a platform that is a composition of equipment (Rehab Table) and software (applications for the patients and for the therapists). As such, rather than addressing one of the above market segments, it can be considered as addressing

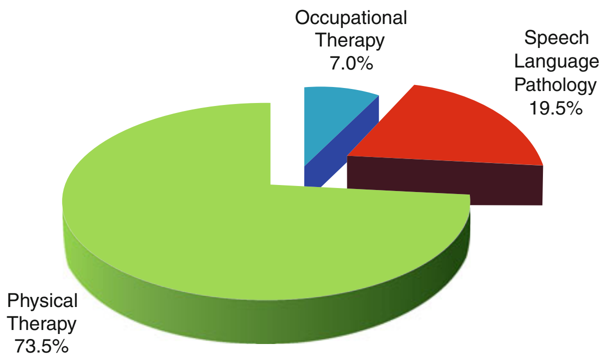

Fig. 9.20 Outpatient rehabilitation market overview [17]

another segment that is related to *Solution Providers*. This means that the entities that will exploit the core project outcomes will offer a total solution (ICT infrastructure) plus a deployment and maintenance service.

9.4.2.1 Key Actors

We discriminate between two key groups of actors engaged in the market related to the StrokeBack rehabilitation system: financial actors and service providers.

Financial actors are those who finance the use of the system; in principal such actors are the government and health insurance companies. In many European countries, the government plays an important role in procuring, launching, supporting, and distributing the tele-rehabilitation service, while taking care about the regulatory aspects of the service deployment and operation. Health insurance companies are also engaged in the associated health service cost payments. The motivation for their intervention is that eHealth and mHealth services can contribute in healthcare cost reduction due to more cost-efficient medical treatments.

The service providers' group includes several key actors: the patients, the therapists, and clinicians (i.e., the healthcare professionals), and the non-professional caretakers (e.g., family members). The patients make use of the system (the Rehab Table) at their residential environment. The non-professional caretakers may help patients during the process of using the Rehab Table. At the clinical environment, the healthcare professionals (clinicians and therapists) make use of the system (the Therapist Station) to set up care plans, monitor the execution of the exercises by the patients and overview the measurements/results. Periodically, the healthcare professionals participate in video communication sessions with their patients.

On the backstage, another group of key actors performs: it includes the equipment manufacturers/integrators who develop and maintain specific system functionalities that support the health service; wholesale and retailers who distribute the product; IT service providers who deploy and maintain the infrastructure; a network provider who offers its broadband network for transport of data between the Rehab Table, the Therapist Station and the central repository, the PHR database.

9.4.2.2 Market Drivers

As major drivers of the market expansion we could mention the following:

- **Ageing population**: The share of people aged 65 years or over in the total EU population is projected to increase from 17.1 to 30.0 %. And the number of 65-year-olds is projected to rise from 84.6 million in 2008 to 151.5 million in 2060. Similarly, the number of people aged 80 years or over is projected to almost triple from 21.8 million in 2008 to 61.4 million in 2060 [14].
- **Fragile population**: Stroke is becoming the leading cause of disability among adults in the European Union (EU) as about one million strokes occur each year

in EU countries [15]. About 10 % of Western Europe's population experiences a disability, as described in a British survey [16]. As populations age, there is an increased level of disability, which is reflected by an increased burden of care, increased costs for health and social care and the impact of co-morbidities. Two important factors have to be considered:

- Survival from serious disease and trauma leaves an increasing number of people with complex problems and functional deficits. Many of these people are young at the time of the event/injury and will survive for many decades. Examples are numerous, e.g., stroke, traumatic brain injury, polytrauma and childhood cancer, where better-organized acute care and rehabilitation have led to greater survival and better outcomes.
- Expectation of good health in Europe. This places further demands on all healthcare dimensions, including at-home rehabilitation services.

• **Technological enhancements** [17]: Tele-rehabilitation via teleconferencing technology affords access to many. However, often, using this type of technology requires skilful hand dexterity to manoeuvre using the mouse or the arrow keys on the keyboard. With the development of motion control for video games, users with impaired hand dexterity now have access to much that computers can offer. Furthermore, this motion-controlled interface serves as a therapeutic intervention to improve upper extremity function. In the past, motion tracking and gesture recognition systems such as Polhemus [18], which has more capabilities yet is extremely expensive, were the only choice for motion tracking and thus cost prohibitive for everyday home use. Recently innovators such as SoftKinetic [19] now offer natural interfaces for videogames and serious games and allow the users to interact with the digital world in a more immersive, transparent and intuitive manner. With this type of technology, moving objects can be captured in depth dimension and in real time. Using this type of technology removes the need for precise finger dexterity required of typical mouse or game controllers with many buttons to push. On parallel, the developments in the teleconferencing arena (e.g., is voice over internet protocol) offer a very inexpensive alternative to telephone calls and provides tele-rehabilitation with audio feedback. In other words, the therapist located at a remote location can communicate with the client using voice rather than having to type via text or call on a typical landline. The development of videoconferencing embedded within game-based tele-rehabilitation offers real-time feedback between therapist and client, thus ensuring proper movement.

9.4.2.3 Customers' Profiles

A customer is defined as one who purchases goods or services from another. In this respect, the customer is not necessarily the end user/patient. In our case, the customers are those that have the capital to invest in innovative, cutting edge rehabilitation technology. This includes everyone from the manufacturer, to the distributor, to the physicians, to the regulatory affairs personnel. With respect to the StrokeBack system a tentative list of customers includes the following:

- Public health authorities, acting on behalf of public hospitals
- Private Hospitals
- Rehabilitation institutes and nursing homes
- Health/Social Insurance Companies
- Manufacturers/distributors of medical products

In all cases, a Business-to-Business (B2B) model is applicable but, depending on the type of healthcare delivery in each country, there are different combinations of customers (e.g., purchase/leasing of the system by a clinic, or by an insurance company, etc.). The main characteristics of the above groups of customers are presented in the following subsections.

Public Authorities

Their main characteristics of this group are the following:

- Small number of potential accounts
- High number of patients
- Long periods of time for negotiations
- Different groups of decision makers to be convinced (political and medical, at national, regional, and local levels)
- Public tenders

The main advantages that the StrokeBack solution would offer to these clients are:

- Cost containment
- Higher motivation for their patients, through provision of optimized physical activity supervision programs
- Better resources usage (free beds, serve more patients with the same staff)

Private Hospitals and Rehabilitation Centres

These customers are characterized by:

- Large number of potential accounts
- Large number of patients
- Quick negotiation process
- Centralized decision makers
- Direct orders

The main advantages that the StrokeBack solution would offer to these clients are:

- Cost containment
- Better resources usage (free beds, serve more patients with the same staff)
- Decrement of trial-and-error

- Less time necessary for patient's treatment
- Competitive advantage (a new service not yet offered by other hospitals)

9.4.2.4 Analysis of the Competition

Physical Rehabilitation Systems

The Philips Orthopaedic coach [20] supports the independent training of patients with video instructions and audio-visual feedback related to the quality of the performed motions by using inertial motion sensors. It focuses on hip and knee exercises using only few sensors. Training sessions are also documented and can be reviewed by therapists. The system is approved for use under medical supervision only, however, it is currently not in the market. A comparable system working with two on-body IMUs is Hocoma's Valedo Motion [21], focussing on back exercises.

Apart from the above-mentioned commercial products, the consortium analyzed an extended set of research prototypes and ongoing research projects related to physical rehabilitation systems. During the analysis several applications were identified that use different blends of technological infrastructure (various input technologies, handled and hands-free devices as input controller, optical sensors; HMD device for visualization, visualization with projection technology, audio, and tactile feedback). In more details, the following research projects were analyzed:

- GOET project (Game on Extra Time) [22]: Games on Extra Time project is not typically dealing with the rehabilitation of stroke patients, but is a good example, how can a development system containing interesting interactive games with full experience can be an efficient help, e.g., for children with learning disabilities, i.e., a special age group dealing with several disabilities for the organising of daily activities.
- LimbsAlive [23]: The LimbsAlive, a project that started in 2010, specializes in the rehabilitation of the hand and arm for people of all ages who have hemiplegia, often through stroke. LimbsAlive project focuses on developing two handed skills—essential for independence.
- GReAT [24]: The GReAT research project is to investigate the use of technology in gesture therapy for people with aphasia (a communication disorder that occurs after stroke).
- ATRAS [25]: The ATRAS project was founded to develop an integrated service model incorporating innovative technology for the rehabilitation of the upper limb, following stroke. The stroke patients are exposed to a bigger psychic load than the "healthy" user group, because of their obvious restrictions of motion. They can feel frustration or shame, just because they are not capable to do general daily routine activities because of their illness. This is the reason why the introduction of a new telemedicine-based method into the treating process of post-stroke therapy is such an important question. As previous studies have already proved, using VR-based environment and modern technical devices for the rehabilitation of post-stroke

patients, can be an expense-effective solution besides the conventional therapies. After training for 2–3 h a day for 8 days, all of the patients showed increased control of hand and arm during reaching. They all had better stability of the damaged limb, and greater smoothness and efficiency of movement. Kinematic analysis showed that they also had improved control over their fingers and were quicker at all test tasks. In contrast their uninjured arm and the arms of control game players' group, who had normal hand/arm function, showed no significant improvement at all.

Physical Activity Monitoring Systems

Physical activity and health-related fitness systems, such as ActiGraph or ActiHeart, and fitness games, such as Wii-FitPlus, are becoming quite common across the EU and the USA. One can consult Gebruers et al. [26] for a more exhaustive review. Commonly, these fitness systems provide a summary of the subjects' physical activity based on activity classification deduced from features extracted from accelerometer signals. However, these systems often support only a limited set of activities (e.g., walking and running) and are not precise in their calculation of energy expenditure. Moreover, they often lack feedback and motivational elements regarding the user's activity, which nonetheless helps to preserve or increase motivation. Fitness games provide these motivational elements. Current video games include feedback provided by motion sensors, either on the body or based on external cameras, in order for users to follow some fitness exercises, but only few parameters are taken into account and the proposed methods are not documented and not adapted for medical purposes.

9.4.3 SWOT Analysis

This section presents a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis for the field of rehabilitative therapy concerning arm and hand weakness in residential environment. The SWOT analysis is a commonly employed framework in the business world for analyzing the factors that influence a company's competitive position in the marketplace with an eye to the future. However, the SWOT framework can also be usefully applied outside of the pure business domain. It is expected that this structured examination of the factors relevant to the current and future status of VR rehabilitation will provide a good overview of the key issues and concerns that are relevant for understanding and advancing an application area.

SWOT is an acronym that stands for Strengths, Weaknesses, Opportunities, and Threats, and is a commonly employed framework in the business world for analyzing the factors that influence a company's competitive position in the marketplace with an eye to the future. Generally, a SWOT analysis serves to uncover the optimal match between the internal strengths and weaknesses of a given entity and the environmental trends (opportunities and threats) that companies face in the market.

Table 9.3 SWOT analysis for ICT rehabilitation systems for home environments

Strengths	*Weaknesses*
• Saving travel of patients to therapist	• Costs of technical equipment
• Increasing intensity of training	• Costs of technical support
• Extension of the training period	• Dependent on internet presence and adequate bandwidth
• Motivational support for training	• Non-human feedback
Opportunities	*Threats*
• Standardization of training	• Reduced human contact
• Monitoring of training results	• Poor useful exercises for the dedicated patient
• Execution of multi-centric clinical trials (comparison of different interventions through a large number of matched patients)	• Learning of erroneous movements
• Use of new technologies	• Paretic attacks during exercises
• Dissemination of new interventions	

The common components of the SWOT analysis include (Table 9.3):

- **Strength** can be viewed as a resource, a unique approach, or capacity that allows an entity to achieve its defined goals, e.g., for precise control of stimulus delivery within a realistic training or rehabilitation simulation.
- **Weakness** is a limitation, fault, or defect in the entity that impedes progress toward defined goals, e.g., a limited field of view and resolution in a head-mounted display can limit usability and perceptual realism.
- **Opportunity** refers to internal or external forces in the entity's operating environment, such as a trend that increases demand for what the entity can provide or allows the entity to provide it more effectively, e.g., a growth in the interactive digital gaming area has driven development of the high-quality, yet low-cost graphics cards needed to make VR deliverable on a basic PC.
- **Threat** can be any unfavorable situation in the entity's environment that impedes its strategy by presenting a barrier or constraint that limits achievement of goals, e.g., management's belief that VR equipment is too expensive to incorporate into mainstream practice.

9.4.4 Exploitation Strategy

Within StrokeBack project the exploitable outcomes are in the form of a total product concerning the execution of tele-rehabilitation, the so-called system StrokeBack. This system was to be exploited by the project partners. An essential role is taken by the commercial partners as Intracom Telecom, RFSAT, and MEYTEC.

At the post-project phase these three partners would develop specific marketing and sales strategy, taking into consideration intellectual property exploitation agreements that are already formed in the context of the project. Intracom Telecom focussed on expanding its role as turn-key ICT solution provider to rehabilitation centers in the markets where it mainly operates (Europe, Middle East and Africa—EMEA). RFSAT focussed on the exploitation of assistive technologies using computers and innovative methods of human–computer communication even in the field of neuro-rehabilitation. MEYTEC launched marketing activities for the use of telerehabilitation for stroke patients in the German healthcare system.

The first set of marketing activities (aimed at dissemination of exploitable outcomes of the project) that were pursued throughout the project, include presentations of the StrokeBack system to German professional societies, such as the following:

- German society of Telemedicine [27]
- German society of Neurological Rehabilitation [28]
- German Stroke Society [29]
- Network of Competence Stroke [30]
- Foundation of Stroke Help [31]

9.5 Potential Individual Exploitation Results of the Project

9.5.1 Rehabilitation Related Body Area Network

The StrokeBack sensor platform, called GHOST, consists of several independent sensor nodes forming a wireless BAN for monitoring movement pattern via local acceleration and position sensing at each node. Movement data will be gathered and stored locally on each node while the sensor nodes are worn by the patient throughout the day. At the end of the day, all data will be transmitted to a local base station with more processing power, most probably the patient home station, where the data will be assessed for classification of Activities of the Daily Living. The BAN will further be used to measure acceleration parameters during execution of the WMFT for assessment of patient abilities.

In addition, the GHOST platform is used to construct sensor-equipped objects for enhanced rehabilitation therapy means. The first agreed object is a cube with sensing stuff inside, which can determine its position and forward it in real-time to a host for application as a game controller. We may further develop respective interactive games dedicated for applying the cube for hand movement training. All equipped objects are of further interest for exploitation.

