Pervasive Sensing and M-Health: Vital Signs and Daily Activity Monitoring

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Abstract. Recent advances in pervasive sensing, mobile, and pervasive computing technologies have led to deployment of new smart sensors and smart sensor networks architectures that can be worn or integrated within the living environment without affecting a person's daily activities. These sensors promise to change vital signs and motor activity monitoring from snapshot mode to continuous monitoring mode, enabling clinicians, therapists but also accompanying persons of elderly or people with chronic diseases or disabilities to provide healthcare services based on remote continuous monitoring of the patient, pervasive health monitoring or pervasive healthcare. Using computer resources expressed by networks of servers, storage applications and Web services health monitoring and healthcare might be rapidly provisioned and released with minimal management effort or service provider interaction by using computational intelligence and Semantic Web.

A brief literature review on healthcare challenges, the deployment of unobtrusive sensors that may be used as part of pervasive sensing systems for vital signs and daily motor activity monitoring, mobile health applications and pervasive computing for pervasive health monitoring and pervasive healthcare are presented in this chapter. The chapter encompasses examples of unobtrusive sensors for health and motor activity monitoring as well as Android OS and iPhone mobile applications from Apps Store for vital and sensory function test, emergency, stress management, brain activity management, nutrition, and physical exercises. Mobile healthcare architectures developed with the contribution of the authors for vital signs and motor activity remote monitoring as well as for indoor air quality monitoring and alert on respiratory distress, which includes wearable devices (wrist worn device) and sensors integrated in objects such as walker and wheelchair are also presented in this chapter.

The presented pervasive sensing and pervasive computing approaches for health monitoring and care underscore the capabilities of this kind of systems to assure more closely coordinated forms of health and social care provision as well as personalized healthcare for better quality of life.

Keywords: pervasive sensing, mHealth, cardiorespiratory assessment, motor activity, pervasive computing.

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1 Introduction

The combination of reducing birth rate with increasing life expectancy has raised the need to urgently address aging population pressure on healthcare systems. This healthcare "time bomb" has accelerated the growth in pervasive distributed healthcare technologies that should reduce health interventions costs and improve quality of care for elderly. Strong evidences exist now showing that declining the disability among the elderly for the past several decades [1] was mainly related with improved medical technology and behavioural changes. As is known, disability is closely tied to medical spending, so that reductions in disability can lead to an offset in public and private medical costs. For instance, the United State of America spends $250 billion annually, or 2.5 per cent of the gross domestic product (GDP), on medical care for the elderly [1]. Furthermore, the new health information technology (HIT) for elderly enables a paradigm shift from the established centralized healthcare model to a pervasive, user-centred and preventive overall health management.

Across the developed world, we are witnessing the healthcare environment changing towards integrated and shared care, in which besides the responsibility of health professionals and other caregivers, each individual has the responsibility in managing the issues related with their health. This vision of the future healthcare system may be mainly achieved by deployment of pervasive health monitoring and pervasive healthcare technologies that may allow more closely coordinated forms of health and social care provision as well as personalized medicine. Pervasive healthcare (PH) is an emerging field with considerable technological breadth that is expected to have a strong impact for the quality and efficiency of healthcare. This field is still a nascent one, with a good deal of exploratory research [2]. Pervasive healthcare may be defined from two perspectives: i) as the application of pervasive computing technologies for health care, and ii) as making health care available everywhere, anytime and to anyone [3]. The pervasive healthcare applications include pervasive health monitoring, intelligent emergency management system, pervasive healthcare data access, and ubiquitous mobile telemedicine. Pervasive health monitoring and pervasive healthcare combine various type of health information technologies as: mobile health (see section 4. mHealth), personal health records (PHRs), patient centered medical home (PCMH), e-Patient (health consumer who uses the Internet to gather information about a medical condition of particular interest to him, and who uses electronic communication tools - including Web 2.0 tools - in coping with medical conditions, see http://en.wikipedia.org/wiki/E-patient), eHealth Collaborative (community wide health information exchanges, e.g. www.maehc.org). For large adoption of these technologies, researches and pilot deployment should emphasize the added value to health and social care, the cost-effectiveness of implementation, the security and the privacy of patient health data storage and communication, as well as 'clinical proof-of-concept'.

Sensor-enhanced health information systems may provide subject-centered services in a semantically interoperable environment (see section 5. Pervasive Computing). Smart sensors technology has been identified as a strong asset for achieving the vision of pervasive healthcare. Using unobtrusive smart sensors based on inexpensive, unobtrusive low-power sensors and embedded processors with large-scale storage and reasoning for semantic data as well as communication network combined with cloud computing, the pervasive healthcare may improve overall quality of life, increase independence, prevent emergencies, and motivate healthy behaviour and disease prevention.

We present in this chapter a brief literature review on healthcare challenges, the deployment of unobtrusive sensors that may be used as part of pervasive sensing systems for cardiorespiratory and daily motor activity monitoring, mHealth applications and pervasive computing for pervasive health monitoring.

2 Healthcare Challenges

Demographic developments, social changes, increasing cost of healthcare services (the cost of healthcare services has reaching values between 10% to 15% of the Gross National Product in USA or EU [4,5]), and an exponential increase in the elderly population in developed countries [6] have created major challenges for society, policy makers, healthcare providers, hospitals, insurance companies, etc. According to Population Division, DESA, United Nations report [7], the life expectancy in the 21st Century will increase, by important increasing of the 60 or over age group. The report underscores the increasing in developed regions of the 60 or over age group from 21.4% in 2009 to 27.4% in 2025, and referring to the whole world population from 8.5% to 12.5%. This tendency means also the increasing of healthcare demands, which can be solved by increasing the home-telecare services using pervasive sensing and pervasive computing technologies. Moreover, despite the growing complexity in healthcare, there is limited online support at the bedside to help healthcare professionals deliver the best standard of care for each patient. In addition, while controlled clinical trials remain the staple of progress in biomedical science, the additional wealth of information that might be reaped from millions of encounters in day-to-day medical practice remains untapped [8]. This need for effective individualized health monitoring and delivery has resulted in the new concepts - 'personalized healthcare' and 'personalized medicine'. Personalized medicine is a medical model that proposes the customization of healthcare, with all decisions and practices being tailored to the individual patient by use of genetic or other information. Michael O. Leavitt defined Personalized Healthcare [8] as a model that may: predict our individual susceptibility to disease, based on genetic and other factors; provide more useful and Personalized tools for preventing disease, based on that knowledge of individual susceptibility; detect the onset of disease at the earliest moments, based on newly discovered chemical markers that arise from changes at the molecular level; pre-empt the progression of disease, as a result of early detection; and target medicines and dosages more precisely and safely to each patient, on the basis of genetic and other personal factors in individual response to drugs. A more holistic definition for personalized healthcare was proposed at ISPOR International Meeting in 2011 [9] where it was stated that it should extend beyond genetic profiles and incorporate what is known about each patient/person in order to know which interventions are most effective for which patients under what conditions. Personalize healthcare should also incorporate personal needs, preferences, healthcare access, and adherence attribute [9]. Personalized healthcare is envisioned as a system in which doctors, pharmacists, and other healthcare providers customize treatment and management plans for individuals. It will be founded upon vast amounts of information that will be readily accessible at clinics and hospital bedsides. The driver are the many applications of information technology that have blossomed during the biomedical revolution. For example, tools related to electronic health record may allow easy dissemination and flow of data about medical history, genetic variability, and even patient preferences. Patients will ultimately receive this information, specifically as it applies to them [8]. Personalized healthcare could help address difficulties associated with the public health promotion and care delivery by using broader and deeper patient information and applying more complete clinical knowledge to help promote patient-centered health and predict, prevent, aid in early detection of diseases, treat and manage diseases. Through scientific progress, personalized healthcare has great potential to improve quality and reduce overall costs of health promotion and care delivery [10].

Environmental conditions, mainly the indoor air quality, are key factors in wellbeing of the persons that stay for long periods inside buildings. Moreover, changes in climatic conditions and increases in weather variability affect human wellbeing, safety, health and survival in many ways [11]. Although some vector-borne diseases will expand their range and seasonality, and death tolls will increase because of heat waves, also the indirect effects of climate change on basic human needs such as food, water and shelter will be likely to have a big effect on global health [12]. The health of millions of people will be compromised through an increase in the frequency of intense hurricanes, cyclones, and storm surges causing flooding and direct injury, increasing the health risk among those living in urban slums and where shelter and human settlements are poor [13]. With this will come unemployment, homelessness, dislocation, migration, and conflicts. All of these may substantially increase levels of stress, anxiety and depression, impairing mental as well as physical health [14]. Although the World Health Organization (WHO) has identified climate change as an issue to be addressed, funding for rigorous vulnerability assessments that focus on the health effects of climate change remains minimal [14]. Environmental factors are a priority now in the research of complex non-communicable diseases (such as asthma, heart disease, cancer, diabetes and obesity), with the purpose of assessing the impact of the environment on human diseases, in what constitutes the environmental exposure science, today [15].

The importance to fuse the information regarding vital signs, daily motor activity and environment conditions is mainly related to the fact that daily variations in ambient air pollution have been consistently associated with variations in daily mortality, and cardiopulmonary and cardiovascular morbidity [16,17]. This scenario was also stimulated by the realization that Genome Wide Association studies (GWAS) failed to explain most of the variability and heritability in human diseases [18]. Due to this fact, a new concept emerged, the notion of the Exposome [19]. In the Exposome, we ideally have a characterization of the entire lifetime exposure history in a person's life, including lifestyle factors and social habits, external sources of pollution, diet and internal sources (such as inflammation, infection and microbiome – defined by the totality of microbes, their genetic elements and environmental interactions in a particular environment). Therefore, remote-sensing, personalized health monitoring, geographical information systems (GIS), and spatial analysis may be used as tools for standardized programs surveillance and implementation [20,21]. This is important, taking into account that understanding which group of population and where at-risk population is becomes fundamental for implementing any control program and appropriate geographical targeting of resources and cost-effective control.

Although the major area of public concern and government policy, in terms of the impact of air pollution on human health, continues to be the outdoor air, in the last two decades indoor air quality has caused increasing concern due to the adverse effects that it may have on human health. The term "indoors" is used in relative literature to refer to a variety of environments, including homes, workplaces, and buildings used as offices or for recreational purposes. Indoor air quality pollution represents one of the factors associated with the etiology of respiratory distress, the second most common symptom of adults that request emergency transportation to the hospital, associated with a relatively high overall mortality before hospital discharge [22,23].