To facilitate these applications, each sensor node will be equipped with a microcontroller, a Bluetooth low energy transceiver with integrated antenna, flash memory, power management circuits, and a couple of sensors, amongst others a 3-axis

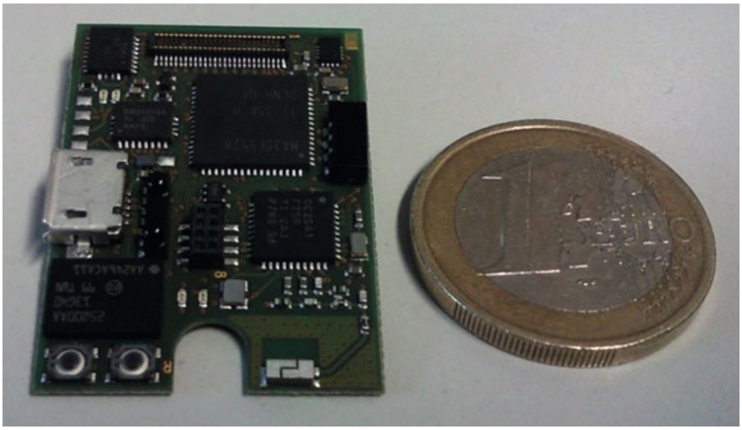

Fig. 9.21 GHOSTv1 base board compared to the size of a 1 Euro coin

accelerometer and a gyroscope. It furthers provides a pin-header for extension with other modules. The sensor node board is flat and small (Fig. 9.21). Every sensor node can be seen as a single product, but may also be exploited as bundle with or without debugging tools and software. For application in StrokeBack, the sensor nodes are packaged into a case of glass fiber without any ports.

9.5.1.1 Market Details

Since IHP and SOTON are research partners and not industry, the focus is on providing a platform for sensor network research with particular focus on wearable BAN applications. The goal is to provide a complete wearable sensing solution for monitoring of body movements with inertial sensors, just as for example provided by the Shimmer platform (www.shimmersensing.com). Nevertheless, the GHOST sensor platform can of course also be used for any other sensor network application, e.g., structural health or environmental monitoring. It can be easily extended with additional modules, for example with other radios and sensors.

Such sensor systems are used by both research teams and industry, which approximately require millions of devices per year in Europe only, given the fact that sensor nodes are relatively cheap and will rather be substituted by newer developments than re-used for other purposes (also thanks to new developments). Due to rapidly increasing network coverage—some EU member states can already claim a network coverage of nearly 100 %—applications for ubiquitous remote monitoring are widely used today. We expect the wireless sensor market to grow rapidly for personal health and wellness (including sports) monitoring, as it can be seen for years, e.g., with sensor-equipped clothes and shoes.

With the final GHOSTv2 variant we target another future market, i.e., sensor network applications for critical infrastructure monitoring and homeland security applications, where highly secure sensor hardware and applications are required.

The special security features provided by the IHP-crypto-microcontroller on the node should assure a prime position in that market area.

9.5.1.2 Tentative Clients Profile

The GHOST sensor platform targets to reach three groups of clients:

1. Primarily, the complete GHOST variant with inertial sensors in hard fiber glass package will be offered for clinical research professionals and caregivers to exploit new ways of therapy in rehabilitation as well as prevention and follow-up care. Their focus is on providing newer and richer data sets for improved decision-making and detailed therapy. These users are mostly non-technical professionals, who demand an ease of use, a plug-and-play feeling and most important, safety of the patient.
2. The GHOST platform in its modular form provides a sound basis for scientists and research teams to investigate and implement remote monitoring applications in different application fields. This user groups want to have free access to software and hardware while at its best freely available tools or open source software can be used.
3. Industry clients will require most support by the hardware and software developer, which is of course limited as long as the GHOST platform is exploited by research partners. However, some unique features of the platform in combination with low price and compatibility to existing industry standards such as USB, Bluetooth LE, Qi wireless power, etc., may strengthen a good competitive position.

9.5.1.3 Competition Analysis

The GHOST sensor platform will be manufactured in two variants, these are:

1. *GHOSTv1*—This variant will be assembled of off-the-shelf components using a MSP430 microcontroller from Texas Instruments. Compared to the Shimmer2 platform, it will facilitate a very flat and compact design factor and provide wireless power supply to support plug-and-play feeling, as required for the studies with patients.
2. *GHOSTv2*—This variant will provide the same main features of GHOSTv1, but will additionally offer unique security functions of the crypto-microcontroller (which is code compatible to the MSP430 family) and a unique ASIC for online feature extraction for movement classification.

Both variants will come along with state-of-the-art processing, storage, and communication means that are comparable or equal to competitive other platforms that are available in the market. It supports the Bluetooth low-energy standard that allows using the sensor platform together with existing mobile phones or tablet PCs.

While the GHOSTv1 platform is in a good competitive position compared to existing platforms, the GHOSTv2 variant will offer distinctive security and processing features that are (to the best of our knowledge) not available on the market in a compact sensor platform. Further good arguments for the GHOST platform are envisioned prices and free access to software and tools. Competitive single devices cost about 250€ (Shimmer3 [32]) up to 2000€ (XSENS MTw [33]) while complete development kits for developers cost about 2500€ (Shimmer3) up to 13,000€ (XSENS). The latter ones often include starter licenses and development tools.

With the GHOST platform we intend to reach market prices of around 200–300€ for single devices for the hardware, depending on respective sensor node configurations. Instead of selling kits and licenses, we will provide an open source basic driver library for developers which can be used together with freely available tools. This should make the platform very interesting for research and early stage developers. Following this strategy, there is no need to provide respective development bundles, since each customer can just configure its own "kit" by merely selecting the number of respective single sensor nodes that are needed. Nevertheless, there is still a chance to launch a spin-off company to provide broader product support and further software developments and bundles.

9.5.1.4 Exploitation Strategy

The StrokeBack sensor platform will be exploited as part of the StrokeBack system as well as a stand-alone sensor platform for various monitoring and distributed computing applications. For use in StrokeBack, the GHOST platform with inertial sensors need to be offered as all-in-one plug-and-play kit in a proper case with embedded software and respective tools such as a suitable charging station.

For the exploitation as a stand-alone sensor platform, the intention is to offer the sensor hardware as modular platform that can be used with freely available tools and software. Therefore respective technical descriptions of each module need to be defined. On top of it, the hardware should be complemented by a selection of basic drivers' that should be available as open source software. Finally, a list of potential free development and debugging tools should be accessible.

It is actually planned to promote the GHOST platform and its derived instrumented objects at scientific conferences and industry/medical fairs via contributed publications and demonstrations. In addition, a website providing technical details, leaflets, and purchasing information will be prepared as soon as possible.

Last but not least, the GHOST platform provides an ideal starting point for further health- and security-related research projects. Therefore we plan to extend the sensor platform with further sensor and communication modules. Due to actual research activities, we amongst others plan to build modules for long-range communication at 868 and 433 MHz as well as 403 MHz, which is the legal bandwidth for communication with implants in Germany and Europe.

9.5.1.5 SWOT Analysis

Following the competition analysis, the SWOT analysis for the GHOST platform as a product is provided in Table 9.4.

Table 9.4 Summary of a SWOT analysis for GHOST sensor platform

Strengths	*Weaknesses*
• Very small, flat form factor • Low power Bluetooth module • Extendable, modular platform • Automatic power management between 4 power sources • No plug-in due to Qi power supply • Integrated crypto-HW (GHOSTv2) with IHP-crypto microcontroller, in particular for ECC • GHOSTv2 includes an unique ASIC for online ADL movement classification	• Needs adapter boards for programming (JTAG, Bluetooth) • Designed for use of Lithium-Polymer (LiPo) batteries • Higher power consumption of crypto-microcontroller (GHOSTv2) compared to MSP430 in GHOSTv1 • No OS support (e.g., Tiny OS)
Opportunities	*Threats*
• Unlimited, full access to hardware • Free open source driver library planned • Free development tools may be used • Novel tiny sensor platform with ECC component and movement analysis • Extension with new modules possible	• Full user support cannot be guaranteed if platform is sold by a research partner • New Shimmer version 3 as most related competitive platform released in August 2013

9.5.2 Serious Games

Serious games were designed for the purpose of solving a problem. Although serious games can be entertaining, their main purpose is to investigate, or advertise. Sometimes a game will deliberately sacrifice fun and entertainment in order to achieve a desired progress by the player. Whereas video game genres are classified by gameplay, serious games are not a game genre but a category of games with different purposes. The categories of serious games that are closely related to StrokeBack are those intended for training, also known as “game-learning.”

Serious Games are computer and video games that are intended to not only entertain users, but have additional purposes such as education, rehabilitation, and training. Serious Games can be of any genre and many of them can be considered a kind of edutainment, but the main goal of a serious game is not to entertain, though the potential of games to engage is often an important aspect of the choice to use games as a support tool. A serious game is a simulation which has the look and feel of a game, but is actually a simulation of real-world events or processes. The main goal of a serious game is to train or educate users, though it may have other purposes, such as marketing or advertising, while offering an enjoyable experience.

In the context of the StrokeBack project we refer to the use of games for Health, such as games for psychological therapy, cognitive training, emotional training or physical rehabilitation uses, in our case post-stroke rehabilitation. Almost 80 % of patients do not regain full recovery of arm and hand function and this really limits their independence and ability to return to work. Technology and mental health issues can use Serious Games to make therapy accessible to adolescents who would otherwise not find a psychotherapist approachable.

9.5.2.1 Market Details

Serious gaming has found already way into stroke rehabilitation area. For example neuroscientists at Newcastle University are developing a series of motion-controlled video games to make stroke rehabilitation more fun and accessible. The team's first title, dubbed Circus Challenge, lets patients digitally throw pies, tame lions, and juggle to help them build strength and regain motor skills. As players progress the game ratchets up its difficulty to match pace with their recovery. With video games people get engrossed in the competition and action of the circus characters and forget that the purpose of the game is therapy. Patients use wireless controllers to learn various circus-related skills, from lion taming and juggling to high diving and trapeze work. As they succeed at various tasks, they go on to more challenging quests that involve greater skill, strength, and coordination.

Games have been designed so that players at different skill levels can still compete. Perhaps most importantly, because of support from the Health Innovation Challenge Fund, the game includes tele-monitoring so that a therapist can watch a patient's progress remotely and help tailor his or her next steps. It is also geared to those in wheelchairs too or with limited mobility, making the game convenient as well as fun could be key to recovery. Although Limbs Alive, the game's publisher, has only described their motion controller as "next-generation," it affirms that the game will be playable on PCs, laptops, and tablets later this year. In an effort to lower costs and provide at-home therapy, the team hopes to leverage a £1.5 million award from the UK's Health Innovation Challenge Fund to build a system that will allow therapists to monitor patient progress remotely.

The idea behind rehabilitation training is the so-called "mirror box" as a strategy towards functional recovery in stroke survivors. For example, in a 2003 study reported in "Archives of Physical Medicine & Rehabilitation," a mirror box was used along with imagined movement with chronic stage stroke survivors to provide a means to provide good examples of movement for the brain to practice movement by the impaired limb. The 4-week protocol included simulated practice on a variety of simple and complex action sequences. Even though participants were in the chronic stage (more than 1-year post-stroke) and the intervention involved no physical practice, gains in actual performance of the impaired limb were seen following the simulation practice.

In a 2009, researchers at University of Queensland in Australia reported that experience with the Wii Fit resulted in an immediate effect on balance and strength. In 2010, St. Michael's Hospital in Toronto is completing a clinical trial assessing the improvement in performance of stroke survivors. Patients assigned to the Wii group will receive an intensive program consisting of eight 60-min Wii gaming sessions over a 14-day period. There are also a few case studies that have reported on the value of using the virtual world of Wii to improve motor performance. For example, a study published in "Physical Therapy" in 2008 reported on an adolescent with cerebral palsy who participated in training sessions using Wii sports games including boxing, tennis, bowling, and golf. Improvements in visual-perceptual processing, postural control, and functional mobility were measured after the training and positive outcomes were found at the impairment and functional levels. While mirror reflection can fool the brain into thinking a limb is present and working fine, the Wii fools the brain into thinking the person is operating within a completely different environment.

The most technological brain games for stroke rehabilitation use robots. Several groups of researchers are developing robotic devices and protocols for their use. Many of the devices are specific to arm movement. In a 2008 study reported in the journal "Brain," chronic stage stroke survivors received 3 weeks of therapy with a hand-wrist robot that would provide reaching assistance when it was needed. For example, the robot might move a hand more quickly or accurately to a moving target. Following this training there were two important effects. First, participants who received robotic assistance in all sessions (as opposed to just half of them) showed the greatest functional gains. Second, brain scanning with MRI revealed increased sensorimotor cortex activation across the period of therapy demonstrating that work with the robot-induced brain changes. One downside to the use of robots is that access is relatively limited. Typically, use is restricted to persons participating in research in a rehabilitation lab or receiving treatment at a clinic housed within a medical research environment.

9.5.2.2 Customers Profile

Games have the ability to engage and challenge people of all ages, they have the ability to help individuals manage chronic illnesses, support physical rehabilitation and contribute to changes in health behaviors. Doctors, nurses, rehabilitation specialists, and other health professionals are also using games and game technologies to advance their skills and enhance how they deliver care and services. The acceptance of games as a valuable health management and training method and popular success of consoles such as Wii and Kinect as well as the growth of smartphone game applications indicate that there is a big potential for continuing to move health and behavior change activities beyond the traditional clinical settings and into the consumers' home, work, and social settings.

9.5.2.3 Competition Analysis

In recent years there has been a boom in the use of serious games for various types of rehabilitation primarily in terms of scientific investigation (Table 9.5), though based on commercially available gaming solutions and immersive user interfaces.

There are already a number of commercial rehabilitation systems based on Virtual Technologies employed for serious rehabilitation gaming already in use at various hospitals. An example can be a system completed at the Rehabilitation Hospital at Sheba Medical Centre, Tel Hashomer. The CAREN (Computer Assisted Rehabilitation Environment) from Motek Medical [34] is a multi-purpose, multisensory system for diagnosis, rehabilitation, evaluation, and recording. It records a person's ability to balance and controls movement. The system works in real time and enables the creation of a range of experiences in a controlled environment that can be repeated using the principles of virtual-reality technologies.