Summarizing, the achievement of personalized healthcare rests on a dual foundation: the growing base of knowledge on public health and the adoption of interoperable health information technologies. To this foundation must be added the development of clinically useful products [8]. Based on sensors miniaturization, embedded signal processing, and networking technology combined with active research in smart materials and nanotechnology, the implemented systems may provide long-term monitoring of health status and healthier lifestyle. In order to achieve that goal, appropriate infrastructures might be necessary to support innovation and adoption of safe and effective diagnostic and therapeutic and procedures.

3 Is Pervasive Health Monitoring Possible?

Various studies emphasize the need for a new healthcare model [24,25,26], that uses unobtrusive smart systems for vital signs and physical activity monitoring [27,28,29,30] in many applications of mHealth technologies [31] for pervasive health monitoring and pervasive healthcare. These technologies may reduce the long-term monitoring cost of healthcare services and improve quality of life. The design, implementation and testing of smart objects for physiological parameters and motor activity measurement channels, as part of pervasive sensing and computing systems for healthcare interventions represent an important challenge considering the particular interaction between the assisted person and the objects, but also the personalized response provided by the systems for different users (assisted person, observer, caregiver).

Several systems for physiological parameters sensing in unobtrusive way are referred in the literature. For instance, various wearable solutions for vital signs monitoring have been described and commercialized in the last years. Some examples are: SmartLife (UK, 2003); ECG shirt GEOView and FALKE KG (Germany, 2004); VTAM (France, 2004); WEALTHY (FP6 EU project); ECG Shirt (Finland, 2006); Sensatex (USA, 2007); MyHeart (FP6 EU project); Philips ECG body vest (2009); SMART VEST (India, 2008), Proetex (FP5 EU project, 2008); VitalJacket, Biodevices (Portugal, 2009); Smartex ECG (Italy, 2009); ECG, EMG, breathing rate and muscular activity (Swedish hi-tech clothing, 2009). The smart T-shirt [32] for electrocardiogram (ECG) and electromiogram (EMG) monitoring use textile electrodes located on the chest for ECG recording, and additional dry electrodes (Roessingh Research and Development) for EMG acquisition. However, wearable systems based on e-textile, characterized by high degree of mobility, continue to have some drawbacks such as the discomfort, which can cause when these are daily used. Moreover, washing to clean the used T-shirt can change the characteristics of the conductive textile fibre, and in this case, the conditioning system associated to the dry electrodes will require adjustments or even major changes.

In the last decade, the deployment of technology for unobtrusive sensing of vital signs and daily activities monitoring is focused on networks of sensors embedded in furniture, appliances, floor, etc. For instance, a non-contact ECG measurement system for cardiac activity monitoring using capacitive coupled electrocardiogram device embedded in the bed was presented [33,34]. Junnila et al [35] developed a ballistocardiographic (BCG) chair that uses an EMFi-film sensor [36] to measure the health status in unobtrusive way. The authors also developed an EMFI based vital signs monitoring system, embedded in an office chair, including advanced processing of cardiac information using wavelets transform [37]. The EMFi sensor was also used for smart wheelchair implementations. Our team have developed a set of smart wheelchair prototypes characterized by various unobtrusive sensors that provide vital signs and motor activity accurate information and also different methods for artefact removal techniques [38,39]. Unobtrusive solutions for simultaneous measurement and transmission to a remote medical server of bio-signals (ECG, BCG) and kinetic signals (acceleration) were also presented [40,41]. The video camera of the smartphone was used to extract information on cardiac activity through the ability to record and analyse the varying color signals of a fingertip placed in contact with its optical sensor [42]. This type of imaging can be described as reflection photoplethysmographic (PPG) imaging and used to extract heart rate (HR), respiration rate, and oxygen saturation based on the dynamics of a pulse oximetry signal [42]. This solution for short-time assessment of cardiac and respiration function is non-invasive and requires special attention concerning the measurement procedure. However, the level of accuracy and reproducibility of this method may be low for long term measurement. Other implemented sensor for unobtrusive measurement of the vital signs is based on microwave radar. Important development of this kind of system was presented by the Lubecke groups [43,44]. For instance, the Doppler radar sensor is used to monitor both the heart rate and the respiration. An interesting application of the microwave radar was reported by Matsui et al [45]. They propose a system for non-contact measurement of heart rate that prevents secondary exposure of medical personnel to toxic materials under biochemical hazard conditions using a 1215 MHz microwave radar, a high-pass filter, and a personal computer.

Other option being explored is the integration of the sensor for unobtrusive sensing into non-clothing items that patients already wear. A ring sensor developed at the Massachusetts Institute of Technology (MIT), for example, might act as an ambulatory telemetric continuous health monitoring device [46]. This wearable biosensor uses photoplethysmographic techniques to acquire data on the patient's heart rate and oxygen saturation. This ring sensor contains an optical sensor unit, an RF transmitter and a battery connected to a microcomputer in the ring itself. This ensures onsite data acquisition, filtering, low-level signal processing, and bidirectional RF communication with a cellular phone that can access a website for data acquisition and clinical diagnosis. Shoes that measure plantar pressure between the foot and shoe during dynamic movement in real-time, which can be used in clinical gait analysis and user's behaviour monitoring were also proposed [47,48]. Moreover, the Wyss Institute at Harvard University has been developing shoes that can sense and ward off an acute medical crisis. The gentle vibrations delivered by the insoles in these shoes have been shown to improve gait and reduce the risk of falls among elderly users. Users could realize numerous benefits including: improved efficiency for performance athletes with less variability in gait and stride length, improved tactile sensation for diabetics to reduce the risk of ulcerations which often lead to amputations, and a clinically proven improvement in balance for both healthy wearers and the elderly who are at a much higher risk of falls [49].

The motor activity sensing and the user identification and localization tracking for healthcare are important requirements for pervasive sensing. In Ambient Assisted Living applications the indoor localization is done mainly using remote sensing technologies (non-mechanical contact technologies) expressed by ultrasound [50] and RF [51,52,53]. Several solutions were presented for smart floor system. RFID technology represents one of the options. Thus, a set of RFID transponders (usually LF RFID passive tags) were integrated in the floor typically in a regular grid. The RFID reader attached to daily used objects (e.g. wheelchair) reads the memory contents of the detected tag that stores the (x,y) coordinates which correspond to the objects position. These kinds of implementations were reported for robot position estimation [54]. The technique was applied by the authors particularly for wheelchair localization [55]. Indoor localization with a footwear system based on RFID and smart floor and an RFID glove for activity monitoring in house was also proposed [56]. Smart floor solutions based on load cells, steel plate sensors and data acquisition modules have been also reported [57,58,59]. However, the associated costs made this kind of solution less attractive. The use of large area proximity sensor arrays embedded in carpets to perform localization and identification tasks, as the latest technology promoted by Future-Shape GmbH [60] presents advantages such as low costs, reliability and flexibility. The use of a smartphone camera for indoor localization was also presented [61]. It combines the image recognition system with a distance estimation algorithm to gain a high-quality positioning service independent from any infrastructure. Stone and Skubic [62] evaluated the accuracy and feasibility of using the depth data obtained from the Kinect (movement sensing system from Microsoft) for passive fall risk assessment. Results showed good agreement between gait measurements computed using the Kinect, those computed using an existing Web-camera based system, and those from a Vicon motion capture system. Furthermore, the depth image from the Kinect not only addresses a major issue in foreground extraction from color imagery (changing lighting conditions), but significantly reduces the computational requirements necessary for robust foreground extraction for fall risk assessment.

Despite important advances in unobtrusive sensing, there are several challenges for pervasive health monitoring: cost reduction; small sensor size; MEMS integration; power source miniaturization and efficiency; low-power wireless transmission; context awareness; data mining; secure data transfer and integration with therapeutic system.

The authors have developing various smart sensors for unobtrusive vital signs and activity monitoring. These smart objects might be used to assist three categories of users: 1) with no or low limitation of motor activity; 2) with moderate and medium limitations of motor activity; 3) with severe limitations of motor activity. We design and implemented a smart wheelchair, a smart walker, smart crutches and a wrist-worn vital signs monitoring device. These objects are augmented with health status and motion sensing by using particular sensors (e.g. radar based ballistocardiography sensor, optical photoplethismography sensors, and accelerometers). Additional functionalities such as user identification (RFID technology, real time data processing (based on microcontroller or DSP platforms), wireless data communication (Wi-Fi, ZigBee data communication protocol) characterize these designed and implemented smart objects. The RFID technology was employed in these systems for the detection and identification of system users, which allows the computation of co-presence to be embodied within the real–world. The system architecture follows as much as possible, the requirements and the characteristics of ambient information systems (AIS) [63]. Therefore, the main goal of our implemented systems was to present the information from the smart sensing modules associated with smart objects such that minimum distraction of the users from their usual tasks may be achieved. The architecture specification is based on the detection of persons involved, mostly in their everyday life activities, with passive interactions, which can be considered as natural and "incidental", with sensing augmented objects (e.g., wheelchair, walker) and the computational platforms (e.g. smartphone, tablet computer) (see Figure 1).

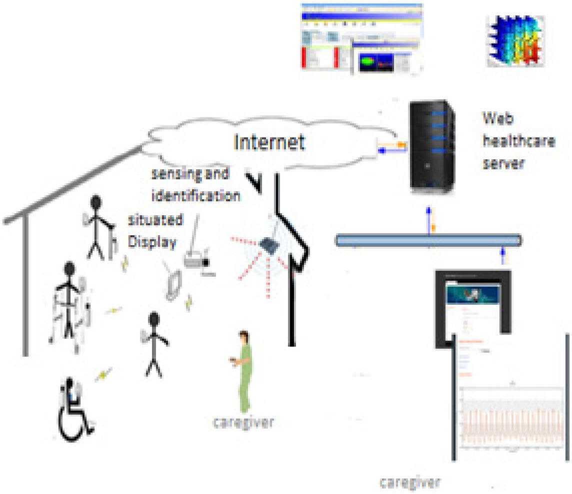


Fig. 1. Diagram of ambient intelligent based on our implemented smart objects

The notion of "incidental interactions" describes actions that are co-opted by the system to serve a purpose other than the one initially thought [64]. An incidental interaction can be seen as a situation where actions, executed for another purpose, are interpreted to improve future interactions in everyday life. In the pretended scenario of application, the basic aim was to ensure that only the detection of the user's co-presence near (or using) the smart object will activate the presentation of healthcare information on the smartphone or tablet computer.