Table 9.5 Classification and comparison of rehabilitation serious games [15]

	Betker et.al.	Ma et Bechkoum	Conconi et.al.	Caglio et.al.	Cameirão et.al.	Burke et.al.	Ryan et.al.	System RehaCom
Use case	Motor	Motor	Motor	Cognitive	Cognitive	Cognitive	Motor cognitive	Motor
Sensor	Body weight movement	Motion tracking + HMD	Speech touch motion biosensors	Console	Motion tracking	Motion tracking	WiiMote Wii balance	Keyboard + Joystick
U/I	2D	3D	3D	3D	3D	2D	2D	2D
Players	Single	Single	Single	Single	Single	Single	Single Multi	Single
Competition	None	None	None	None	None	None	None	None
Genre	Memory	Simulation	Strategy	Simulation	n/a	Simulation	Maze	Assorted
Adaptive	Yes	Yes	Yes	No	Yes	Yes	n/a	Yes
View progress	Yes	Yes	Yes	No	Yes	Yes	n/a	Yes
Feedback	Yes	Yes	Yes	n/a	Yes	Yes	n/a	Yes
Mobility	Home	Clinic	Clinic	Clinic	Clinic Home	Home	n/a	Clinic

Table 9.6 SWOT analysis for VR rehabilitation

Strengths	*Weaknesses*
• Stimulus control and consistency	• Interface challenge 1: interaction methods
• Real-time performance feedback	• Interface challenge 2: connections and displays
• Support "error-free learning"	• Immature engineering processes
• Self-guided use and independent practice	• Platform compatibility
• Interface fitted to user's impairments	• Front-end flexibility
• Intuitive and natural performance record	• Back-end data management, analysis, and view
• Safe testing and training environment	• Potential side effects
• Gaming factors to enhance motivation	
• Low-cost, easy and cheap to duplicate	
• Integrated into standard e-Health practices	
Opportunities	*Threats*
• Processing power and graphics integration	• Insufficient cost/benefit ratio to stimulate wide VR Rehabilitation adoption
• Devices and connections	• Potential lawsuit on aftereffects
• Real-time data analysis and intelligence	• Ethical challenges
• Gaming-industry drivers	• Fear of clinicians not needed
• VR rehabilitation with intuitive appeal	• Limited awareness and unrealistic expectations
• Academic and professional acceptance	
• Match scientific and medical groups	
• Integrate VR with physiological sensing	
• Tele-rehabilitation	

9.5.2.4 SWOT Analysis

The use of serious games and especially those using virtual-reality technology in the areas of rehabilitation and therapy continues to grow, with encouraging results being reported for applications that address human physical, cognitive, and psychological functioning. The SWOT analysis in the context of serious gaming rehabilitation, in particular Virtual and/or Immersive Reality systems is shown in Table 9.6.

9.5.2.5 Exploitation Strategy

The StrokeBack project will aim at developing and marketing an integrated solution incorporating the 3D immersive gaming rehabilitation system as its integral part. The complementary technologies will include 3D tracing of the human body movement with the least use of wearable sensor devices. This will expand on the current internal work in the direction of using custom image projection onto the objects and determination of their 3D shapes from distorted images captured by 2D cameras. This will be combined with the development of 3D visual scanning technologies along with wearable microembedded wireless multi-sensor nodes for application in future 3D Human Machine Interfaces (HMI) interfaces. This will be marketed as an OEM technology for future 3D-enabled devices and as IP for ongoing development and deployment of innovative application in the follow-up funded R&D projects.

The list of enabling technologies expected to be produced and exploited from the StrokeBack project in the context of serious gaming work that might (hopefully) lead to the commercial products includes:

- **Kinect-Server**: a solution allowing use of the Kinect sensor device from any client device irrespective of its type and operating system. Currently the Kinect sensor only supports XBOX and PC (running MS Windows) hardware platforms. A dedicated embedded (cost efficient, i.e., less than 50€) embedded hardware solution (an alternative to a software only approach) would offer ability to access Kinect sensor data by any device via TCP-IP using WEB browser.
- **Physiological wireless sensors**: RFSAT developments have been conducted in collaboration with Shimmer Research and aim at supporting use of Shimmer2R sensor devices from any client device with integration with a variety of Electronic Health Platforms, e.g., ICOM's intLIFE, MS Health Vault, Open EMR, Open MRS, etc.
- **Immersive gaming**: has been pursued by RFSAT within the StrokeBack project, exploiting capabilities of HTML5 and using such technologies as Win GL. This combined with immersive user interfaces (e.g., MS Kinect) is expected to lead to development of an integrated immersive gaming system able to execute on any hardware platform including smartphones, home entertainment, etc.

9.5.2.6 Conclusions

Despite growing interest in using VR and immersive technologies for stroke rehabilitation, the fast advancement of the market in applicable technology development creates a situation of great opportunities for technological innovation and an adoption of developed products on the market. It makes it especially attractive or SMEs able to respond instantly to new technologies with innovation in service and application development, faster than any large industry would be able to respond.

9.5.3 Reimbursement Scheme

In principle, Health Service Providers execute the medical care routines and if necessary, they supply to their patients the technical infrastructure (devices, access to software applications, etc.). This infrastructure is provided to the Health Service Providers by an ICT Vendor. Health Service Providers invoice their effort in the

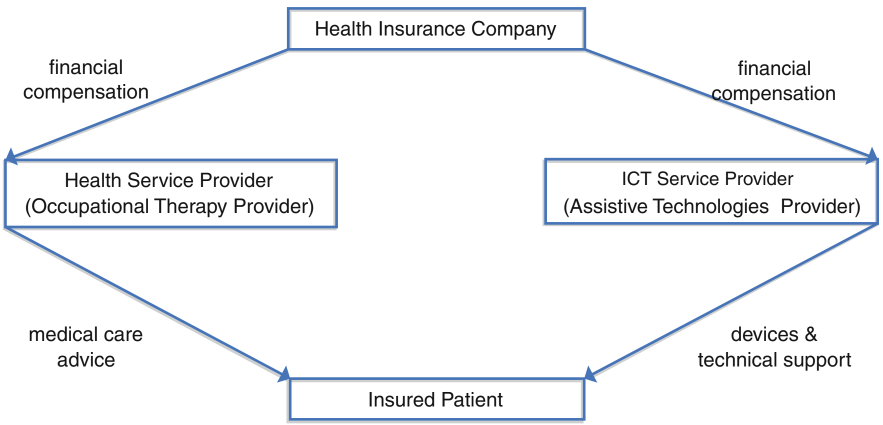

Fig. 9.22 Reimbursement model for rehabilitation service to eligible patients

form of agreed prices to the Health Insurance companies. Typically, there is an agreement between the Health Insurance companies and all concerned Health Service Providers about the maximum costs of the offered rehabilitation service. ICT vendors serve as the supplier for the assisting technologies (e.g., the Rehab Table, the Therapist Station) and regular providers of associated IT services (e.g., software maintenance and updates, hardware maintenance). So, in general they act as ICT Service providers who sign a contract with the Health Insurance Companies, to offer the above-mentioned infrastructure and service offering to the Health Service Providers and the Insured Patients who are eligible for these specific rehabilitation-related clinical service. In some cases the ICT Service Providers also sign a contract with a broadband network provider (wired and/or wireless), so as to make use of their network infrastructure in the provision of the ICT service. In addition, they have license agreements with the owners of the intellectual property of constituting blocks of the total ICT solution. Such a reimbursement model for the provision of clinical services like the StrokeBack platform is presented in Fig. 9.22.

9.5.4 Product Certification Issues

In Europe, before a medical device is put on the market, the device is required to be affixed with a CE mark, which is an indicator of the product's compliance with EU legislation. Medical software was considered intangible and functioned as integral parts of medical devices, when the first draft of European Directives was created in the early 1990s [35]. It was not until 2007, in the preamble of Directives 2007/47/EC4 (European Parliament and the Council, 2007) that European legislators viewed certain types of software, which are "intended for one or more medical purposes set out in the definition for medical devices," as medical devices. Accordingly, regulatory requirements for these categories of medical software have been changed. These changes are reflected in the Active Implantable Medical Device Directives (AIMD) and the Medical Device Directives (MDD) [35]. The latter is further detailed in the subsequent paragraph. In a nutshell, stand-alone software and accessory software of medical devices are considered medical devices, if they are intended to satisfy the purposes explicitly defined in AIMD and MDD. As with physical devices, this type of software must be CE marked and subject to their own respective conformance assessment. Software that is not related to the core functions of a medical device, but as a component or integral part of the medical device, is not considered a medical device by the EU legislator. This type of software does not require a CE mark.

In the USA, the ***Food and Drug Administration*** (FDA) is responsible for regulation on software related to medical devices. For premarket approval, the FDA combines product-oriented and process-oriented approaches [36] to assess the software production quality, where FDA emphasizes on a well-documented and robust quality assurance practice to ensure a “rational” software development process. The most important document used in the FDA’s premarket approval review of medical software is “Reviewer Guidance for Computer-Controlled Medical Devices” (RGCCMD). The guidance defines what data are required for computer-controlled device submission and the three “levels of concerns” to categorize computer-controlled devices. With regards to the post-market surveillance, the FDA oversees marketed computer-controlled devices through Good Manufacturing Practice (GMP). Along with the assurance of device component acceptability and labelling, GMP requires manufacturers to establish QA programs, documentation for their activities products, updates, and revisions. In terms of regulations, the GMP is compatible with the international standards ISO 9001, which is adopted by the European Committee for specification of quality system requirements of medical devices.

The regulatory bodies in both EU and the USA take into account the development process in addition to the pure product-related aspects in the assessment of the medical software. The CE mark certification process requires a manufacturer of medical devices to attest conformity with all relevant New Approach Directives (NAD). However, it is important to recognize that a CE mark by itself, does not indicate conformity to a particular standard, it only indicates conformity to the legal requirements of E.U. Directives. For most of the medical software, CE marking Directives require ISO 9000 standards, common for system quality assessment.

9.5.5 European Guidelines on the Qualification and Classification of Stand-Alone Software Used in Healthcare Within the Regulatory Framework of Medical Devices

Here we summarize the most relevant to StrokeBack extracts of the guidance document issued by European Commission, DG Health And Consumer Directorate B, Unit B2 “Health Technology and Cosmetics” on the issue of Qualification and Classification of stand-alone software [37]. The guidelines presented in that document are part of a set of guidelines relating to questions of application of the EU legislation on medical devices. They are legally not binding. The guidelines have been drafted through a process of consultation of the various interested parties (Competent Authorities, Commission services, industry and Notified Bodies in the medical device sector) during which intermediate drafts were circulated and comments were taken up in the document where appropriate. Therefore this document reflects positions taken in particular by the aforementioned interested parties. Due to the participation of the aforementioned interested parties, it is anticipated that these guidelines would follow within the Member States and, therefore, ensure uniform application of relevant Directive provisions.

9.5.5.1 Qualification Criteria as Medical Device

Software can be used for a large variety of medical purposes. In that respect the arguments do not differ from those used for other medical devices. Stand-alone software can directly control an apparatus (e.g., radiotherapy treatment), can provide immediate decision triggering information (e.g., blood glucose meters), or can provide support for healthcare professionals (e.g., ECG interpretation). Not all stand-alone software used within healthcare can be qualified as a medical device. Stand-alone software may run on different operating systems or in virtual environments. These operating systems or virtual environments do not impact the qualification criteria. Stand-alone software might also be an accessory of a medical device. The risk related to a malfunction of the stand-alone software used within healthcare is in itself not a criterion for its qualification or not as a medical device. It is therefore necessary to clarify some criteria for the qualification of stand-alone software as medical devices. The decision diagram (Fig. 9.23) gives some guidance regarding the necessary steps to qualify stand-alone software as medical device.

- **Decision step 1**: if the stand-alone software is a computer program, then it may be a medical device. If the software is not a computer program, then it is a digital document and therefore not a medical device. Examples of computer programs are software applications, macros, scripts, dynamically linked libraries, batch files, style sheets, and any document containing active formatting or filtering instructions. Examples of digital documents are image files, DICOM files, digital ECG recordings, numerical results from tests and electronic health records (EHR).
- **Decision step 2**: if the software is incorporated into a medical device rather than stand-alone software, it must be considered as part of that medical device in the regulatory process of that device. If it is stand-alone software, proceed to decision step 3.
- **Decision step 3**: if the software does not perform an action on data, or performs an action limited to storage, archival, communication, "simple search" or lossless compression (i.e., using a compression procedure that allows the exact reconstruction of the original data) it is not a medical device. Altering the representation of data for embellishment purposes does not make the software a medical

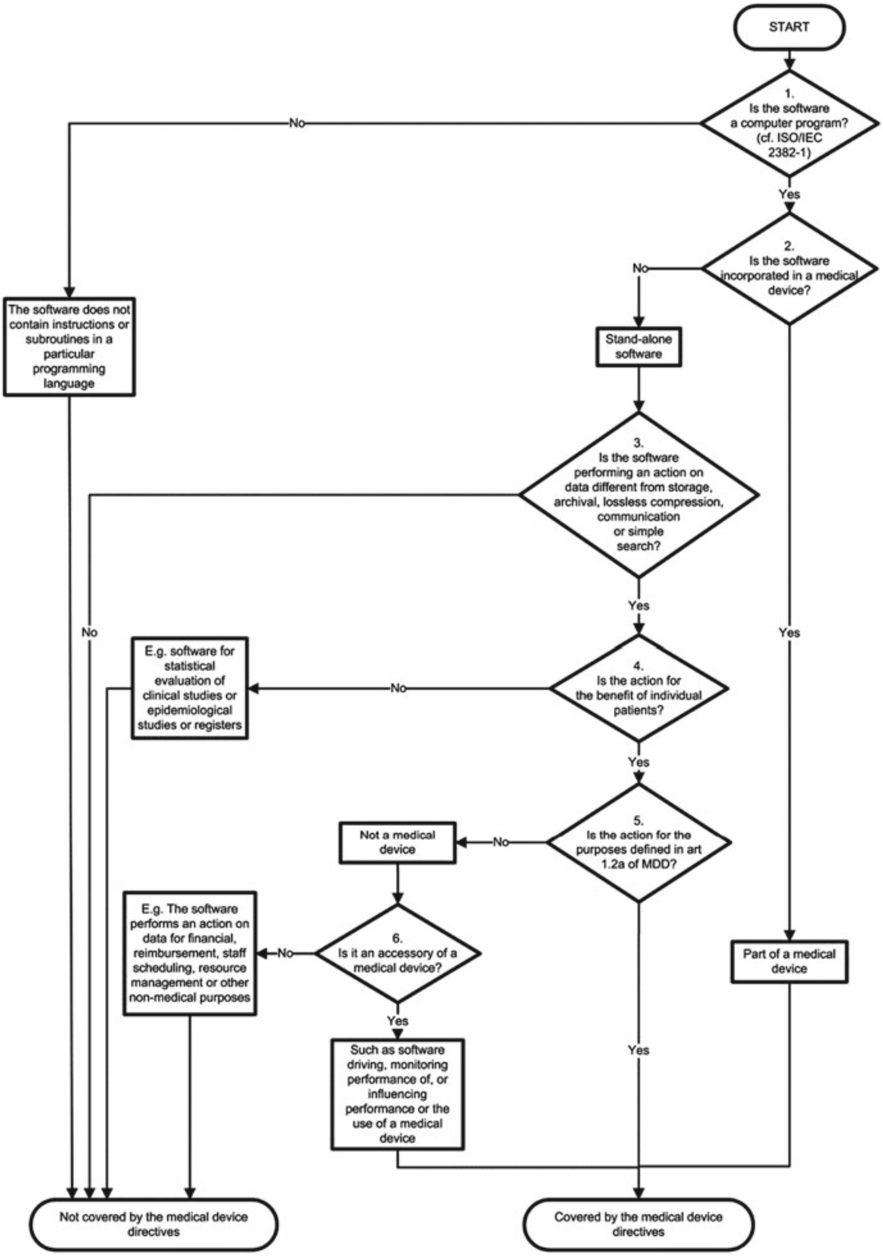

Fig. 9.23 Decision diagram for SW qualification as medical device [26]

device. In other cases, including where the software alters the representation of data for a medical purpose, it could be a medical device. "Simple search" refers to the retrieval of records by matching record metadata against record search criteria, e.g., library functions. Simple search does not include software which provides interpretative search results, e.g., to identify medical findings in health records or on medical images. Software which is intended to create or modify medical information might be qualified as a medical device. If such alterations are made to facilitate the perceptual and/or interpretative tasks performed by the healthcare professionals when reviewing medical information, (e.g., when searching the image for findings that support a clinical hypothesis as to the diagnosis or evolution of therapy) the software could be a medical device.

- **Decision step 4**: an example of software for the benefit of individual patients is software intended to be used for the evaluation of patient data to support or influence the medical care provided to that patient. Examples of software which are not considered as being for the benefit of individual patients are those which aggregate population data, provide generic diagnostic or treatment pathways, scientific literature, medical atlases, models, and templates as well as software for epidemiologic studies or registers.
- **Decision step 5**: if the manufacturer specifically intends the software to be used for any of the purposes listed in Article 1(2)a of Directive 93/42/EEC, then the software shall be qualified as a medical device. However, if only a non-medical purpose is intended by the manufacturer, such as invoicing or staff planning, it is not a medical device. A task such as e-mailing, web or voice messaging, data parsing, word processing, and back-up is by itself not considered as being a medical purpose, according to Directive 93/42/EEC.
- **Decision step 6**: if the software is an accessory to a medical device, it is not a medical device, but it falls under Directive 93/42/EEC. The legal definition of "putting into service" requires that a device is made available to the final user/operator as being ready for use on the Community market. Software made available to users over the Internet or via in vitro diagnostic (IVD) commercial services that are qualified as a medical device are subject to medical devices directives.

9.5.5.2 Classification of Stand-Alone Software

Some stand-alone software may break down into a significant number of applications for the user where each of these applications is correlated with a module. Some of these modules have a medical purpose, some not. Such software may be intended to cover many needs, e.g.:

- Collect and maintain administrative patient details.
- Keep on file the medical history of the patient.
- Invoicing and other accounting functions.
- Provide a link to the social security system for reimbursement.
- Provides links to drug prescription systems or drug dispensing outlets.

- Provides assistance for medical decision-making (e.g., radiotherapy dosage).

This raises the issue as to whether the whole product can be CE marked when not all applications have a medical purpose. Computer programs used in healthcare mostly have applications, which consist of both medical device and non-medical device modules. The modules which are subject to the MDD must comply with the requirements of the MDD and must carry the CE marking. The non-medical device modules are not subject to the requirements of medical devices. It is the obligation of the manufacturer to identify the boundaries and the interfaces of the different modules. The boundaries of the modules which are subject to the MDD should be clearly identified by the manufacturer and based on the intended use. If the modules which are subject to the MDD are intended for use in combination with other modules of the whole software structure, other devices or equipment, the whole combination, including the connection system, must be safe and must not impair the specified performances of modules, which are subject to MDD.

The sector of software pursuing a medical purpose is rapidly evolving. The list of examples provided below is not exhaustive. The examples have been drafted in the light of today's state-of-the-art, in order to give the reader a better understanding of the application of the principles set out in the guideline. In the light of the technological progress, further examples will be regularly added into the "*manual on borderline and classification in the community regulatory framework for medical devices*" [38]:

- **Hospital Information Systems (HIS)**: Hospital Information Systems mean, in this context, systems that support the process of patient management. Typically they are intended for patient admission, for scheduling patient appointments, for insurance and billing purposes. These HIS are not qualified as medical devices. However they may be used with additional modules, as described hereafter. These modules might be qualified in their own right as medical devices.
- **Decision support software**: In general, they are computer-based tools, which combine medical knowledge databases and algorithms with patient-specific data. They are intended to provide healthcare professionals and/or users with recommendations for diagnosis, prognosis, monitoring, and treatment of individual patients. Based on steps 3, 4, and 5 of Fig. 9.23, they are qualified as medical devices.

  – Radiotherapy treatment planning systems are intended to calculate the dosage of ionizing irradiation to be applied to a specific patient. They are considered to control, monitor, or directly influence the source of ionizing radiation and are qualified as medical devices.
  – Drug (e.g.: Chemotherapy) planning systems are intended to calculate the drug dosage to be administered to a specific patient and therefore are qualified as medical devices.
  – Computer Aided Detection systems are intended to provide information that may suggest or exclude medical conditions and, therefore, qualified as medical devices. For example, such systems would be able to automatically read X-ray images or interpret ECGs.

- **Information Systems**: Information systems that are intended only to store, archive, and transfer data are not qualified as medical devices in themselves. However they may be used with additional modules. These modules might be qualified in their own right as medical devices:

  – **Electronic Patient Record systems**: Electronic patient record systems are intended to store and transfer electronic patient records. They archive all kinds of documents and data related to a specific patient. The electronic patient records themselves are not computer programs, therefore, they should not be qualified as a medical device, i.e., an electronic patient record that simply replaces a patient's paper file does not meet the definition of a medical device. The modules used with electronic patient record system modules that might be qualified in their own right as medical devices are for example: an image viewer with functionality for diagnosis based on digital images; a medication module.
  – **Clinical Information Systems—CIS/Patient Data Management Systems—PDMS**: A CIS/PDMS is a software-based system primarily intended for, e.g., intensive care units to store and transfer patient information generated in association with the patient's intensive care treatment. Usually the system contains information such as patient identification, vital intensive care parameters, and other documented clinical observations. These CIS/PDMS are not qualified as medical devices. Modules that are intended to provide additional information that contributes to diagnosis, therapy, and follow-up (e.g., generate alarms) are qualified as medical devices.
  – **Pre-hospital Electrocardiograph (ECG) System**: A system for managing pre-hospital ECG is a software-based system intended for ambulance services to store and transfer information from patients, which are connected to an ECG monitor, to a doctor at remote location. Usually the system contains information about patient identification, vital parameters, and other documented clinical observations. These Pre-hospital ECG Systems are not qualified as medical devices. Modules that provide patient's treatment information to the paramedics in the ambulance to start the patient's treatment while the patient is being transported are qualified as Medical Devices.
  – **Radiological Information System (RIS)**: A RIS is a software-based database used in radiology departments to store and transfer radiological images and patient information. The system normally includes functions for patient identification, scheduling, examination results, and imaging identification details. These RISs are not qualified as medical devices. However, if such a system includes additional modules they might qualify as medical devices according to step 3 in Fig. 9.23.

- **Communication Systems**: The healthcare sector uses communication systems (e.g., email systems, mobile telecommunication systems, video communication systems, paging, etc.) to transfer electronic information. Different types of messages are being sent such as prescriptions, referrals, images, patient records, etc. Most of the communication systems handle other types of messages other than medical information. This communication system is intended for general purposes, and is used for transferring both medical and non-medical information.

Communication systems are normally based on software for general purposes, and do not fall within the definition of a medical device. Communication system modules might be used with other modules that might be qualified in their own right as medical devices. As an example we refer to software generating alarms based on the monitoring and analysis of patient specific physiological parameters.

- **Telemedicine systems**: Telemedicine Systems are intended to allow monitoring and/or delivery of healthcare to patients at locations remote from where the healthcare professional is located.

  – **Tele-surgery**: is intended to conduct a surgical procedure from a remote location. Virtual-reality technology may be used to support a remote surgeon to control a surgical robot performing the surgical procedure. Tele-surgery systems should be qualified as medical devices according to steps 3, 4, and 5 of Fig. 9.23. Remote control software used in combination with tele-surgery robots is qualified as a medical device. Communication modules themselves are not medical devices. Modules that are intended to influence surgical procedure are qualified as medical devices.
  – **Video appointment software**: Video appointment software is intended to perform remote consultations between clinics and patients. It does not fall under the Medical Devices Directives.
  – **Home care monitoring**, **wired or mobile**: The telecommunication system (mobile, wireless, wire, etc.) is not as such a medical device.

- **Web systems for monitoring data**: A web system for the monitoring of clinical data typically interacts with a medical device (e.g., implanted devices or homecare devices), and uses a transmitter to send the information over the Internet, a landline telephone, or a mobile network. The information is collected and stored on a web server usually run by an external party who is generally the manufacturer of the system. The information can be reached by authorized health professionals or the patient through an internet connection.

  – **Monitoring of performance of medical devices**: Modules that are intended to monitor the medical performance of medical devices fall under the Medical Devices Directives. This includes the clinical performance and failures that could affect medical performance of the device. One example of such product is a web system for monitoring of active implants such as pacemakers or Intracardiac defibrillators (ICDs).
  – **Monitoring of non-medical performance of medical devices**: Modules that are intended to monitor non-medical performance of medical devices do not fall under the scope of Medical Devices Directives. Example: software for the monitoring of medical devices in hospital systems for the purpose of maintenance and repair. Software modules on server(s) might be qualified in their own right as medical devices depending on their intended purpose.

- IVD software:

  – **Laboratory Information Systems (LIS) and Work Area Managers (WAM)**: LIS and WAM mean, in this context, systems that support the process from patient sample to patient result. Typically they have pre-analytical functions for ordering, sorting, and distribution of test samples. The main task is the management and validation of incoming information obtained from IVD analysers connected to the system, such as calibration, quality control, product expiry, and feedback (e.g., retesting of samples needed) through interconnections with various analytical instruments (technical and clinical validation). Finally the post analytical process takes care of communication of laboratory results, statistics and optional reporting to external databases. The software normally supports the following functions: Ordering of laboratory tests, samples with labels and sorting; Technical and clinical validation, connection to analytic instruments; Laboratory results and reports on paper, fax, or electronic records that can be directly returned to e.g., the ordering clinic's patient record; Analytical instruments can be interfaced with HIS, Electronic Patient Record Systems, Infectious control databases, etc.[1] The results are available, readable and understandable without the intervention of the software. LIS and WAM are not qualified as medical devices in themselves. However they may be used with additional modules. These modules might be qualified in their own right as medical devices.

– **Expert System**: Where software is intended to capture and analyze together several results obtained for one patient by one or more IVD devices by means of in vitro examination of body samples (possibly combined with information from medical devices) to provide information falling within the definition of an IVD medical device, e.g., differential diagnosis, this software is considered as an IVD in itself. Examples are:

  Software that integrates genotype of multiple genes to predict risk of developing a disease or medical condition.

  Software that uses an algorithm to characterize viral resistances to various drugs, based on a nucleotide sequence generated by genotyping assays. It helps to generate new information (virus resistance profile) from available information on the genotype of the virus.

  Software intended to be used in microbiology for the identification of clinical isolates and/or the detection antimicrobial resistances.

The information provided by the software is based on data obtained with IVD medical devices only or possibly combined with information from medical devices. The software is an IVD medical device or an accessory of an IVD medical device.

– **Interpretation of raw data**: In the case where software is necessary to render raw data, obtained from an IVD by means of in vitro examination of body samples, readable for the user, this software is to be considered as an accessory to an IVD when it is specifically intended to be used together with this IVD to enable it to be used in accordance with its intended purpose. Example:

[1] Software intended to modify a representation of available IVD results is not considered an IVD medical device, e.g. operations of arithmetic (e.g. mean, conversion of units) and/or plotting of results in function of time, and/or a comparison of the result to the limits of acceptance set by the user.

software intended for the analysis and interpretation of ELISA reader optical density results, line patterns, or spot patterns of a blot.
– **Home care monitoring**, **wired or mobile**: Stand-alone software intended for archiving patient results or for transferring results from the home environment to the healthcare provider is not an IVD device. The results are available, readable, and understandable by the user without the intervention of the software.

9.5.6 IPR Issues

The exploitable outcomes of the project are in the form of a total product concerning the execution of tele-rehabilitation so-called "StrokeBack system." There are few by-products and/or constituting components that are considered as individual intellectual property (IP), such as the PHR and Care Management platform, the BAN, a number of single exercises/serious games, the Patient-Station, the Therapist-Station. In that sense the consortium anticipates two types of exploitation license agreements. The first is the IP license agreement that is related to the license for integrating certain pieces of hardware/software in the project core product StrokeBack, and the second is the product license agreement, which is related to the license for marketing and selling the product in specific (most probably geographic areas related) markets.

A schematic of the relationships among the StrokeBack partners in the exploitation of the intellectual property generated in the context of the project (foreground) is shown in Fig. 9.24.

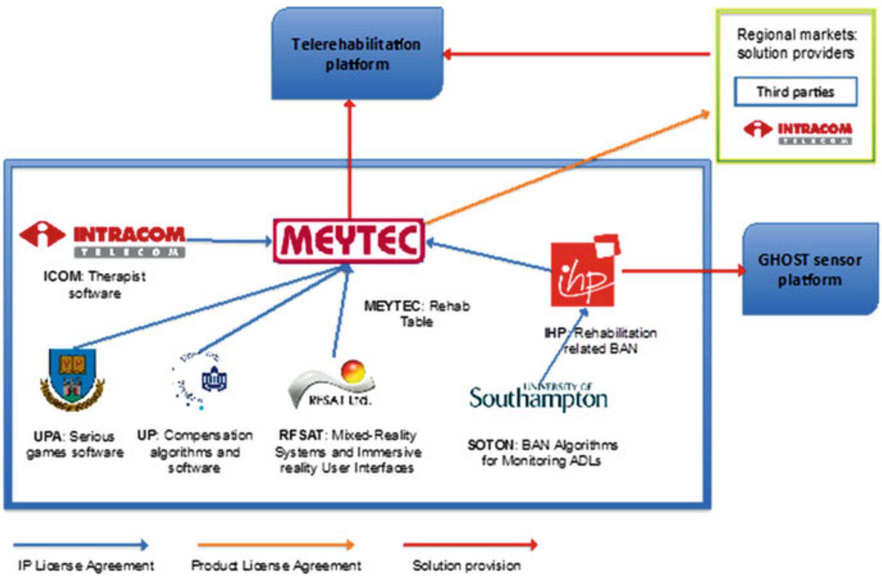

Fig. 9.24 Relationships among partners in exploitation of project results

Table 9.7 Needs for CE marking of various StrokeBack subsystems

Sub-system	Partner	CE mark needed?	Rationale
Rehab Table	Meytec	Yes	The **Rehab Table** is a device designed for use by patients. It encloses the hardware component "**Rehabilitation Table**" and the software component "**Rehab Shell**" and a set of components "**Exercises**". The software "Rehab Shell" does not perform actions on data different than storage, communication, reporting, and visualization. The software components of type "Exercises" analyze user actions, visualize a game story, and store movement data of the patient
PHR and Care Plan SW	ICOM	No	The **PHR and Care Plan Software** is a computer program (Decision step 1). The **PHR and Care Plan Software** is a stand-alone software (Decision step 2). The **PHR and Care Plan Software** does not perform actions on data different than storage, archival, communication, reporting, and visualization
			Therefore it cannot be considered as a medical device (Decision step 3). In a broader sense, **PHR and Care Plan Software** falls under the category of *Home care monitoring* and therefore it is not a medical device
BAN	IHP	No (trials)	The BAN, or respectively every single sensor node, is a mobile system that non-invasively gathers movement data, not primarily medical data. According to legal regulations, the sensor nodes need to meet the Europe norms for **safety** and for **electromagnetic compatibility** to gather permission to be used in the trials with patients. Compliance with both norms can be issued by the producer
			Hence, BAN devices do not need to be certified as medical device as long as they are used for data gathering only, while the patient is treated according to the conventional care pathway. However, if medical care decisions in a final product would be made, the BAN most probably need to be certified as medical device, but that lies beyond the scope of the project

9.5.7 The Issue of CE mark for StrokeBack Subsystems

Indication of the StrokeBack needs for requesting CE mark is shown in Table 9.7.