The computing platform is used to update the acquired values on a server through database synchronization procedures between the mobile device database and the server's database. As it is presented in Figure 1, the implemented architecture may contain a public situated display for general usage and smart mobile devices, including touch screens, casually available to the users of the space, distributed closely to the smart objects (e.g., wheelchair). A RFID reader attached to the situated display is used to identify a user, or a wheelchair, and, afterwards, it requests the server personalized information. The application for the presentation of information and interaction with the user in the smart wheelchair was designed for a touch panel, while for the other smart objects, such as the walker, the walking stick or even the wrist-worn vital sign and motor activity monitor device was done using a smartphone. The situated displays are used to provide contextual information at decision points. It is presented information about the smart object identification and localization, the last verification of the smart object measurement channel, the smart object registered, statistics of the measured data during the latest measurement session (e.g. maximum heart rate, minimum heart rate, number of detected impacts between the smart object and other objects), the time of the latest utilization session. The software components are associated with two main layers: the ambient intelligence healthcare layer (AIH-L) and the user layer (U-L) (Figure 2).

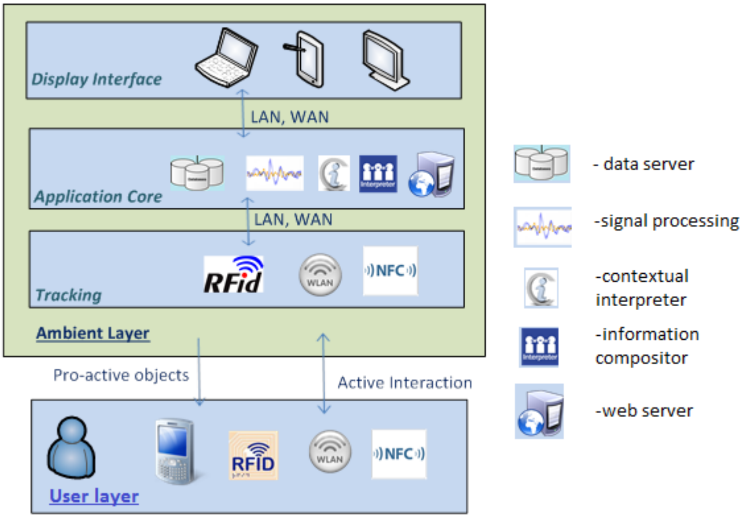


Fig. 2. Software component architecture

The AIH-L includes the software components that serve the smart objects (e.g. wheelchair, wrist-worn device) used by elderly or persons with motor disabilities, the touch panels, situated display or other pervasive computing devices such as smartphone or tablet computers. Regarding the AIH-L implementation, one of the main requirement is the pro-activity [65] in relation to the users, which means to understand the intent of the user in order to predict his/her future behaviour. Thus a tracking software component is implemented for identification and localization of the user of a smart object that delivers appropriate information (e.g. fall warning, time for medication) through the available HMI (human machine interfaces) associated to the system, in order to minimize the user's administrative overheads and assist the user to achieve his/her goals. The display interfaces are expressed by computing devices such as laptops, tablet computers or situated displays. As components associated with the user layer are mentioned the smartphone (the main interaction device), RFID tag or reader, wireless LAN and near field communication capabilities. The application core component performs analysis of the information given by the tracking component, and the data fusion with contextual information related to the object, the user profile, the processed data associated with vital signs and motor activity monitoring. According to the above-mentioned functionalities the application core includes:

- database server,
- signal processing unit,
- contextual interpreter,
- information compositor module,
- Web server.

3.1 Smart Wrist Worn Device for Vital Signs and Motor Activity Monitoring

The smart wrist-worn device that was designed to enable multi-parametric monitoring, in non-invasive and unobtrusive way, includes vital signs measurement channel (cardiac activity through photopletismography) and body-kinematics measurement channel associated with daily motor activities assessment. A set of warning digital outputs connected to LEDs signalise the low quality of the signals, battery low charge and critical values of measured parameters (e.g. values of heart rate higher than 95bpm when the user is resting). The computing of the signal in the implemented smart wrist device is made by a PIC24F microcontroller platform that is also responsible for signal acquisition, primary processing, data storage, and data communication. The signals provided by the sensors are Analogue processed before they are acquired.

3.1.1 Sensing and Signal Conditioning

The vital signs are sensed using a reflective photoplethysmography sensor based architecture. It includes two infra-red IR (940nm) - Red (660nm) LEDs and a light to voltage converter (Figure 3). A switching and current driver module was implemented using bipolar transistors to assure optimal control of two bicolour LEDs (Infrared- λ_{IR}=940nm, Red- λ_{Red}=660nm). The control signals (PULSES, N_PULSES, CTRL_RED, CTRL_IR) are provided by a microcontroller using the appropriate digital output lines and PWM output followed by low pass filter characterized by fc=0.5Hz. Alternating between "1" and "0" as values of PULSES and N_PULSES, the RED and IR LEDs paths are activated allowing the measurement of light absorption by blood during the cardiac cycle. A broadband radiation light to voltage converter (LVC) from Nelcor is included between the two LEDs delivering a photoplethysmography (PPG) voltage signal during the IR and Red light excitation. The use of two bi-colour LEDs increases the repeatability, robustness and PPG signal quality independently of the position of PPG sensor on the wrist.

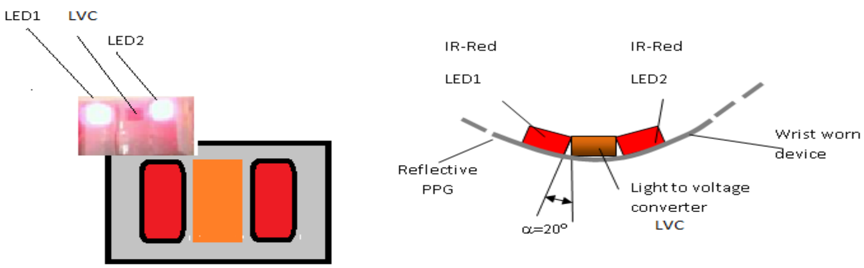


Fig. 3. Reflective photoplethismography sensor

The PPG signals from the light to voltage converter are filtered using a low pass filter (LPF) and high pass filter (HPF). LPF and HPF based on LM324 operational amplifier are used to diminish the influence of signals base-line wondering and to increase the signal to noise ratio (SNR). Some of the characteristics of the implemented filters are: LPF- 2-poles Butterworth, cut-off frequency of 20Hz; HPF- 2-poles Butterworth, cut-off frequency of 0.05 Hz. Considering the PPG dynamic range, an automatic gain control scheme (AGC) was implemented using a digital potentiometer (CAT5114 from Catalyst) and an instrumentation amplifier (INA122). Based on the implemented scheme, PPG amplitude values are in the 0.4 to 2V interval. An inertial sensor (MEMS accelerometer MMA7260) is used both to sense the daily motor activity - expressed by the activity index of the person , and for fall detection. It provides information on patient motion as Vax, Vay and Vaz voltage signals. These signals are low pass filtered and applied to analogue inputs of the microcontroller (Figure 4).

3.1.2 Microcontroller Platform

In figure 4 are presented the sensing and signal conditioning components of the microcontroller platform that were previously described. Important tasks such as signal acquisition, primary processing, LEDs user interface control, and data storage and data communication are performed by the PIC24F microcontroller based on an implemented firmware developed in MPLAB C30 compiler from Microchip. The LEDs switching and digital potentiometer control are done using a set of digital lines (RA3, RA4 for LED on/off function, RA5, RA6, RA7 digital potentiometer adjustment through the CS, UD, INC of DPOT). Regarding the light intensity control, a two channel current driver is implemented using the microcontroller RD1 and RD2 PWM outputs. The AC and DC components of the PPG signal are acquired using the AN3 and AN2 analogue input channels of the microcontroller. The acquisition rate is 200S/s and the programming recurs to TIMER2 of the microcontroller. The voltage signals delivered by the MEMS accelerometer through the Vax, Vay, Vaz outputs are acquired using the AN9, AN10 and AN11 analogue inputs and the same sampling rate that is used in the PPG acquisition case.

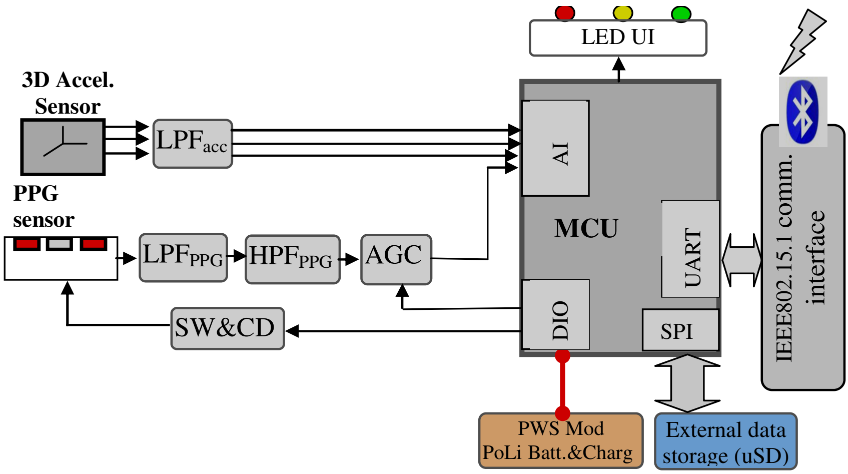


Fig. 4. Smart wrist worn - Microcontroller platform and conditioning circuits block diagram (AI – analog input, MCU-PIC24F microcontroller, SPI – serial peripheral interface, UART – universal asynchronous receive-transmit interface, DIO – digital input output port)

The implemented embedded primary processing software uses the PPG acquired samples to extract the HR value and blood oxygen level (SpO_2 values). An adaptive threshold peak detection algorithm was used to obtain more accurate values of HR. The main steps of the implemented algorithms are:

i) computation of the average value of 2.5s PPG acquired data, mean(V_ppg(t));
ii) calculation of the maximum value of the 2.5s PPG data, max(V_ppg(t));
iii) adaptive threshold th_a calculation:

$$th_a\big|_{\Delta t} = \frac{1}{2}\left(mean(V\_ppg(t)) + \max(V\_ppg(t))\right) \tag{1}$$

iv) determination of peak locations that exceed the threshold level for 2.5s time interval;
v) peak localization calculation and average time interval calculation between two successive detected peaks for Δt=5s time interval;
vi) HR calculation.

The SpO_2 calculation procedure uses the "normalized ratio", R, and a polynomial model of SpO_2=SpO_2(R) empirical characteristic. The microcontroller data, including the PPG samples (wave), the time interval between two successive PPG peaks (DELTA), the HR, the SpO_2 value, and the 3D accelerometer voltage values digital codes (ACCEL_X, ACCEL_Y and ACCEL_Z) are stored in an 8 bytes data array as shown in Figure 5.

0	1	2	3	4	5	6	7
INFO	WAVE	DELTA	HR	SPO2	ACCEL_X	ACCEL_Y	ACCEL_Z

Fig. 5. Smart wrist-worn device data array format

The INFO byte is used to store additional information regarding the smart bracelet functioning (e.g. battery low). Two data synchronization bytes (00 and FF) constitute the preamble joining the data bytes assuring the data reading robustness at the smartphone side. The formatted data is radio transmitted to the smartphone using an ARF32 Bluetooth module connected to the USART port of the PIC24F microcontroller. The update rate used in the preliminary tests was higher than 20 updates/s and lower than 200 updates/s for a programmed USART baud rate up to 19200bps. The robustness of the implemented solution was tested for different positions of the optical sensing device on the wrist. Example of signals obtained by implemented wrist-worn is presented in figure 6.

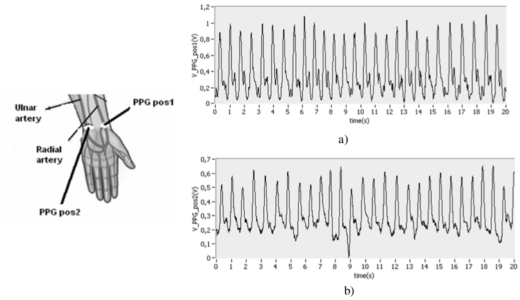


Fig. 6. The PPG signals for two positions of the sensing module on the wrist: a) PPG pos1 b) PPG pos2

Activities of Daily Living (ADLs) that refer to daily self-care activities within an individual's place of residence are sensed using the 3D programmable accelerometer embedded on the wrist-worn device. Thus, for a normal activity when the patient is holding an object (e.g. book) the evolution of acceleration for the X,Y,Z axis are presented in Figure 7. Based on statistics calculation additional information regarding the performed activity can be extracted. In this application the standard deviation was used. Particular information about standard deviation (SD) evolution calculated for time intervals of Δt =5s is presented in Figure 8.

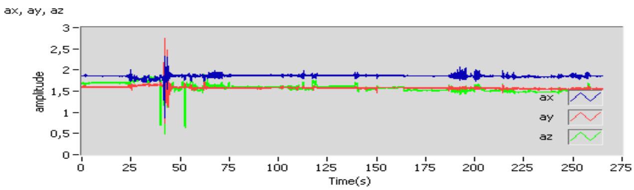


Fig. 7. The evolution of ax, ay, az acceleration during ADL

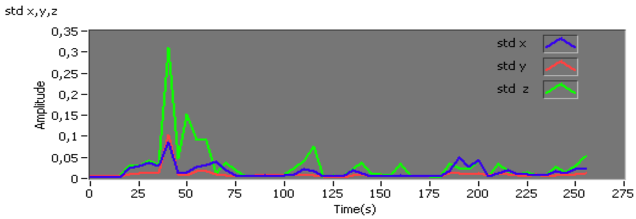


Fig. 8. The evolution of std x, std y, std z standard deviations of the measured accelerations during ADL

Imposing an activity standard deviation threshold, the activity and non-activity intervals for x, y and z axis are calculated and graphical represented in Figure 9.

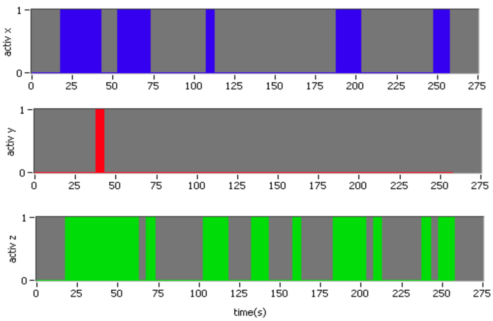


Fig. 9. Activity and non –activity associated with the x, y and z axis expressed by boolean activity indexes

Considering the whole time and the time intervals characterized by $activ_x$, $activ_y$ or $activ_z$=1 the activity index expressed in percentage is calculated. Thus, for the particular case of normal activity presented in Figure 9 the activities values are $activ_x$=28.85%, $activ_y$=1.92% and $activ_z$=46.15%.

3.2 Smart Wheelchair for Vital Signs and Daily Activity Monitoring

The necessity to obtain the information on health status and motor activity for people with severe motor disabilities has been leading to various smart wheelchairs prototypes developed by the authors' research group - important results related with hardware and software implementation being published. One of the implementation is presented in Figure 10. Various types of sensors for cardiorespiratory and motor activity assessment were used in smart wheelchair architectures implemented solutions: sensors for photoplethysmography (PPG) [66]; EMFit based ballistocardiography (BCG) [67]; capacitive coupled electrocardiography (ccECG) [68]; contact electrocardiography (ETX-ECG) and skin conductivity based on e-textile electrodes [69]. Taking into account that a way to increase the flexibility, modularity and the reliability of a system is to reduce the size and number of sensors without diminishing significantly the number of measured parameters, we developed a smart wheelchair and smart walker based on use of microwave Doppler radar sensors as non-electrical and non-mechanical contact sensors for cardiorespiratory but also for motor activity monitoring [39]. Measuring in an unobtrusive way the respiration and cardiac activity represents a challenging issue taking into account that non-invasive but obtrusive methods interfere with normal cardiorespiratory pattern at an unconscious level when a subject is aware of their vital signs monitoring [70]. There are approaches for non-invasive respiratory assessment as the use of smart spirometer with Bluetooth communication capabilities [71] or by processing the signal from plethysmography, electrocardiography (ECG) [72] or photoplethysmography [73]. The used Doppler radar is able to perform unobtrusive measurement both of respiratory rate and heart rate. The smart wheelchair includes a set of measurement channels related with two microwave Doppler radar sensors (DRS1, DRS2). The intermediary frequency signals are filtered and acquired by an acquisition and communication module (see Figure 12). The Doppler radar sensor is positioned back to the wheelchair backrest for user cardiorespiratory function assessment and wheelchair motion monitoring. Thus, DRS1 radar sensor is fixed in a plastic base mounted back to the backrest of the wheelchair (5 to 15 cm distance to the backrest) and 40 cm over the wheelchair seat (see the Figure 10) and it is oriented to capture the heart and the chest motion, while DRS2 is fixed on a plastic base parallel to one of the wheels, 30 cm apart from the wheel centre capturing the information about the wheels motion. To assure modularity and portability, various implemented smart objects (smart wheelchair, smart walker) use the same acquisition and Bluetooth communication solution expressed by a microcontroller based on ACM (Acquisition and Communication Module). After signal acquisition and data coding, the data is transmitted to a mobile pervasive computer platform that runs a mobile operating system (Android OS in our system prototype). The embedded software application performs graphical user interface functionalities but also assure the data storage in a local database.

The information related to cardio-respiratory activity and physical activity of the wheelchair user is stored in a smartphone or tablet computer database and is synchronized from time to time with the Web based healthcare information system database. Additionally, the remote database provides electronic health record information regarding the user profile (e.g. name, age, diseases, medication) and also hardware and software specifications regarding the use of the smart object (e.g. wheelchair in this case).

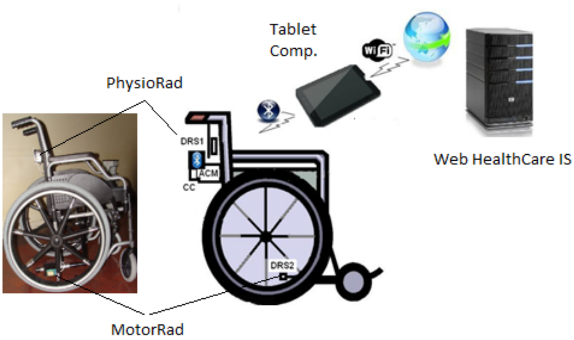


Fig. 10. System architecture based on a smart wheelchair (CC – conditioning circuit, DRS1, DRS2 - Doppler radar sensors, ACM – acquisition and communication module)

A brief description of the microwave Doppler radar of the conditioning circuit (CC), and of the acquisition and data communication module is presented in the following paragraphs.

3.2.1 Microwave Doppler Radar Sensor

A Frequency Modulated Continuous Doppler radar sensor (DRS1) was embedded in the wheelchair to perform the non-contact measurement of chest motion caused by the respiratory and cardiac activity. The requirement of small motion amplitudes detection associated with cardiac and respiration motions (cardiac amplitude motion are less than 0.15mm, respiration amplitude motion are less than 2mm), and also the necessity to minimize the size of the used Doppler radar device including the antenna for easily integration in daily used objects, make from the 24GHz FMCW Doppler Radar (IVS-162 DRS) an appropriate solution [39]. Moreover, the 24GHz microwave Doppler radar assures better resolution of low amplitude motion comparing with 2.4GHz - 10.5GHz which are mainly used for remote respiration monitoring in rescue scenarios [74]. The block diagram of the used radar is presented in Figure 11. The main components of the FMCW radar are: transmit TX and receive RX antennas; a low noise amplifier LNA connected to the RX antenna; two mixers (direct mixer M1 and quadrature M2) that are used to extract the direct or in-phase (I(t)) and quadrature (Q(t)) signals that are used to estimate the direction of the target motion (e.g. body motion).