The CE marking signifies that the product conforms with the EC directives that apply to it: DIN EN 60601-1, DIN EN 60601-1-1, DIN EN 60601-1-2, DIN EN 980, and DIN EN 1041. MEYTEC as the developer and manufacturer of the Rehab Table devices will claim compatibility with the European norms for safety and for electromagnetic compatibility on its own.

MEYTEC and BBK agreed that the device had no certification as a medical device at the time of the trials with users. The Declaration of conformity included: manufacturer's details (name and address, etc.); essential characteristics the product complies; any European standards and performance data; if relevant the identification number of the Notified Body; and a legally binding signature on behalf of the organization.

IHP as the developer and manufacturer of the BAN devices may claim compatibility with the European norms for safety and for electromagnetic compatibility on its own. Nevertheless, IHP intends to sub-contract a professional company with executing respective performance and compliance tests to ensure patients safety and proving compliance with both norms. Preparations of respective test settings and applications have been started already.

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Chapter 10
Evaluations with Patients and Lessons Learned

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Abstract A set of exercises for different stages of stroke recovery has been collected and combined with the analysis of relevant literature and our practical clinical knowledge. This allowed for more reliable clinical testing of relevant exercises in a telerehabilitation setting, supported by teleconferencing. Based on the results of these efforts, we defined basic principles for treatment of the upper limb using preferred distal movements and evidence-based therapeutic methods of treatment. We developed a set of concrete rehabilitation exercises, focusing on motor function training including bimanual activities, coordination, reach, grasp and dexterity tasks. According to the results of discussing selected exercises and technical capabilities, we modified the rehabilitation exercises and present the final selection in this chapter.

10.1 Planned Evaluations

10.1.1 Selection and Rehabilitation Training

The S2e guideline of the German neurologic rehabilitation society "Motoric rehabilitation of the upper extremity in stroke patients" [1] was our most important database. Furthermore, we considered relevant review articles [2]. On the one hand, we extracted principles of motor learning and on the other hand concrete therapeutic interventions. We will pursue three types of training, "Selective Repetitive

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Movements" (SRM) of the upper limb, "Arm Ability Training" (AAT) and "Music Supported Therapy" (MST) as possible interventions. "Selective Repetitive Movements" of the upper limb is a therapeutic approach for patients even with massive impairment; it employs no complex movements, a high repetition rate and can easily be shaped to the rising performance of the patients [3]. "Arm Ability Training" is used to increase grip, steadiness, coordination, dexterity, aiming, strength endurance and speed of hand and finger movements. It includes eight different items and is favourably used in less to moderate handicapped stroke patients [4]. "Music Supported Therapy" was recently developed and evaluated. It includes repetitive and shaping elements and employs direct auditory feedback. It uses instruments in a step-by-step learning practice for patients with less or moderate impairments [5].

10.1.1.1 Clinical Knowledge Versus Telerehabilitation Experiences

We built up a video conference system to investigate telemedical therapeutic interventions in this setting. In general, younger aged patients performed better, communication with aphasic patients was complicated (in some cases even impossible) and neuropsychological deficits were often a barrier. In particular, complex verbal instructions were often not understood by the patients. "Selective Repetitive Movements" and "Arm Ability Training" were the best feasible therapeutic exercises in this context. In our opinion, this is explained by the good visual demonstrability of these exercises. As a baseline, the clinicians have agreed on the following basic principles for the project evaluations:

1. To restrict training exercises to upper limb only
2. The therapy to employ evidence-based training interventions
3. To focus on motor performance, sensitivity and cognitive capabilities

10.1.1.2 Subsets of Training Interventions

Following the agreed technical specifications, three subsets of training interventions were developed:

- "Selective Repetitive Movements" subset includes the joints and the movements of the upper limbs with a focus on hand rehabilitation exercises. Because distal movements are able to proximalize, we focused on distal movements. The specific movements are detailed later in this chapter. We claim that such rehabilitation training exercises may be perfectly combined with immersive serious games. High repetition frequencies are monotonous in general. That could be avoided by a serious gaming structure. Motivation, compliance and attention could be forced, too.
- "Arm Ability Training" subset uses objects of daily living. For this reason, we see a huge potential for motivating patients. In particular, patients with deficits in the activities of their daily living are addressed. Not only motor performance but also sensitivity and cognitive capability are necessary to execute the interventions and will be trained in this subset in a focused way.

- "Music Supported Training" subset requires no specific musical education. It employs music as a motivation instrument. Different musical instruments can be used and we decided to use a MIDI-enabled keyboard. The "musical supported training" is strictly structured.

A comprehensive training guideline ensures a reliable and standardized instruction of the patients. On the one hand, the three training intervention subsets make it possible to enclose patients with different impairments in the telerehabilitation setting. On the other hand, there is enough variability for a certain patient to choose different training interventions and to preserve his/her motivation and compliance. We presented and discussed the upper mentioned subsets of interventions with all consortium partners. The three proposed subsets were accepted and are presented in detail later. In the following sections, the subsets of training intervention are presented.

10.1.1.3 Serious Gaming with "Selective Repetitive Movements"

This kind of training is suitable for patients with massive impairments. Movements should be done active by one joint or as less complex as possible. Favourite movements are the distal movements: pronation, supination, dorsiflexion, palmar flexion, ulnar abduction, radial abduction, finger flexion, finger extension, finger spread, thumb abduction and pinch grip. One task should not be done less than 5 min, at most 15 min. One task means, e.g. executing dorsiflexion as often as possible, at largest range of motion, as fast as possible in the given time.

The goal of each task should be to get a larger range of motion, more strength and better endurance to achieve basic hand functions. Basic hand functions are important for involving the paretic upper limb in the activities of daily living. To ensure success, each exercise needs to be adapted to the rising performance limit. This procedure is called shaping. Generally, shaping modalities include the following types of exercises:

- With or without gravity
- Movement speed
- Training duration (per exercise)
- Use of weights
- Use of limits or checkmarks

Pronation and Supination

Pronation and supination (Fig. 10.1) are turning motor activities of the forearm. Turning point is the elbow. Pronation shows dorsal side of the hand at the top. Supination shows palmar side of the hand on the top. Dorsal is the back of the hand. Palmar is the flat of the hand. While exercising pronation or/and supination, the forearms lay on a table.

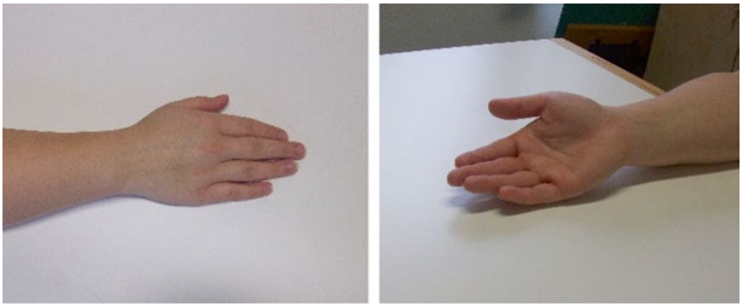


Fig. 10.1 Pronation (*left*) and Supination (*right*)

Fig. 10.2 Position 0° (*left*), Dorsiflexion (*middle*) and Palmar flexion (*right*)

Dorsi and Palmar Flexions

Dorsiflexion and Palmar flexion are one joint motor activities of the hand (Fig. 10.2). The wrist is the used joint. While exercising Dorsiflexion or/and Palmar flexion, the forearm lays on a table. In basic position one, the forearm is in position 0° without gravity. Dorsiflexion is the activity in the back of the hand direction. Palmar flexion is the activity in the palm of the hand direction. Basic position two with forearm on a pack allows to train movements over a wider range of motions.

Radial and Ulnar Abductions

Radial abduction and ulnar abduction are one joint motor activities of the hand. The wrist is the used joint. Radial abduction goes in thumb direction. Ulnar abduction goes in cubital direction. While exercising radial abduction and/or ulnar abduction, the forearm mostly lays with the palm on the table, basic position one shown in Fig. 10.3 without gravity. Basic position two: forearm on a pack, position of the wrist in pronation/supination direction 0° and in Dorsiflexion/Palmar flexion 0°, shown in Fig. 10.4 with gravity.

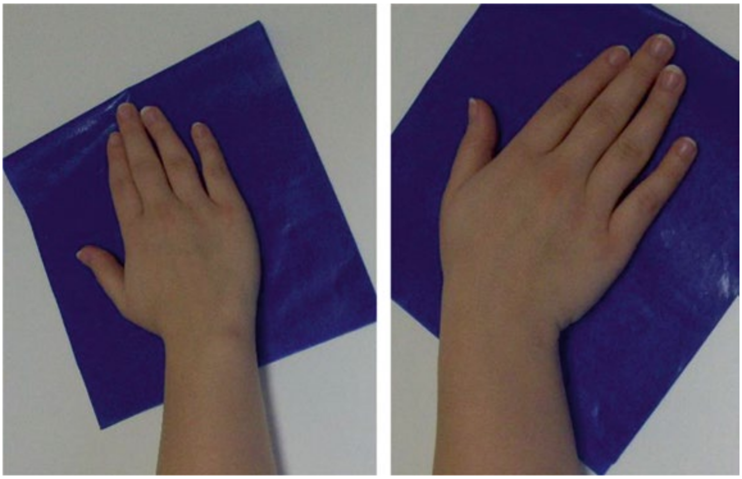


Fig. 10.3 Radial (*left*) and Ulnar (*right*) abduction

Fig. 10.4 Radial (*left*) and ulnar (*right*) abduction against gravity

Finger Flexion and Extension

Finger flexion and finger extension are simple motor activities of the hand using multiple joints. All small finger joints are the used joints. Needed joints are metacarpophalangeal joints (knuckle joints), proximal interphalangeal joints and distal interphalangeal joints. Finger flexion is making a fist. Finger extension is to open the fist. While exercising finger flexion or/and finger extension, the forearm lays on a table. Basic position one (supination/pronation 0°, dorsiflexion/palmar flexion of the wrist 0°) and basic position two (palm of the hand on a pack and finger extension with gravity) are shown in Fig. 10.5.

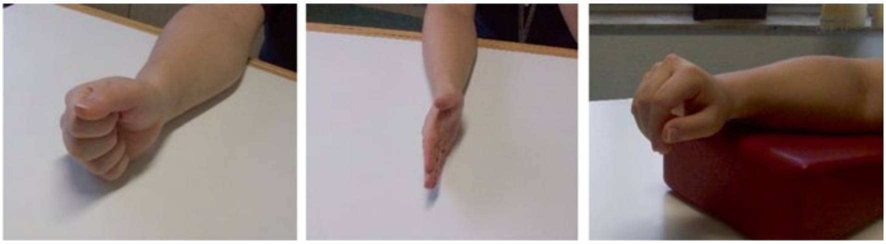


Fig. 10.5 Finger flexion (*left*), extension (*middle*) and with gravity (*right*)

Fig. 10.6 Thumb abduction (*left*) and adduction (*right*)

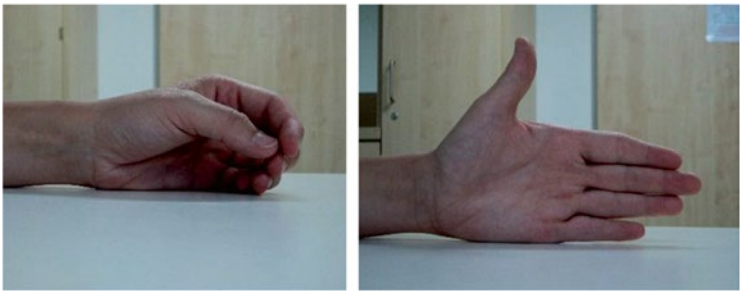


Fig. 10.7 Starting position (*left*) and thumb abduction against gravity (*right*)

Thumb Abduction and Adduction

Thumb abduction and thumb adduction are one joint motor activities of the thumb. The metacarpophalangeal joint of the thumb is the used joint. Thumb abduction direction goes away from hand. Finger adduction direction goes close to hand. While exercising thumb abduction or/and thumb adduction, the forearms and the palm of the hand lay flat on a table (Basic position one, without gravity). Basic position two: forearm and ulnar side of the hand lay on the table (shown in Fig. 10.6 without gravity and in Fig. 10.7 with gravity).

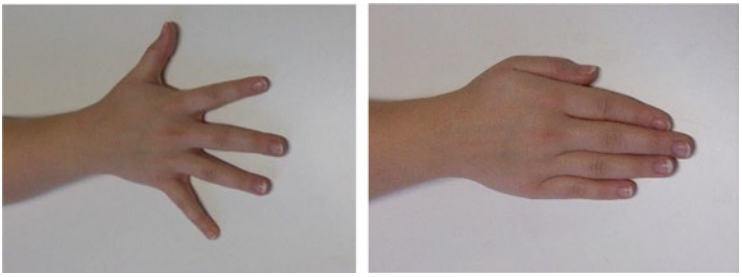


Fig. 10.8 Finger abduction (*left*) and adduction (*right*)

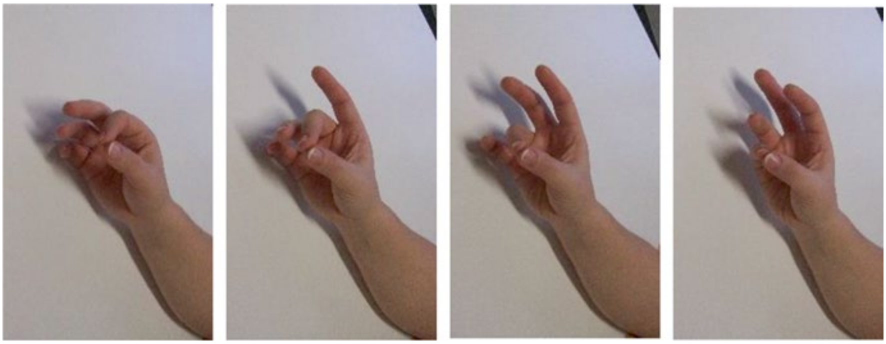


Fig. 10.9 Thumb to index-middle-ring-small finger (from *left* to *right*)

Finger Spread (Finger Abduction and Adduction)

Finger abduction and finger adduction, also called "finger spread", are motor activities of the metacarpophalangeal joints of all five fingers. Basic position one, forearm and palm of the hand lay flat on a table, as shown in Fig. 10.8 without gravity.

Pinch Grip

Pinch grip (shown in Fig. 10.9) is a motor activity of the hand using different fingers selectively. Two fingers are used. The thumb is in opposition to one of the other fingers (digit II to digit V). The finger pulps need to contact. Used joints are all small finger joints (metacarpophalangeal joints, proximal interphalangeal joints and distal interphalangeal joints). While exercising pinch grip, the forearm and the ulnar side of the hand lay on a table (Basic position one).

Possible Options for SRM

Repetitive training of simple movements is monotonous. Even increasing success will not keep the motivation of the patient on a high level. Serious gaming may increase the attention and motivation of the patient. Each "level" of a game is

Fig. 10.10 Pronation (*left*), Position 0° (*middle*) and Supination (*right*)

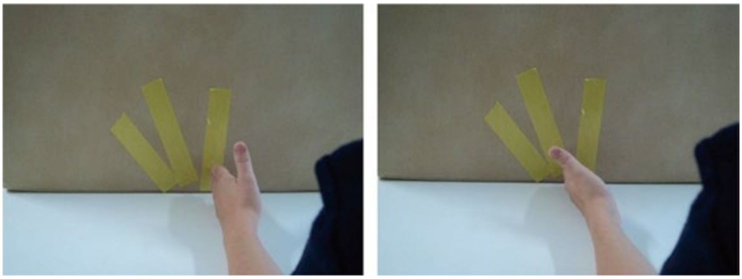


Fig. 10.11 Position 0° (*left*) and Supination to a given checkmark (*right*)

reached when specific tasks are fulfilled. In our context, fulfilling of tasks is defined by moving in a certain direction, with a minimal movement speed, with a specific number of repetitions and so on. In other words, we can define the sequence of tasks by modifying the shaping variables of the trained movements. For each movement, a sequence of shaping variables needs to be developed. In the following sections, we describe the principle shaping possibilities for each movement.

Pronation and Supination

Shaping possibilities include movement speed, training duration (per exercise), use of weights and use of limits or checkmarks. Figure 10.10 shows a shaping example for use of weights, a training possibility with a dumb-bell.

Shaping examples for use of checkmark are shown in Fig. 10.11. The patient is advised to reach a checkmark. After enlarging the range of motion to the first checkmark, the next checkmark is the next target.

Dorsiflexion

Shaping possibilities include gravity, movement speed, training duration (per exercise), use of weight and use of limits or checkmarks. Some shaping examples for working against gravity are shown in Fig. 10.12. Shaping examples for using weights and training with a dumb-bell are presented in Fig. 10.13. Shaping examples for use of checkmarks are demonstrated in Fig. 10.14.

Fig. 10.12 Starting position (left) and Dorsiflexion against gravity (*right*)

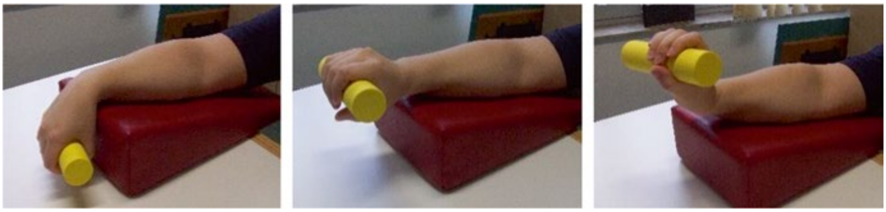


Fig. 10.13 Starting position (*left*), position 0° (*middle*) and Dorsiflexion with dumb-bell (*right*)

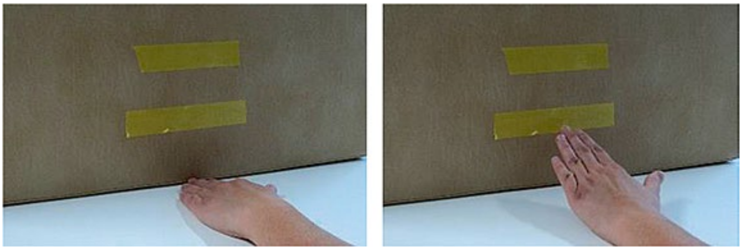


Fig. 10.14 Starting position (*left*) and Dorsiflexion with a checkmark (*right*)

Palmar Flexion

Shaping possibilities include gravity, movement speed, training duration (per exercise), use of weight and use of limits or checkmarks. Shaping examples for use of weight, training with a dumb-bell are shown in Fig. 10.15. More basic position and shaping example to train against a resistance are presented in Fig. 10.16, for example, a flexible ball has to be squeezed.

Ulnar Abduction

Shaping possibilities include: movement speed, training duration (per exercise), use of weight and use of limits or checkmarks. Shaping examples for use of weight and training against resistance are shown in Fig. 10.17 with anti-slip foil that increases the resistance. Similarly, shaping examples for use of checkmark are shown in Fig. 10.18.

Fig. 10.15 Starting position (*left*), position 0° (*middle*) and P-flex against resistance (*right*)

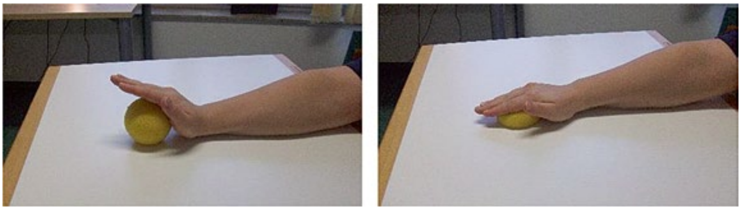


Fig. 10.16 Starting (*left*) and end (*right*) positions

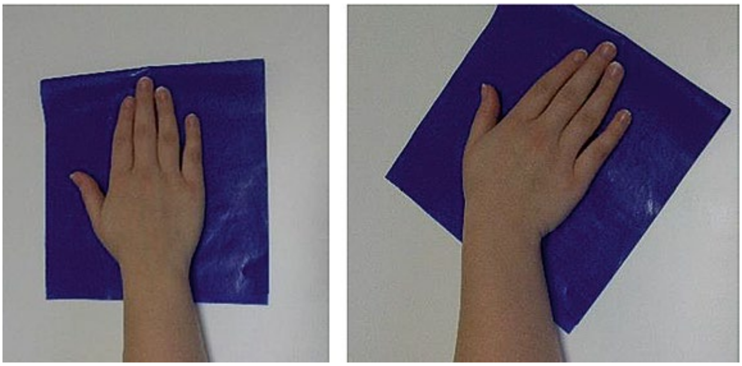


Fig. 10.17 Starting position (*left*) and Ulnar abduction against resistance (*right*)

Fig. 10.18 Starting position (*left*) and Ulnar abduction with checkmarks (*right*)

Fig. 10.19 Starting position (*left*), Position 0° (*middle*) and radial abduction against gravity (*right*)

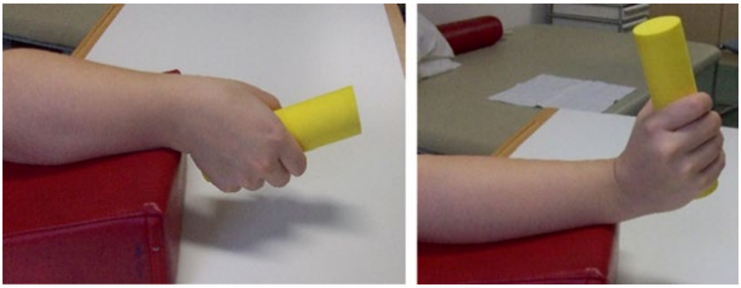


Fig. 10.20 Starting position (*left*) and radial abduction with a dumb-bell (*right*)

Radial Abduction

Shaping possibilities include gravity, movement speed, training duration (per exercise), use of weights and use of limit or checkmark. Shaping examples for working against gravity are shown in Fig. 10.19. Similarly, shaping examples for use of weights, training with a dumb-bell are presented in Fig. 10.20.

Finger Extension

Shaping possibilities include gravity, movement speed, training duration (per exercise), use of weight or resistance and use of limit or checkmark. Shaping examples for working against gravity are shown in Fig. 10.21. Similar shaping examples for use of checkmark are presented in Fig. 10.22. More shaping examples for working against gravity by using single or selective fingers are demonstrated in Fig. 10.23.

Finger Flexion

Shaping possibilities include movement speed, training duration (per exercise) and the use of weight or resistance. Shaping examples for working with resistance using a fist and fingers are shown in Fig. 10.24 for few selective fingers.

Finger Abduction and Adduction

Shaping possibilities include movement speed, training duration (per exercise) and use of weight or resistance. Shaping examples for use of resistance are shown in Fig. 10.25.

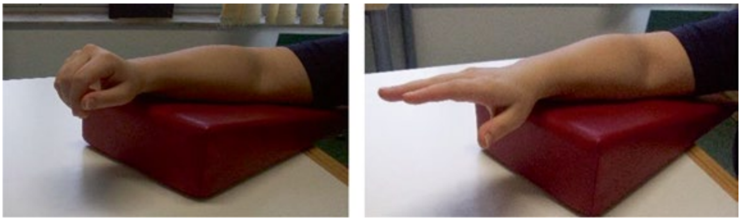


Fig. 10.21 Starting position (*left*) and finger extension against gravity (*right*)

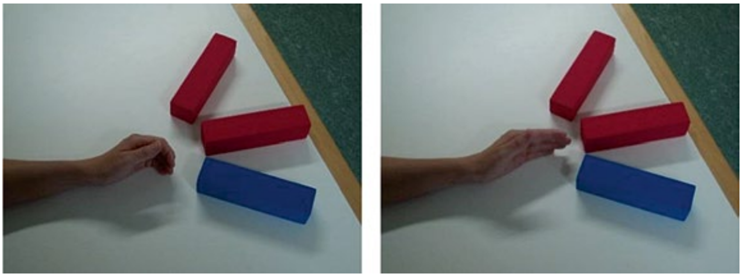


Fig. 10.22 Starting position (*left*) and finger extension by a checkmark (*right*)

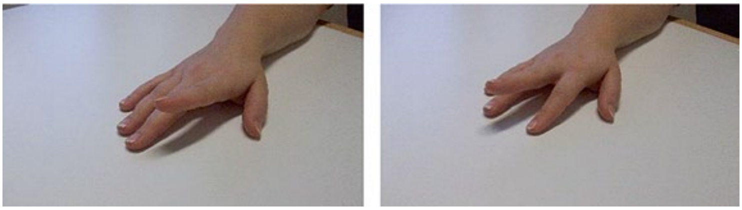


Fig. 10.23 Finger extension: index finger (*left*) and *middle* finger (*right*)

Fig. 10.24 Flexion with resistance: for five fingers (*left*) and index one (*right*)

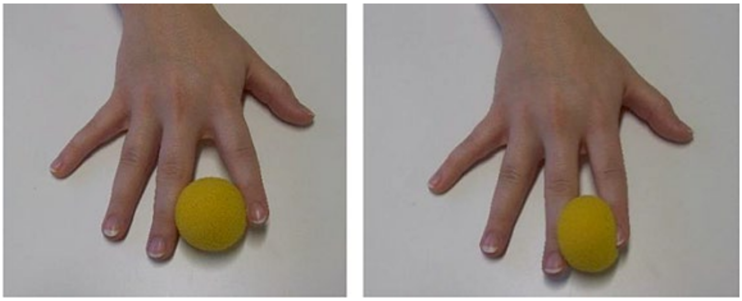


Fig. 10.25 Starting position (*left*) and finger adduction against resistance (*right*)

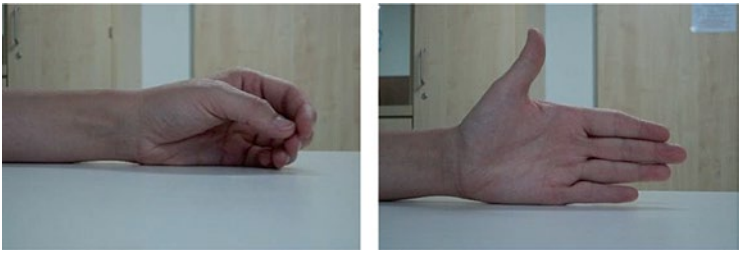


Fig. 10.26 Starting position (*left*) and thumb abduction against gravity (*right*)

Fig. 10.27 Starting position (*left*), thumb abduction (*middle*) and abduction by a given checkmark (*right*)

Thumb Abduction/Adduction

Shaping possibilities include gravity, movement speed, training duration (per exercise) and use of limit or checkmark. Shaping examples for working against gravity are shown in Fig. 10.26. Additional shaping examples for use of checkmarks are presented in Fig. 10.27.

Pinch Grip

Shaping possibilities include movement speed, training duration (per exercise) and use of weight or resistance. Shaping examples for use of resistance are shown in Fig. 10.28.

Fig. 10.28 Pinch grip without (*left*) and against resistance (*right*)

10.1.1.4 "Using Objects" According to Arm Ability Training

This subset of training intervention is employable for patients with mild to moderate impairments. It is advisable to exercise highly repetitive (many repetitions during a training session) and often (many training sessions during a week). We proposed seven objects and their correlating tasks.

The goal of each task is to get better grip force, steadiness, coordination, dexterity, aiming, strength endurance and speed of hand and finger movements. Training should stimulate the patient to involve the paretic upper limb more extensively in the activities of daily living. See the described distal movements below for further details. Each exercise needs to be adapted to the rising performance limit as well. Shaping possibilities will be described for each object in detail. General shaping possibilities include: speed, weight and level of difficulty.

Coins

The goal is to improve grasping, dexterity, coordination, speed and aiming.

The structure

- *Material*: marked base and the objects to turn (coins, glass nuggets, buttons, flat washer)
- *Options*: sizes, numbers and kinds of objects like coins to turn are given
- *Arrangement*: objects are located in a row of ten
- *Procedure*: there are four of these rows one below the other. At the beginning of the exercise, the first row is at the top. The first object is located opposite to the affected arm. An exercise takes 1 min, turned objects are counted. Each "one-minute exercise" is repeated four times (Fig. 10.29)

Fig. 10.29 Example of "Coins"

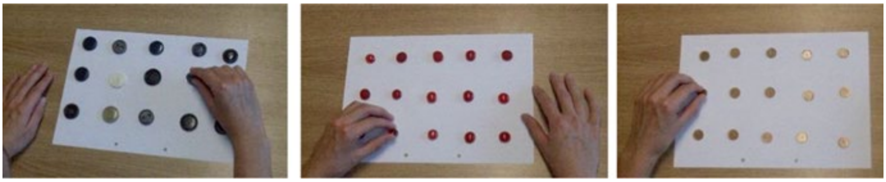


Fig. 10.30 Buttons (*left*), glass nuggets (*middle*) and coins (*right*)

Options

- Use small objects (small coins, flat washers, …)
- Use bigger objects (buttons, big coins, glass nuggets, …)
- Use many different sizes or few different sizes

  Shaping example using small and smaller objects is shown in Fig. 10.30.