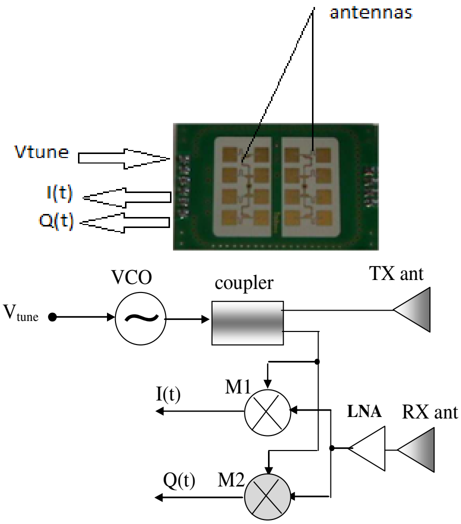


Fig. 11. FSK/FMCW Doppler radar sensor block diagram: M1, M2-mixers, TX, RX-transmit and receive antenna, VCO - voltage controlled oscillator, LNA-low noise amplifier

According to Choi et al. [75], the cardiac small motions, which correspond to blood pumping on the vessels, and the respiration motion are modulating the reflected RF signal that is acquired by the RX antenna. Thus the V_{RX} voltages associated with RX antenna is given by:

$$V_{RX}(t) = A_{VRX} \cdot \mathrm{Re}\left(e^{j2\cdot\pi\cdot f_0 \cdot t + \Phi(t)}\right) \quad (1)$$

where A_{VRX} represents the amplitude of the reflected wave and Φ(t) represents the time varying phase caused by the periodic displacement due to breathing and cardiac activity. In this case, Φ(t) can be expressed by:

$$\Phi\ (t) = 2\pi \frac{2\,d(t)}{\lambda_0} = 2\pi \frac{2}{\lambda_0}\left(n\lambda_0 + x_{resp}(t) + x_{cardio}(t)\right) \tag{2}$$

where d(t) is the distance between the radar antenna plane and the body of the user seated on the wheelchair, λ_0 is the wavelength of the Doppler radar wave - λ_0=12,5mm for 24GHz , $x_{resp}(t)$ represents the motion associated with respiratory activity, $x_{cardio}(t)$ represents the small motion associated with cardiac activity. Since the change of the respiration and cardiac motion amplitudes (less than 2mm) are small compared with wavelength, the demodulated signal, $V_{out}(t)$, depends on respiration and cardiac motion:

$$V_{out}(t) \propto \mathrm{Re}\left(e^{j\left(n4\pi + \frac{4\cdot\pi\cdot\left(x_{resp}(t)+x_{cardio}(t)\right)}{\lambda_0}\right)} \right) \tag{3}$$

where $x_{resp}(t)$, $x_{cardio}(t)$ being extracted from the V_{out} by analogue filtering. The ballistocardiography signal, $x_{cardio}(t)$, [39], is originated by small movements of the body, induced by ballistic forces (recoil and impact) associated with cardiac contraction and ejection of blood.

3.2.2 Signal Conditioning, Acquisition and Wireless Communication

The conditioning circuits associated with the radar system encompass a set of analog active filters that perform the respiration and the cardiac signal extraction. In the respiration case a 2nd order active low pass filter, Butterworth type, characterized by fc=0.3Hz cut-off frequency was designed and implemented. To extract the cardiac signal a 2nd order, band pass active filter, Butterworth type characterized by f_{c1}=0.7Hz and f_{c2}=15Hz was implemented. To adapt the signals to the acquisition module voltage input range a set of programmable gain amplifiers (PGA1 and PGA2) were also implemented. It includes INA122 instrumentation amplifier and CD4051 that perform the switching actions under the control ACM through the digital lines. In the particular case of microwave Doppler radar sensor (DRS2) system, which measures the distances travelled by the wheelchair during a specified period (hours, day, week), the I2(t) output signal provided by the radar is filtered using a 1st order high pass filter HPF2 (1st order fc=0.3Hz) and amplified by the A3 amplifier. In order to sense the motion the Q2(t) signal can be used and the phase difference between two signals, $\Delta\varphi_{I2,Q2}$ indicate the motion sense (moving in front, moving back).The block diagram of the implemented conditioning, acquisition and data communication module is presented in Figure 12. The ACM performs an analogue to digital conversion using a 16bit ADC (ADS8344) that communicates through the SPI bus with the MCU (16F673 PIC). The digital values of the acquired samples are delivered in hexadecimal form to the mobile device using Bluetooth communication. Additional processing of the signals delivered by the DRS1 microwave Doppler radar is done mainly at the mobile device level (smartphone, tablet computer) in order to extract the respiration rate, the heart rate and the activity index. The activity index is calculated based on the evolution of the V_{RX} signal amplitude and frequency variance in time, when the cardiac activity is not estimated due to large movement artefacts. The acquired I2 signals delivered by DRS2 microwave Doppler radar are also used for activity index (e.g. wheelchair motion and the related parameters such as the distance and the average velocity).

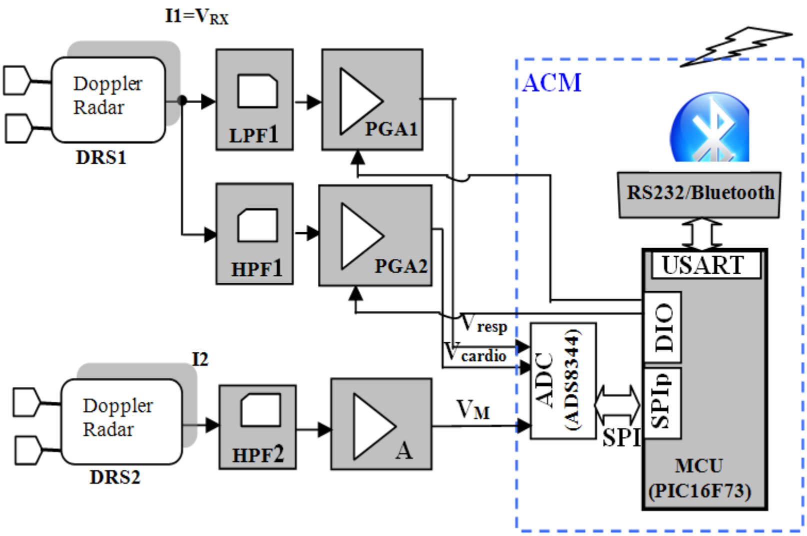


Fig. 12. Signal conditioning, acquisition block and wireless communication block diagram (HPF1, HPF2 – high pass filters, LPF1 – low pass filter, PGA1, PGA2 – programmable gain amplifier, A – instrumentation amplifier, ACM-BS- acquisition and data communication module Bluesentry Architecture)

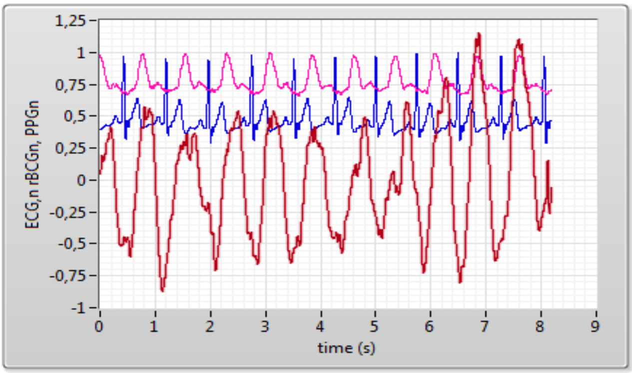


Fig. 13. Cardiac signals provided by the Doppler radar sensor module (dark-red) and standard PPG (magenta) and ECG (blue) standard cardiac activity measurement devices

A graphical representation of cardiac signals obtained using references equipment for ECG, and implemented radar based device is presented in figure 13. In the Figure may also be observed correlation of the shape and time of the peak changes in amplitude of the radar signal with PPG signal that underlines the capacity of the radar device to be used in mechanocardiography.

3.3 Smart Walker for Motor Activity Analysis

As part of the ambient intelligent for healthcare a smart walker was implemented. Based on the sensors such as microwave Doppler radar, force sensors, accelerometers the rehabilitation process is assisted in order to highlight the progress during the physiotherapy sessions by using the smart walker. Thus the gait recovery might be evaluated based on data processing of the signals acquired from the sensors that are wirelessly transmitted to a host computer or a mobile device. The sensors, the conditioning circuits and the acquisition and communication module are integrated in the walker which measures, through the radar, the kinematic of the body in unobtrusive way, without mechanical and electrical contact. The mechanical coupling between the user and the walker during the training session made possible extraction of information on applied force related with walker usage, acceleration imposed to the walker that can be associated with gait cadence and gait velocity, and also impact force. The walker velocity and the travelled distance are obtained using a radar that is positioned near one of the walker wheel. Measuring the motion of a metallic target fixed on the wheel the number of turns is measured. The distribution of the sensors and the smart prototype implementation is presented in Figure 14. The contact forces applied by the user on the walker hand supports are measured using a set of four piezoresistive sensors (Flexiforce A201-100 from Tekscan) [76], while the acceleration imposed to the walker during usage is measured by a 3D MEMS accelerometer ADXL335 from Analog Device.

Fig. 14. Smart Walker implementation: DRS1, DRS2 – Doppler radar sensor, accelerometer sensor, F1, F2 – force sensors

The use of four force sensors - two for each hand support - is justified both by reduced active region of a disk (9.53mm), making necessary the extension of active contact region joining the surfaces from multiple piezoresistive sensors, as well as the necessity to obtain differential signal input associated with differences in hand region forces applied by the walker's user. The correlations between applied force, gait (measured by using the same type of Doppler radar sensor, already used in wheelchair prototype) and walker acceleration are captured. In the implemented architecture only the direct intermediary frequency signal was used to extract the kinematics and kinetics of legs. The forces applied on the walker hand support are different during the training gait according with the user rehabilitation stage (the force is up to an imposed threshold - Fth>150N when the user strongly grabs the walker, and is less 150N when user lightly grabs the walker). Taking into account the piezoresistive characteristics of the sensors, a conditioning circuit including a four channel non-inverter amplification scheme based on LM324 and a reference voltage was designed. The dependence between VFij (i,j ={1,2}) output voltage signal and the applied force was obtained using a calibration scheme base on a load cell (DDE 500N from Applied Measurements Limited). Taking into accountthe analogue input requirements of the analogue to digital converter, an amplification/attenuation scheme based on INA 122 was designed and implemented for the I1(t) output channel of DRS1. Taking into account the intermediary frequency signals I2(t) associated with DRS2 a Schmitt Trigger scheme was implemented and obtained pulse are acquired by one of analogue inputs of the acquisition and data communication module (ACM). Considering the uniformity of the solution the ACM architecture is the same that was used for the smart wheelchair implementation, the frequency acquisition rate being up to 200S/s and the communication rate through Bluetooth is up to 115200bits/s. A set of remote control commands are used on the mobile device or the host computer side to configure the number of channels and the sampling rate. Thus to start the acquisition, the microcontroller receives through the wireless communication (Bluetooth communication protocol) a command from the host unit. The digital values of the acquired samples from different measurement channels are delivered in hexadecimal form to the mobile device or computer that performs hexadecimal - to decimal voltage values conversion, normalization, voltage - to- force conversion, voltage - to- acceleration conversion. Referring the gait signal sensed by the Doppler radar (DRS1) a set of statistical parameters such as variance or kurtosis, are calculated as features that are used together with the values provided by force, acceleration and motion channel (DRS2) for gait type recognition that is performed at a server level. The physical activity is also estimated through the values of the travelled distance and velocity of the walker during the training session.