Nuts and Bolts

The goal of the "Nuts and Bolts" (Fig. 10.31) is to improve grasping, dexterity, coordination, speed, aiming and bimanual activities.

The structure

- *Materials*: bolts and nuts in different sizes.
- *Options*: sizes and numbers of bolts and nuts to screw are given.
- *Arrangement*: objects are in columns arranged by size with nuts towards the affected side.
- *Objective*: the unaffected hand holds a bolt. Screws and bolts need to be assembled. They are at the top at the beginning of the exercise. Each "one-minute exercise" is repeated four times.

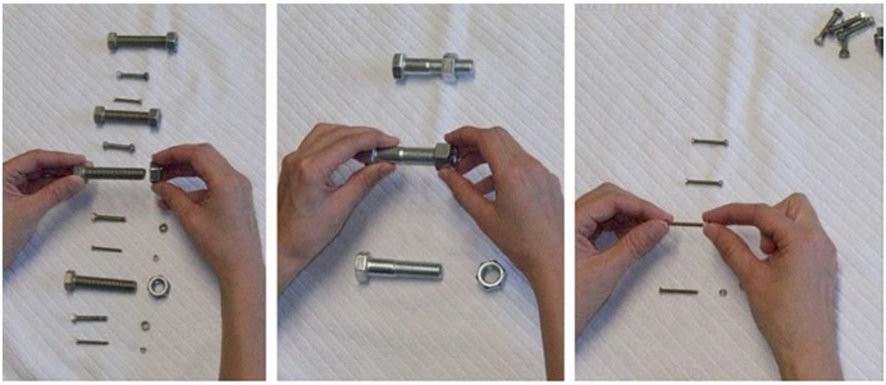


Fig. 10.31 "Bolts & Nuts" (*left*): low (*middle*) and high (*right*) difficulty

Options

- Low level of difficulty:
  - Medium and big bolts and nuts (2–3 different sizes)
  - Use of few bolts and nuts (8–12 kinds/pieces)
  - A non-paretic hand may assist
- High level of difficulty:
  - Medium and small bolts and nuts (3–5 different sizes)
  - Many bolts and nuts (12–18 kinds)
  - Only screw with the paretic hand (healthy hand uses a bolt)

Construction Blocks

The goal is to improve grasping, dexterity, arm moves, bimanual activities, coordination and endurance

The structure

- *Material*: blocks in three different sizes (e.g. mega blocks™, Duplo™, Lego™) and different colour profiles.
- *Objective*: the task is to build up a given construction out of single pieces and blocks. Time is measured and given as a feedback. Different settings are used to differentiate between levels.

Options

- Different number of blocks (less/10 to many/75)
- Lower level, e.g. "build a tower"/build a small tower of ten pieces
- Higher level, e.g. "build a high tower" of 50 pieces or build a tower, house or car by instruction
- Construction design shown on screen

Fig. 10.32 Squeezed "Knulli" (*left*), game alternatives (*middle*) and objects (*right*)

"Knulli"

The goal of the "Knulli" (Fig. 10.32) is to improve grasping, dexterity, bimanual activities, coordination and strength endurance

The structure

- *Material*: "Knulli" and small objects (coins, paper clips, nuts, buttons, nuggets, beans, pebbles).
- *Objective*: feed "Knulli" with objects (paretic hand can be used to hold or to pick up). "Knulli" opens its "mouth" when squeezed. Time is measured.

Options

- Depending on how the mouth is cut, it is easy or hard to open it
- Hand strength training:
  - "Knulli" at the affected hand
  - Use the easy/hard "Knulli"
  - Take it with the whole hand/take it only with the fingers
  - Open the mouth for long/less time
- Dexterity training:
  - "Knulli" in the unaffected hand
  - Using more small objects or using more big objects
  - Pick every piece separately
  - Collect lots of objects into the hand and put it separate into the mouth
  - More or less objects

Cans

The goal is to improve arm moves, grasp, coordination and strength endurance.

The structure

- *Material*: stair-designed frame, cans, weights (Fig. 10.33).
- *Construction*: stair-designed frame, left and right or around the screen.

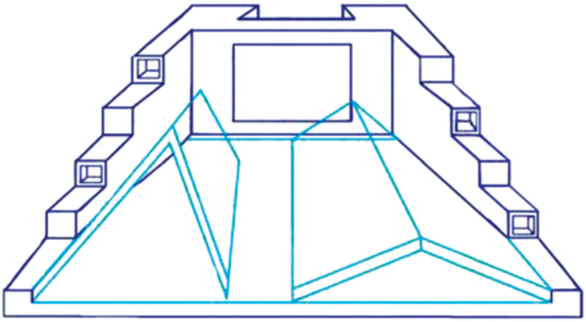


Fig. 10.33 Training field for "cans" exercise

Fig. 10.34 Variations: tower (*left*), sort by colour (*middle*) and on top (*right*)

- *Objective*: to put the can or cans on the given step or build up a construction. Time is measured and given as a feedback. Different settings are used to differentiate among levels.

Options

- Different weights of cans
- Different numbers of cans (less/10 to many/plenty/25)
- Different heights (desk level up to highest level)
- Within 1 min to stack three cans up and then take three cans down, as often as possible
- Variations: build a tower or a pyramid, in front, on a step, etc. (Fig. 10.34) or with cans upside down

Multifunction Board

The goal is to improve grasping, dexterity, arm moves, coordination and strength endurance (Fig. 10.35).

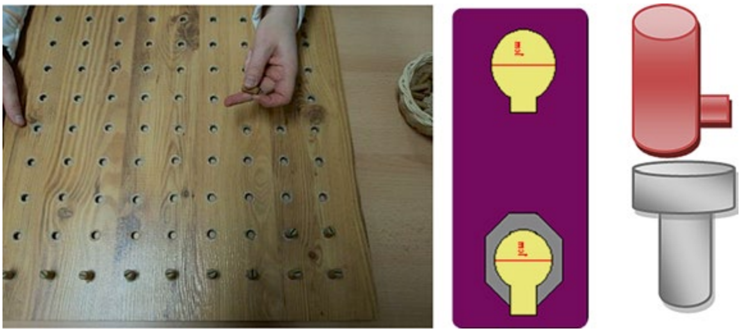


Fig. 10.35 The Board (*left*), “keyholes” (*middle*) and example “keys” (*right*)

The structure

- *Material*: Multifunction board, sticks, bolts, ropes.
- *Construction*: Plexiglas board (40 × 40 cm) with 64 shaped “keyholes”.
- *Options*: the board offers a large variety of therapeutic exercises using sticks, bolts and ropes:
  - Using real nuts or mill a thread directly into the Plexiglas board
  - Using two sticks and a bolt
- *Procedure*: time is measured and given as a feedback. Various difficulty levels are possible.
- *Objectives*:
  - *Horizontally*: the patient has several sticks in his hand and puts them individually into the holes, e.g. screwing bolts into nuts/threads, playing a “Solitaire—the anchoritic game”.
  - *Vertically*: the aim is to use threads according to on-screen instructions, e.g. to make a knot.

Options

- Horizontal or vertical board placement
- More of less sticks
- Different types of sticks
- Follow instruction

“Cube”

The goal of the “Cube” (Fig. 10.36) is to improve grasping, dexterity and fingers coordination with selective finger moves.

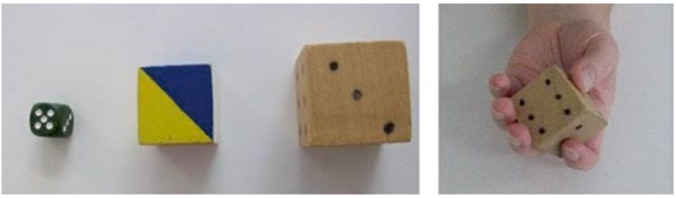


Fig. 10.36 Cubes (*left*) and cure rotating exercise (*right*)

The structure

- *Material*: cubes of small, medium and big sizes, with points or colours.
- *Objectives*: to rotate the cube in the given way.
- *Procedure*: time is a measure of success. Different difficulty levels are used.

Options

- Cubes of different sizes
- Different duration of exercises
- Variable rotation speed
- Cube used as a controller, e.g. play a song/video by turning the cube in the palm of the paretic hand (open and read "Fun-mails"/Slogans; start a comic; start an audio story and play it with the right speed/tempo)

10.1.1.5 Music Supported Therapy

This subset of training intervention is employable for patients with mild to moderate impairments. No musical knowledge is necessary. A MIDI piano (with only eight white keys are needed g–g′) is used, as in Fig. 10.37. The training is structured in 11 consecutive learning levels (see detailed description below). It is proposed to train five times a week with training sessions of 30–45 min. Repetition, shaping and auditory feedback (acoustic-sensorimotor coupling) are the employed principles of motor learning [5].

The patient sits at a height-adjustable desk (in an ergonomic upright position). A blanket in front of the keyboard on the table enables the patient to lay down the lower arms. The exercising note sequence or task is given or played at first by the therapist. In our case, lightening keys of the pianos will give the instructions. Second, the patient tries to play the sequence. If it is necessary, the patient gets help from the lightening keys of the piano. Training programme is adapting to patients' needs by changing a number of notes played (1, 2, … 8), a speed and sequences or numbers of used fingers. Each task is done 3–5 times correctly before the next task or level follows. If the task is not correctly done, the patient has to try again (Tables 10.1 and 10.2).

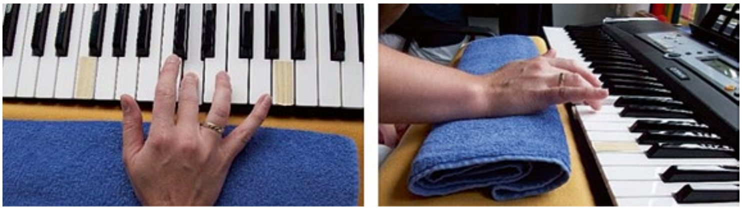


Fig. 10.37 Music supported therapy using the piano keyboard

10.1.2 Evaluations of Models

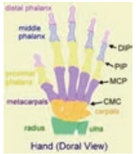
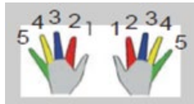
In the section above, we detailed the rehabilitation trainings that were used for evaluating the StrokeBack architecture and the StrokeBack contribution to improving the rehabilitation speed. To achieve this goal, the rehabilitation trainings need to be researched taking into account different aspects such as attractive representation of the training and efficient implementation of the training and may be most challenging real-time evaluation of the actual execution of the training by the patient. Since we aimed at taking several parameters into account which are uncorrelated, we also needed to develop a model, which describes their interdependencies. The parameters we mean are correctness of execution of rehabilitation trainings and its improvements, vital parameters during the training and during normal life, cognitive capabilities and the aforementioned parameters.

We already agreed that merely applying a couple of fixed training exercises is unsuitable from the therapeutic point of view due to the complex and wide range of individual impairments after suffering a stroke. The loss of cognitive and motion abilities will vary for each patient. As a result, we investigated a training system that can be individually trained/configured by the therapists for certain patient to fit the clinical requirements of stroke rehabilitation. Therefore, the StrokeBack system needs to “learn” new exercises on the fly, which means to model individual movement automatically in a way that allows the system to evaluate movements according to the modelled exercise later.

The calculation of three-dimensional vectors of all upper body parts provides the basis for the exercise evaluation model and also the compensation tool. The final tool is envisioned to record a complex exercise as a series of consecutive very small movements, which should then be repeated by the patient as rehabilitation exercise. The current version of this tool can automatically record exercises by manually choosing a start and stop position. Exercises can also be stored and loaded later.

We are aware of the fact that the patient can definitely not exactly repeat the same movement as it has been recorded. In addition, the measurement and calculation of the body joints by the Kinect is subject to certain deviation error. Therefore, a tolerance range for movements should be configurable by the therapist. Hence, the tool should be configurable according to the patient’s current state of rehabilitation

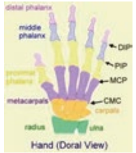
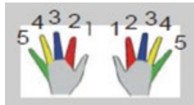
Table 10.1 Instruction manual

Level	Feature	Task	Keys	Direction	Sequence	Tries	Occupational (active/ passive) MCP, PIP, DIP exercise 	Fingers used 
1 (1 note)	Single note	1	1, 2, 3, 4…	Up	In line	8	Isolated movements of selected fingers	1/2/3/4/5
		2	8, 7, 6, 5…	Down	In line	8		1/2/3/4/5
		3	1, 7, 3, 6…	Up/down	Mixed	8		1/2/3/4/5
		4	111, 222…	Replay 3×	In line	8		1,1,1/2,2,2/3,3,3
2 (2 notes)	Note steps	1	1 2, 2 3, 3 4…	Up	In line	7	Isolated movements of selected fingers combo moves of two nearby fingers	1/2/3/4/5
								1,2/2,3/3,4/4,5
		2	1 2, 5 6, 2 3…	Up	Mixed	7		1/2/3/4/5
								1,2/2,3/3,4/4,5
		3	8 7, 7 6, 6 5…	Down	In line	7		1/2/3/4/5
								2,1/3,2/4,3/5,4
		4	6 5, 2 1, 8 7…	Down	Mixed	7		1/2/3/4/5
								2,1/3,2/4,3/5,4
		5	1 2, 2 1, 2 3…	Up/down	In line	14		1/2/3/4/5
								1,2/2,1/2,3/3,2…
		6	4 5, 7 6, 1 2…	Up/down	Mixed	14		1/2/3/4/5
								1,2/2,1/2,3/3,2…