3.4 Pervasive Sensing of Environmental Impact Factor on Health

Smart sensors and pervasive computer technology may enable new model of healthcare delivery that can use information obtained through pervasive sensing on physiological parameters, motor activity but also information about monitored patient localization, or about environment conditions (e.g. air quality parameters).

Human exposure to indoor air pollution is difficult to quantify due to the fact that it is largely determined by micro-environmental characteristics. Pollution levels in one home may be quite different from those in another, depending on the presence and usage of sources of pollutants and on the ventilation habits. Many different methods can be used to measure the level of gaseous air pollutants by mobile or portable device. For example, gas chromatography (GC) and mass spectroscopy (MS) devices provide a high degree of data accuracy, but require some kind of sample preparation that limits its utilization in field measurement scenarios. However, most of these above mentioned techniques measure average concentrations over several hours or even days, at one sampling location, which limits their use in studies of pollutants with acute effects. As is reported in the recent approved European project SYNPHONIE www.synphonie.eu, no reference methods for indoor monitoring presently exists. In their proposal, indoor air quality will be monitored mainly using diffusive sampler, techniques routinely used for measuring ambient air pollution, but that are not suitable for large scale indoor surveys because of cost, bulk, noise or amount of air displaced. Different measurement systems has been developed recently for indoor use [22,23,77]. Laser-inducted breakdown spectroscopy (LIBS) offers real-time response and high accuracy and does not require sample preparation. Recent LIBS devices are small enough to be used as mobile units. Semiconductor sensors are not as accurate as spectroscopy-based devices but they are much smaller and easy to integrate with a data collecting unit. A distributed architecture including smart sensor network that deliver data to a Web server for air quality monitoring and advanced data processing software modules was described by authors [22]. The data from the sensors may be visualized on the smartphone display. The graphical user interface implemented in a smart phone permits the selection of relative humidity and respiration graphs Figure 15.

a) b)

Fig. 15. The graphical user interface implemented in the smart phone for chest belt sensor case a) relative humidity selected graph, b) respiration selected graph

Analysing Figure 15.a) can be observed the evolution of the relative humidity in time while Figure 15.b) presents the evolution of the respiration wave (for a moving time window of 20 s). The numerical values of the calculated respiration rate as well as the air quality condition expressed by temperature and relative humidity values are also included on the application dashboard developed based on Android SDK. Additionally, an audio alarm was implemented for critical air quality conditions and anomalous respiration behaviour (e.g. asthma attack).

4 mHEALTH

Mobile eHealth or mHealth broadly includes the use of mobile telecommunication and multimedia technologies in health care delivery. The term mHealth was coined by Professor Robert Istepanian as use of "emerging mobile communications and network technologies for healthcare" [78]. mHealth: includes the use of mobile devices for collecting and summarizing subject's health data, providing healthcare information to practitioners, researchers, and patients, real-time monitoring of patient vital signs, and direct provision of care (via mobile telemedicine) [79]. A definition used at the 2010 mHealth Summit of the Foundation for the National Institutes of Health (FNIH) was "the delivery of healthcare services via mobile communication devices" [80].

Are included in mHealth technologies the use for health services and information, of the fixed line telephone, cell phone, tablet computer, MP3 or MP4 players, microcomputers, laptop computers, PDAs as well as mobile operating system technologies. Technologies relates to the Operating Systems that orchestrate mobile device hardware while maintaining confidentiality, integrity and availability are required to build trust. This may foster greater adoption of mHealth Technologies and Services, by exploiting lower cost multipurpose mobile devices such as tablets PCs and smartphones. Operating Systems that control these emerging classes of devices include Google's Android, Apple's iPhone OS, Microsoft's Windows Mobile, Nokia Symbian OS and RIM's BlackBerry OS. Advances in capabilities such as integrating voice, video and Web 2.0 collaboration tools into mobile devices, may significantly benefits the delivery of healthcare services. Smartphones or tablet computers, as pervasive computing component, provide interesting HMI for user, accompanying person or health professionals. Application software running on smartphones, which supports different type of mobile OS (e.g. iOS, AndroidOS, Windows Phone) may provide clinical information on patient state but also may give tools to the patients to take better care of themselves. Biofeedback procedure based on data from the sensors might be processed on the mobile platform or can be sent to the Cloud [31] that might perform advanced data processing, data storage and integrate the feedback on biofeedback system. There are open issues on Cloud Computing acceptability related with his availability and security of data. It is discussed the necessity to create a 'Healthcare-specific Cloud' [81] that specifically addresses the security and availability requirements for healthcare system.

The mHealth field operates on the premise that technology integration within the health sector has the great potential to promote a better health communication to achieve healthier lifestyles, improve decision-making by health professionals (and patients), enhance healthcare quality by improving access to medical and health information, and facilitate instantaneous communication in places where this was not previously possible [82,83]. It follows the hypothesis that the increased use of technology can help to reduce healthcare costs by improving efficiencies in the healthcare system and promoting prevention through behaviour change communication [98]. With greater access to mobile phones to all segments of a country, including rural areas, the mHealth has potential of lowering healthcare costs. Mobile phones have made a recent and rapid entrance into many parts of the low- and middle-income world, with the global mobile phone penetration rate drastically increasing over the last decade. Moreover, the mHealth approach that is rapidly gaining ground in many developing countries, allow real time data access and management in locations with no infrastructure other than a cell phone tower [84]. Moreover, countries with relatively poor infrastructure are utilizing mobile phones as "leapfrog technology" to bypass 20th century fixed-line technology and jump to modern healthcare technology. Mobile phones are spreading in low- and middle-income nations because the cost of mobile technology deployment is dropping and people are, on average, getting wealthier [85]. At the end of 2011, there were 6 billion mobile subscriptions, estimates The International Telecommunication Union (2011) [86]. That is equivalent to 87 per cent of the world population. And it is a huge increase from 5.4 billion in 2010 and 4.7 billion mobile subscriptions in 2009. Mobile subscribers in the developed world has reached saturation point with one or two cell phone subscription per person. This means market growth is being driven by demand developing world, led by rapid mobile adoption in China and India, the world's most populous nations. These two countries collectively added 300 million new mobile subscriptions in 2010 - that’s more than the total mobile subscribers in the US. At the end of 2011 there were 4.5 billion mobile subscriptions in the developing world (76 per cent of global subscriptions). Mobile penetration in the developing world now is 79 per cent, with Africa being the lowest region worldwide at 53 per cent. Mobile subscriptions outnumber fixed lines 5:1 (more so in developing nations); Mobile broadband outnumbers fixed broadband 2:1. With stats like this, it is easy to see why the experts predict that mobile Web usage will overtake PC-based Web usage. This will happen more quickly in developing nations (if it isn’t happening already) where fixed Web penetration remains low. In developed nations, this will happen more slowly [87]. International Data Group (www.idc.com) believes that mobile Web usage will not overtake PC Web usage in the US until 2015. Regardless of the timescale, this inevitability makes mobile Web strategy more important than PC Web strategy in the long term. Smartphone technologies are now in the hands of a large number of physicians and other healthcare workers in many countries. Adoption of smartphone for mHealth in low and middle income countries is conditioned by deployment of the infrastructure that enables web browsing, GPS navigation, email, availability and efficiency in both voice and data-transfer systems in addition to rapid deployment of wireless infrastructure.

Within the mHealth space, projects operate with a variety of objectives, including: increased access to healthcare and health-related information (particularly for hard-to-reach populations); improved ability to diagnose and track diseases; timelier, more actionable public health information; and expanded access to on-going medical education and training for health workers. Although far from ubiquitous, the spread of smartphone technologies opens up doors for mHealth projects such as technology-based diagnosis support, remote diagnostics and telemedicine, Web browsing, GPS navigation, access to Web-based patient information, and decentralized health management information systems. The mHealth field houses the idea that there exists a powerful potential to advance clinical care and public health services by facilitating health professional practice and communication and reducing health disparities through the use of mobile technology. Overall, mobile communication technologies are tools that can be leveraged to support existing workflows within the health sector and between the health sector and the general public [88]. For instance, education and awareness programs within the mHealth field are largely about the spreading of mass information from source to recipient through short message services (SMS). In education and awareness applications, SMS messages are sent directly to users' phones to offer information about various subjects, including availability of health services, lifestyle management, testing and treatment methods, and disease management. For instance, Text4baby Russia (SMSmame in Russian) is a public health information service for new and expectant mothers intended to improve maternal and child health indicators. Subscribers to the free service, available throughout the Russian Federation, receive health information tailored to their baby's due date/birth date about nutrition, exercise, smoking prevention, mental health, government benefit packages, etc. This program is implemented by a Russian NGO, the Health and Development Foundation, and was developed under the auspices of the U.S.-Russia Bilateral Presidential Commission [89] on the basis of the U.S. text4baby program and sponsored by Johnson & Johnson (see more project in http://en.wikipedia.org/wiki/MHealth). SMSs has also the advantage of being relatively unobtrusive, offering patients confidentiality in environments where disease (especially HIV/AIDS) is often taboo. Additionally, SMSs provide an avenue to reach far-reaching areas - such as rural areas - which may have limited access to public health information and education, health clinics, and a deficit of healthcare workers [90].

The potential of mHealth lies also in its ability to offer opportunities for direct voice communication (of particular value in areas of poor literacy rates and limited local language-enable phones) and information transfer capabilities that previous technologies did not have. That is, there is evidence that the existence of a so-called “digital divide” along the socio-economic gradient is less pronounced in mobile phones than in other communication technologies such as the Internet [91]. There are applications related with the use of in-built smartphone sensors (e.g. phone camera, accelerometer, etc) that already have thousands of users. In the table 1 and 2 are presented application that we identified in App Stores, which focus in various health issue, based on technological capacity of smartphone.