3 (2 notes)	Note range	1	1 2, 1 3, 1 4…	Up	In line	7	Isolated movements of selected fingers/jump combined moves of two fingers	1/2/3/4/5
								1,1/1,2/1,3/1,4/1,5
		2	8 7, 8 6, 8 5…	Down	In line	7		1/2/3/4/5
								5,1/4,1/3,1/2,1/1,1
		3	1 2, 2 1, 1 3…	Up/down	In line	14		1/2/3/4/5
								1,2/2,1/1,3/3,1…
		4	1 4, 1 7, 1 3…	Up	Mixed	7		1/2/3/4/5
								1,1/1,2/1,3/1,4/1,5
		5	8 7, 8 3, 8 4…	Down	Mixed	7		1/2/3/4/5
								1,1/1,2/1,3/1,4/1,5
		6	1 4, 3 1, 1 3…	Up/down	Mixed	14		1/2/3/4/5
								1,2/2,1/1,3/3,1…
4 (3 notes)	Note steps	1	1 2 3, 2 3 4…	Up	In line	6	Isolated moves of selected fingers combo moves of three nearby fingers combo moves with jumps	1/2/3/4/5 & 1,2,3/2,3,4…
		2	4 5 6, 2 3 4…	Up	Mixed	6		1/2/3/4/5 & 1,2,3/2,3,4…
		3	8 7 6, 7 6 5…	Down	In line	6		1/2/3/4/5 & 3,2,1/4,3,2…
		4	4 3 2, 6 5 4…	Down	Mixed	6		1/2/3/4/5 & 3,2,1/4,3,2…
		5	1 2 3, 3 2 1…	Up/down	In line	12		1/2/3/4/
								1,2,3/3,2,1/2,3,4…
		6	6 7 8, 5 4 3…	Up/down	Mixed	12		1,2,1/2,3,2… all directions
5 (3 notes)	Note range	1	1 2 4, 1 2 5…	Up	In line	15	Combined moves of three different fingers/isolated movements of selected fingers	1,2,3/1,2,4/1,2,5/2,3,5
		2	1 3 4, 1 4 5…	Up	In line	15		1,2,3/1,3,4/1,4,5/2,4,5
		3	4 3 1, 5 4 1…	Down	In line	15		4,3,1/5,4,1/5,4,2
		4	4 3 1, 5 4 1…	Down	In line	15		4,3,1/5,4,1/5,4,2
		5	4 2 1, 5 2 1…	Down	In line	15		4,2,1/5,2,1/5,3,2

(continued)

Table 10.1 (continued)

Level	Feature	Task	Keys	Direction	Sequence	Tries	Occupational (active/ passive) MCP, PIP, DIP exercise 	Fingers used 
6 (4 notes)	Note steps	1	1 2 3 4, 2 3 4 5…	Up	In line	5	Isolated moves of selective fingers combined moves of four nearby fingers, combined moves with jumps	1/2/3/4/5
								1,2,3,4/2,3,4,5
		2	4 5 6 7, 1 2 3 4…	Up	Mixed	5		1/2/3/4/5
								1,2,3,4/2,3,4,5
		3	8 7 6 5, 7 6 5 4…	Down	In line	5		1/2/3/4/5
								4,3,2,1/5,4,3,2
		4	4 3 2 1, 6 5 4 3…	Down	Mixed	5		1/2/3/4/5
								4,3,2,1/5,4,3,2
		5	1 2 3 4, 4 3 2 1…	Up/down	In line	10		1/2/3/4/5
								1,2,3,4/4,3,2,1
		6	4 5 6 7, 4 3 2 1…	Up/down	Mixed	10		1/2/3/4/5 & 1,2,3,4/4,3,2,1
								1,2,1,2/2,3,2,3 all directions
7 (4 notes)	Note range	1	1 3 4 5, 1 4 5 6…	Up	In line	10	Combined moves of four different fingers	1,2,3,4/2,3,4,5/1,3,4,5
		2	1 2 4 5, 1 2 5 6…	Up	In line	10		1,2,3,4/2,3,4,5/1,2,4,5
		3	1 2 3 5, 1 2 3 6…	Up	In line	10		1,2,3,4/2,3,4,5/1,2,3,5
		4	5 4 2 1, 6 5 4 1…	Down	In line	10		4,3,2,1/5,4,3,2/5,4,3,1
		5	5 4 2 1, 6 5 2 1…	Down	In line	10		4,3,2,1/5,4,3,2/5,4,2,1
		6	5 3 2 1, 6 3 2 1…	Down	In line	10		4,3,2,1/5,4,3,2/5,3,2,1

8 (5 notes)	Note steps	1	1 2 3 4 5, 2 3 4 5 6…	Up	In line	4	Isolated moves of selected fingers, combined moves of five nearby fingers, combined moves with jump	1/2/3/4/5 & 1,2,3,4,5
		2	4 5 6 7 8, 1 2 3 4 5…	Up	Mixed	4		1/2/3/4/5 & 1,2,3,4,5
		3	8 7 6 5 4, 7 6 5 4 3…	Down	In line	4		1/2/3/4/5 & 5,4,3,2,1
		4	5 4 3 2 1, 7 6 5 4 3…	Down	Mixed	4		1/2/3/4/5 & 5,4,3,2,1
		5	1 2 3 4 5, 5 4 3 2 1…	Up/down	In line	8		1/2/3/4/5 & 1,2,3,4,5/5,4,3,2,1…
		6	5 4 3 2 1, 8 7 6 5 4…	Up/down	Mixed	8		1/2/3/4/5 & 1,2,3,4,5/5,4,3,2,1…
9 (5 notes)	Note range	1	1 3 4 5 6, 1 2 4 5 6…	Up	In line	12	Combined moves of five different fingers	1,2,3,4,5
		2	1 2 3 5 6, 1 2 3 4 6…	Up	In line	12		1,2,3,4,5
		3	6 5 4 3 1, 6 5 4 2 1…	Down	In line	12		5,4,3,2,1
		4	6 5 3 2 1, 6 4 3 2 1…	Down	In line	12		5,4,3,2,1
10 (song/2–8 notes)	Note range & note steps	1	Scale	Easy	In line	6	Isolated moves of selected fingers, combined moves up to five nearby fingers	1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
		2	Note repetition	Easy	In line	7		1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
		3	Scale	Medium	In line	8		1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
		4	Note repetition	Medium	In line	8		1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
		5	5-note repetition	Advanced	In line	6		1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
		7	All songs	Difficult	In line	100		1,1,1/2,2,2/3,3,3… & 1/2/3/4/5
11 (10a) (songs/2–8 notes)	Note steps/range	6	Scale/note repetitions/note jumps	Easy/medium/advanced/difficult	In line/mixed	20	Isolated moves of selected fingers, combined moves of up to five different fingers	1,1,1/2,2,2/3,3,3… & 1/2/3/4/5

Table 10.2 Notes about the schedule

Notes		Fingers	Comments
Key 1 = note g	Key 5 = note d	1 = thumb	*In line* = systematic up and down of single notes
Key 2 = note a	Key 6 = note e	2 = index	*Mixed* = up and down of single notes alternate, but randomized
Key 3 = note h	Key 7 = note f	3 = middle	
Key 4 = note c	Key 8 = note g′	4 = ring	
		5 = little	

and expected precision of movements. To cope with this, we investigated means to allow evaluating whether the execution of movements is valid or out of certain scope according to individually adaptable margins within the tolerable room of movements. The current version measures deviation from ideal movements by variation in the off-axis angles of each vector representing a certain body part, e.g. the upper or lower arms. The allowed deviation from the recorded exercise can now be set manually while starting the monitoring tool. The monitoring tool has been extended to support multi-exercise monitoring. Each recorded exercise can be configured to trigger a certain event up on correct execution. The tool provides monitoring several previously recorded exercises in parallel.

10.1.3 Ethical Procedures of the Evaluation Studies

An official application for a proof-of-principle study to be executed in the Berlin-Brandenburg-Klinik has been requested in order to comply with necessary ethical and clinical requirements. The study refers to the StrokeBack project and its main achievements, i.e. the patient station, its mobile variant and the Body Area Network (BAN) for daily life monitoring. The key question of this investigation is whether the StrokeBack rehabilitation measures can be applied in daily life outside a clinic? Technical means and rehabilitation quality will be evaluated too. Therefore, several state-of-the-art rehabilitation measures and questionnaires for patients, therapists and technicians are part of the rehabilitation cycle under investigation. The application also lists respective inclusion and exclusion criteria for patients willing to participate in the study. Selected patients will be guided how to use the StrokeBack system during their stationary rehab phase and can optionally use the StrokeBack system for another 3 weeks at home. Therefore, a maximum of four systems might be used in parallel. Regular tests and measures will be executed to analyse and compare evaluation outcome of StrokeBack with state-of-the-art assessments.

The StrokeBack study needed to adhere to national and international law and rules for clinical trials. In addition, each project member participating in a study needed to commit to privacy protection compliant with German laws. The approval has been granted without additional conditions. Consequently, StrokeBack studies have been conducted at the Berlin-Brandenburg-Klinik in Bernau in Germany.

10.1.3.1 Execution and Control of Study

The quality of the StrokeBack study was controlled by consequently following a number of guidelines and documents for patients and therapists. Those included appropriate patient information and informed consent between scientists and patients too. In order to be able to produce comparable results of equal quality for all patients in the study, the evaluations were started following unified guidelines for therapists and patient documented as checklists. Different checklists have been prepared for patients, therapists and assessment means.

The patient information sheet provided to the subjects introduced the StrokeBack project and informed about its goals, strategies and rehabilitation means to be investigated. It further described the envisioned rehabilitation workflow and what the patient can expect from his/her participation and what the patient was expected to do, respectively. Based on the patient information sheet, a face-to-face interview with the patient was conducted in order to sign an informed consent paper to accept participation in the study. Certainly, this agreement could be terminated by the patient at any time.

For patient–individual assessment of the study performance, different questionnaires were filled for every patient taking part in the study. Given answers would provide a basis for assessment from different viewpoints determining rehabilitation outcome, usability and technical feasibility of the StrokeBack approach.

10.1.3.2 Assessment and Validation of Rehabilitation Effectiveness

The StrokeBack study was accompanied by a couple of standard rehabilitation tests and measures to assess the success of the rehabilitation means. Every patient included in the study participated for 6 weeks. Within this time, the assessment means were executed four times, i.e. every 2 weeks over the duration of the study.

The WMFT has been introduced in previous deliverables as the standard measure to determine the physical abilities of a patient. The WMFT consists of 17 small tasks that are to be performed by the patient whilst the therapist rates the performance with marks in between 0 (very bad, no functionality) and 5 (best, normal).

In this task, the patient has to put 9 little timber slats from a small box into 9 holes of a flat board and back into the box one by one. The goal for the patient is to do this as fast as possible. For comparison, both the affected and the unaffected arm have to perform the test.

This test is done in sitting position. The proband has exactly 1 min to move small dices from one box over a small wall into another box (from left to right or vice versa). The number of dices successfully moved within this minute is rated as a score. The patient has to perform this test twice using the affected and unaffected arm, respectively.

The Barthel Index assesses motor skills and thereby the state of rehabilitation. It is a score-based analysis done by an observing person, i.e. the therapist or clinician in our case. It validates the way of daily life of the patient and includes the following activity areas: visit of a toilet, eating and drinking, mobility, transfer, bathing/showering, walking, clothing, incontinence and stair climbing. Ten activities will be rated with a score from 0 (worst, completely dependent) up to 10 (best, completely independent). The sum of all scores finally determines the actual state of the patient.

This is questionnaire based on a rating system that is to be filled by an interviewer. The patient has to answer 49 specific questions about daily activities, personality, family affairs, speech, mobility, social behaviour, etc. Each question will be rated with 0 (bad) to 5 (very good/normal) points. Higher points accordingly determine a better rehabilitation state.

10.2 Conclusions

This chapter presents the rehabilitation exercises pursued in StrokeBack in detail and describes the scientific and practical principles underlying these exercises. We aimed to rely on three different types of interventions, i.e. "Selective Repetitive Movements" combined with serious gaming, "Using objects" according to AAT and "Music Supported Therapy". Technical compliance tests have been conducted to validate technical possibilities and limitations of the proposed exercises when capturing movements with a single camera.

We have refined all aspects of therapeutic interventions pursued in StrokeBack. We still rely on the common occupational therapy, concentrating on hand rehabilitation, automatic clinical assessment of patient's motor skills/recovery progress according to the WMFT and feasible occupational training using real objects.

We aimed to follow the following three main directions:

1. "Selective Repetitive Movements" in combination with serious games: This kind of training is suitable for patients with massive impairments. All movements (or single exercise) should be carried out using one active body joint only or as least complex movement complex as possible. Favourite movements are distal movements, such as pronation, supination and dorsiflexion. One exercise should be carried out in between 5 and 15 min, trying to reach the widest range of motion as fast as possible in the given time. The goals of these exercises are to achieve a larger range of motion, more strength and better endurance to achieve basic hand functions.
2. "Usage of Objects" according to AAT: This subset of training intervention is employable for patients with mild to moderate impairments. It should be executed as often as possible in a highly repetitive manner. The usage of seven objects and their correlating tasks have been given in D2.2. This training should encourage the patient to involve the paretic upper limb more extensively in the activities of daily living.
3. "Music Supported Therapy": This subset of training intervention is employable for patients with mild to moderate impairments. A piano, or more exactly only eight adjacent white keys from notes g–g′, is applied for this kind of therapy.

Nomusical knowledge is required. It is proposed to train five times a week in training sessions of 30–45 min.

For training with repetitive movements, wrist monitoring tool based on near-field use of the Kinect (refer to Chap. 7) has been implemented by RFSAT. It allows recognizing four basic movements of the hand, i.e. up, down, left, right, while the wrist and the lower arm, respectively, are not moved at all.

Regarding training with instrumented objects, IHP investigated using one or more of StrokeBack BAN nodes to be integrated into a die (refer to Chap. 3). The task of the integrated node is then to gather and report the orientation of the die in real time while being used in therapy, e.g. which side of the die is currently on top. This sensor-equipped cube has been prototyped. Furthermore, IHP assembled an instrumented version of the multifunction board as well. Using cubes, dies or other objects for simple tasks is common in occupational therapy. The goal was to provide simple but effective occupational therapy means for home use.

For MST, a MIDI-enabled keyboard with lighting key and access to the central processing station has been purchased. This keyboard will be programmed for therapy use (described earlier in this chapter). Certainly, both therapy means will be useful for patients with mild to moderate impairments only.

Besides the training exercises, the daily activities to be monitored by the BAN throughout the day have been further refined after the analysis and assessment of data from first tests with stroke patients, from April 2014 until early 2015. This seems feasible to further investigate the following subset of ADL:

1. Reach and retrieve object
2. Lift cup to mouth and return to table
3. Swing arm in horizontal plane through 90° and return
4. Rotate wrist through 90° and return

A second recording of movement data with stroke patients done at BBK included the R-WMFT and a semi-naturalistic scenario (making a cup of tea) has been performed in March 2013. Recorded data are taken to further investigate correctness of classification algorithms as well as to determine the most effective training means for the clinical assessment scenario.

A long-term sensor recording (over 3 weeks long) including monitoring of basic movements and the semi-naturalistic scenario has been accomplished (refer to Chap. 4). There, five patients have been selected to repeat all exercises twice a week to monitor changes during their rehab stay over time. Gathered data has been utilized to further improve accuracy of the algorithms applied for ADL recognition. These algorithms have been used as basis for developing the novel movement detection ASIC.

Partner UP has merged the tool for individualized training and the novel compensational analysis component into one single tool, finally called Exercise Evaluation Tool (EET). On the one side, the EET can therefore be used for training of upper limb with recorded movement sequences, which the patient has to follow. The EET automatically analyses the correctness of these exercises. The previous version has been extended by further fine-tuning options for separate limb parts (shoulder, upper arm, lower arm), e.g. how much the patient's movement in each part can vary from the original exercise. On the other hand, similar features have been implemented to detect compensational movements during training, e.g. whether the patient remains in upright position when training with objects.

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