Table 1. Android OS applications for health monitoring and care

Android OS		
Name	**Developed by**	**Role**
Vital and Sensory Function Test		
Instant Heart Rate	Azumio Inc	heart rate meter.
Cardiograph	Macro Pinch	heart rate meter.
Handy Logs Heart	Handy Logs	heart rate meter.
iBP	Leading Edge Apps LLc	is a blood pressure tracking and analysis tool. iBP uses color icons to indicate when BP values are normal, high, or hypertension.
Breath Biofeedback	Android Research	respiration biofeedback.
Breath Pacer Lite by Android Research	Android Research	respiration.
MT Health Test	MT DevTeam	includes color blindness test, hearing test, stress test, psychological test.
Vision Test	3 Sides Cube Eye	allows brief tests to measure visual acuity, test for astigmatism and ability to distinguish colors.
Test Your Hearing	EpsilonZero	easy hearing tests are presented to test frequency range and frequency differentiation.
NHS Direct	NHS Direct	facilitates an assessment, information on health condition and give advices for health preservation.
Emergency		
BHF Pocket CPR	Zoll Medical Bio-Detek	teaches Hands-only CPR skills according to the latest American Heart Association and European Resuscitation Council CPR and ILCOR Guidelines.
ICE: In case of Emergency	Appventive	store important information about user medical needs in case of an emergency.
ICE	Sera-Apps	the first helper is able to see who to call and which person he deals with in only a few clicks.
First Aid	Health Team	first aids is designed for helping to follow the right procedures in an emergency.
Stress Management		
Stress Check	Azumio	quantify level of stress, determine the effects of different stressors, allow control of stress.
My Calm Beat	Brain Solutions	training respiration for relaxation.
Cardiac Coherence	Haraweb	training on how breathing can reduce stress.
Respiroguide Pro	Vital-EQ	training respiration for better concentration, stress anxiety, ADHD and trauma healing.

Table 1. (*Continued*)

Stress Management Guide	Bigo	stress management.
Buddhify	21awakeLtd.	it's a introduction to meditation and the techniques involved.
Sleep Deeply	Hypnotherapists Direct Ltd	helps to relax and drift to sleep quickly and easily.
Brain Activity Management		
Brain Booster-Mind Refresher	Imoblife Inc	brain wave stimulation
Brainwave Tuner Lite	Imoblife Inc	brain wave stimulation application that generates tones with binaural beats, which can change brain frequency towards the desired state, allow relaxation or enhance attention.
Sleep Talk Recorder	MadINSweeden	offers a window into the subconscious, "those mumbling you can never quite remember the morning after could be your inner genius coming out. By placing the smartphone near the bed it will automatically turn on and begin recording when it senses sound during the night."
Nutrition		
WWDiary	Canofsleep.com	food tracker and weight tracker.
Carbs&Cals	Chello Publishing	encompasses over 1400 foods with images. This enable to determine visually the number of calories and carbs by selecting the appropriate food type and portion size in the application.
Calory Calculator	Benjamin Lochmann New Media GmbH	calories calculation.
E Numbers Cal	TappyTaps: Food Additives	information on E numbers and artificial additives, including side effects, and rates over 500 additives on a scale of 1-5 based on how bad they are for health. It also explains why they're used, what they do, where they come from and more.
Additives v3	Lyubozar Dimitrov	provide quick reference to simplified information about food additives labeled on foods.
DietPoint.Weight Loss	SimpLabs Ins	weight loss assistant with largest collection of diet plan and community support.
BMI Calculator	Androidcrowd	body mass index calculation.
BMI Calculator	Zileex Media	body mass index calculation.
BMI Calculator	You Droid	body mass index calculator that supports both English and Metric measurement units.

Table 1. (*Continued*)

Easy Weight Loss	Hypnotherapist Direct Ltd	help users to relax and feel comfortable with the decision to loose weight.
Weight Loss Tips	aap_swap	weight loss tips from the expert in diet, exercices, beauty, health, food&nutrition.
Physical Exercices		
Fitness Buddy: 1700 exercise	AppOneCause	by selecting the area of the body that user want to work is possible to select from a variety of exercices and all come with pictures and animations to ensure that are executed correctly. Performing exercises incorrectly can often do more harm than good and there are more than 3000 images and animations to makes sure this does'nt happen. The apps allow to add new exercices and to save the preferred ones to a favorite list. There are also exercices designed specifically for men and women.
Streth Exercices	Imoblife Inc	exercices for users with constant back-aches and waist pains.
MapMyWalk+	MapMyFitness	measures how far a subject walk (based on GPS) on a daily basis, and how many calories are burning.

Table 2. iPhone applications for health monitoring and care

iPhone OS		
Name	**Developed by**	**Role**
Instant Heart Rate	Azumio Inc	heart rate meter.
iTriage	Heathhagen	the application make Microsoft HealthVault (Microsoft Personal Health Records) data viewable via an iPhone app. Empower consumer with control and convenience to effectively manage their personal health care, and improve health care delivery for provider and payers.
Kaiser Permanente	Kaiser Permanente	the KP app gives Kaiser Permanente health plan members the tools to access their medical records, make appoint-ments, refill prescriptions, view most lab test results, send non-urgent mes-sages to their doctors, and more.
Cure A-Z	Plum Amazing Soft-ware LLC	shows how to combine the best of natural and prescription therapies to live in optimal health.
Heath4Me	United Health Group	health services management.

Table 2. (*Continued*)

Meal Planning by Food on the Table, Fast Food Calories	Abs Workout	calories calculation, meal planning.
Calories counter & Diet Tracker	My Fitness Pal	calories calculation.
DrinkTracker - The Breathalyzer Simulator & BAC Calculator, Outta Here!	Drink Traker Zazzle	keeps a record of what the user have been drinking with the fully editable one-tap drinks list. Apps automatically compares alcohol intake and metabolic removal rate and updates current Blood Alcohol Content every 60 seconds. Use Google Maps to get travelling directions (home or to the next pub), find a taxi in immediate vicinity of user, or email a friend with current location for a pickup. It also allows for phone or SMS contact via Contacts list from within the application.
Pedometer Free GPS+	Arawella Corporation	physical exercices meter.
Fitness Buddy:1700+ Exercices	AppOneCause	by selecting the area of the body that user want to work is possible to select from a variety of exercices and all come with pictures and animations to ensure that are executed correctly. Performing exercices incorrectly can often do more harm than good and there are more than 3000 images and animations to makes sure this does'nt happen. The apps allow to add new exercices and to save the preferred ones to a favorite list. There are also exercices designed specifically for men and women.

Apple AppStore, Android Market, Microsoft Mobile Marketplace, Nokia Ovi have made possible not only for start-ups but small research Laboratories and even individual developers to quickly attract a very large number of users. Also, the Apps Store allows developers to deliver new applications to large populations of users across the globe leading to the deployment of new applications and the collection and the analysis of data far beyond the scale of what was previously possible.

New included sensor in smartphone such as HD video and audio capabilities, accelerometers, GPS, ambient light detectors, barometers and gyroscopes enhance the methods of describing and studying cases, close to the patient or consumer of the health care service. In *participatory sensing* the user actively engages in the data collection activity (i.e., the user manually determines how, when, what, and where to sample). In *opportunistic sensing*, the data collection stage is fully automated with no user involvement. The benefit of *opportunistic sensing* is that it lowers the burden placed on the users mainly when the application is complex or not personally appealing [92]. *Personal sensing* applications are designed for single individual, and are often focused on data collection and analysis [92]. This could include diagnosis, education, treatment and monitoring. For instance Scully et al. [42] recently have shown that the technology available in a standard mobile phone camera has the potential to be used as an accurate multi-parameter physiological monitor – heart rate, breathing rate, oxygen saturation. However, various open issue exist in designing application for health monitoring and health care related with technologies that can support the continuous sensing on mobile phones, the programmability of the phones and the limitation of the operating systems that run on them, the dynamic environment presented by user mobility, persuasive user feedback.

Although mHealth application is still considered in its infancy is very important to focus more our research on testing the efficacy and reliability of the proposed application in order to diminish the possibility to reinforce entrenched knowledge gaps. The research should try to respond to questions as: What are the added value of mHealth application for person health and healthcare system? What breakthroughs are needed in order to perform robust and accurate classification of health state and subject behaviour using continuous sensing data? How can be performed privacy-sensitive and resource-sensitive reasoning and to provide useful and effective feedback to users in applications when noisy data and noisy labels are part of the information? What are the designing that may motivate more a change of behaviour or habit? How the privacy and security of data can be better protected? For instance the heart rate, respiration rate or hemoglobin oxygen saturation measured performed by smartphone using embedded camera can be acquired at least 5-10 time more cheaply using the commercial devices (pulse oximeters). Moreover, commercial devices have better sensitivity and specificity in acquiring these values because hardware and software include function for reduction of movement and skin color artefact during measurement. The added value that can be obtained towards heart rate and respiration function measurement using smartphone is continuously, pervasive monitoring of person for long time as we deployed with our applications. While smarphones continue to provide more sensing and communication bandwidth, computation, memory, storage, the cell phone is still a resource-limited device if complex signal processing and inference are required. The need of continuous sensing when using smartphone for pervasive health monitoring raises considerable challenges in comparison to sensing applications that require a short time window of data or a single snapshot (e.g. a single image or short sound clip). There is also an energy tax and resources associated with continuously sensing. Various solutions for this problem are presented in recently works [93,94,95]. However, more research is needed to exceed limitation of continuous sensing, to diminish the communication overhead and for privacy and security of stored and communicated data.

In our Lab we implemented applications for continuous sensing of heart rate, respiration, daily activity by developing a system that accurately acquired and process data from the smart sensors developed in our Lab. Figure 16 presents a model of implemented architecture that join pervasive sensing and pervasive computing elements that were used for cardiorespiratory and motor activity sensing system.

Mobile pervasive computing devices are completely connected and constantly available. In the presented intelligent ambient for healthcare scenario, mobile devices are expressed by smartphones and tablet computers. The embedded software for mobile devices was developed considering the following requirements:

- intermediate processing of the data acquired by the sensors integrated in the smart objects;
- human computing interfacing including graphical representation of locally processed data and data provided by the server,
- data communication including the communication between the mobile device and smartphone through Bluetooth and bi-directional synchronization with the web healthcare server using the Wi-Fi or 3G-UMTS internet connectivity.

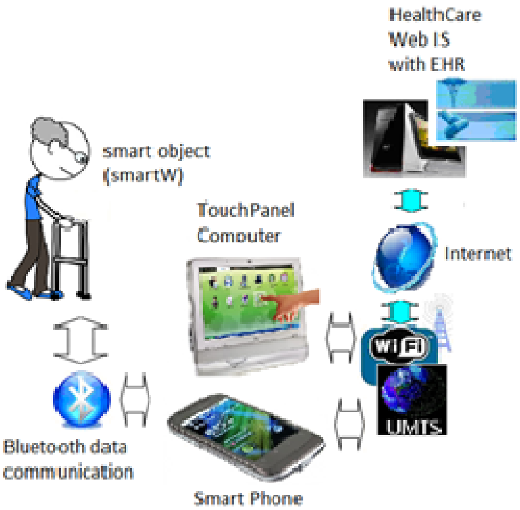
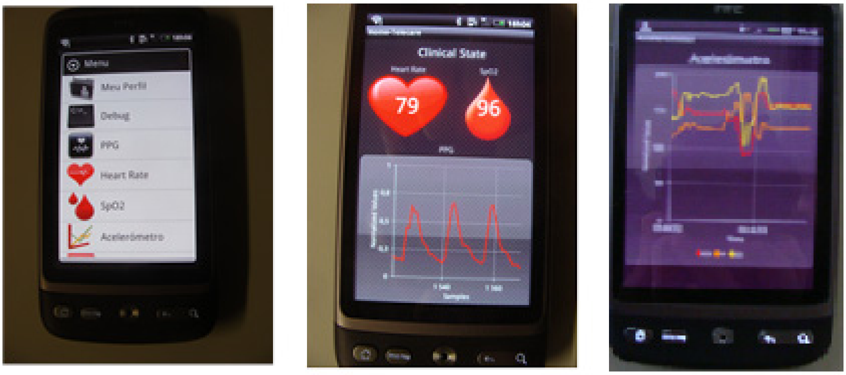


Fig. 16. M-Health architecture for vital signs and body kinematics monitoring (smart W-smart walker, HealthCare Web IS – web based information system for healthcare)

Important part of health monitoring systems implemented in our Lab is the computation unit materialized by low power, low-cost low processing capabilities devices as microcontrollers (e.g. MSP430 series) or Digital Signal Processors (e.g. ADI's new low power SHARC® 2147x) that are able to perform advanced signal processing algorithms (e.g. DWT, CWT).



a) b) c)

Fig. 17. The graphical interface of the pervasive computing device (Android OS smart phone) a) main menu, b) 0vital signs interface, c) motor activity interface

The acquired and processed data are transmitted through the communication interfaces (e.g. Bluetooth, ZigBee or Wi-Fi) to the HMI, generally expressed by smartphone or tablet computer (e.g. HTC Desire and a Toshiba Folio were already used).

Appropriate software was implemented on the mobile computing platform in order to process and display the data from the smart object sensors. In the smart wrist-worn device case the formatted data transmitted using a Bluetooth interface to a smartphone, which includes the application for communication, intermediary data processing and user interface developed under Android OS. A dashboard and a general menu board of the smartphone embedded software application are presented in Figure 17. In Figure 17.a. is presented the Android OS application main menu that is used to select the vital signs and motor activity monitoring interfaces. Figure 17.b presents the implementation of vital signs monitor graphical interface that includes the heart rate and SpO_2 digital display the PPG wave being visualized in a graphical display while the Figure 17.c includes the acceleration values evolution during the daily motor activity. For the particular case of smart wheelchair the graphical user interface was implemented on the tablet computer level and presents the evolution of cardiac signal (radar ballistocardiography), the respiration and the values of the heart rate and respiration rate (Figure 18).

The general graphical user interface of the application embedded in the smartphone is presented in Figure 19. As can be observed, the main menu of the Blue-Sentry 1.0.2 application embedded on the smartphone level, includes different categories such as smart object (e.g. smart walker) measuring channel control, data synchronization, user profile and preferences. The smart object measurement channel control permits to select the visualization of one single or multiple measuring channels according to the user or health professional necessity. Thus, "single" selection permit to visualize the evolution in time of only one measurement parameter with higher resolution, while for "multiple" selection two of the measured channel can be selected and the evolution of measured quantities is presented in a set of comparative graphs.

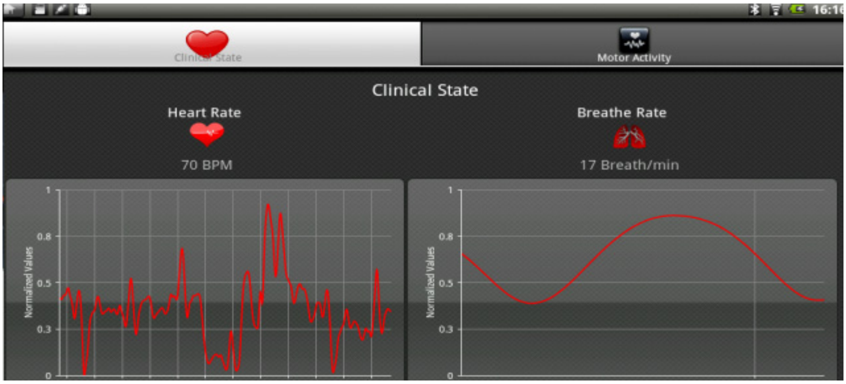


Fig. 18. Cardiac, respiratory and motor activity graphical interface implemented on the Android OS Tablet computer

Fig. 19. The dashboard of the implemented AndroidOS software for walker user

In Figure 20 are presented a set of two BlueSentry application panels that are obtained after the selection of "Multiple" button. In Figure 20.a is presented simultaneously the evolution of the left arm support applied force and the detected legs motion using the radar sensor while Figure 20.b is presented the evolution of detected legs motion together the counter signal evolution, and Figure 20.c the applied force and the walker acceleration during normal usage are presented.

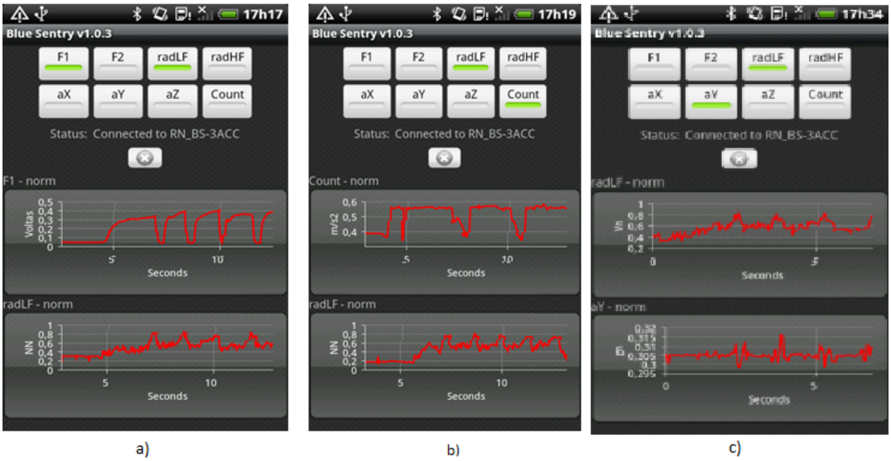


Fig. 20. The BlueSentry application GUI a) radar motion sensor – force wave visualization, b) radar motion sensor – radar counter visualization c) radar motion sensor – acceleration wave visualization

The preferences are used to set-up particular parameters associated with particular walker' user training or to the particular physiotherapy exercises associated with smart walker use. The data obtained from the smart walker measurement channel is transferred automatically (from time to time e.g. 2 min) or manually by direct command to the HealthCare Web IS database for advanced processing (e.g. gait pattern recognition). The synchronization permits to actualize the information on the smartphone side concerning measurement data processing algorithms, thresholds, alarms, user profile and preferences.

The Android SDK and the Java programming language were used in our work as software technologies to implement data communication, data processing and representation on the smartphone display as well as the data management. A set of Activity Classes were considered: *ServerSync* that permits to manage all the information regarding the application; *SingleChannel* that assures the graphical representation of individual wave associated with smart object measurement channels (e.g gait wave from smart walker radar channel); *MultipleChannel* that assures multiple graphical representation of clinical status. A flowchart associated to the *SingleChannel* activities classes interaction with Java methods of Bluetooth Service is presented in Figure 21.

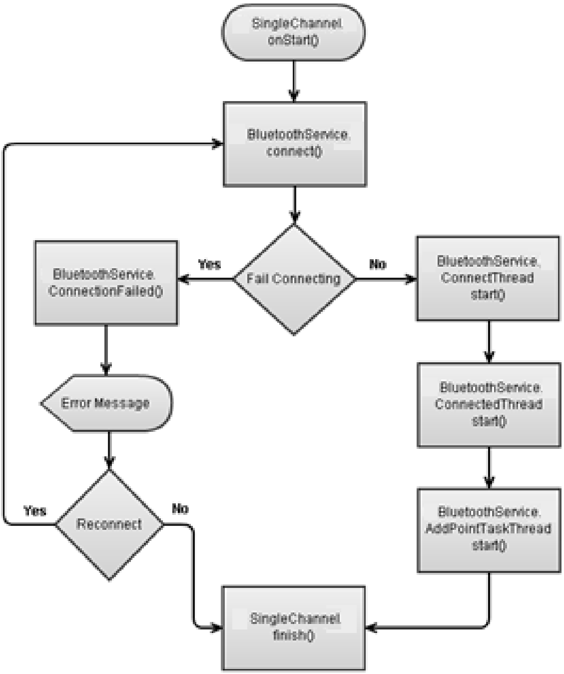


Fig. 21. DashBoard.java flowchart

Activity classes that also were implemented in the smartphone: *Main* that shows a menu associated with the selection of the main application classes; *Profile*, related to the patient profile, includes personal information and clinical data such as medical exams, registered illnesses, and indicated medication; *DatabaseList* that presents a list of particular elements for each patient shown on the smartphone display; *BluetoothService* that is related with Bluetooth data communication; *BluetoothDebug* that permits to display the data that is received from the acquisition and communication module in numerical format. If a set of smart objects with Bluetooth communication compatibility are present in our designed ambient intelligent for healthcare, a list of available devices is shown to the caregiver using the touch panel computer. The user is able to choose the smart object according to the ID of the person that is associated with the smart object. The selection can be done automatically according to the healthcare assessment schedule that is daily updated on the computing device (PC) of health professional (e.g. nurse, physician) or accompanying person mobile platform (e.g. tablet PC or smartphone).

The identification of smart objects is done in the present scenario using the MAC address of the Bluetooth device. Using the aiCharts graphical library, a graphical representation of the signals acquired by the acquisition and communication module integrated in the smart objects is carried out. Thus in the wrist worn case, the evolution of PPG wave as so as the acceleration values are presented while in the walker case gait wave (obtained through the radar), force wave and acceleration waves are presented on the display. The mobile device software also includes a database that was developed using the SQLite library, while the bidirectional data synchronization with a server database was done using a set of methods included in a synchronization class. The *contextual interpreter* developed as a server application manages the data coming from wireless acquisition and communication modules, or from RFID tag making all the needed associations between the user, corresponding profile and the values of vital signs and motor activity parameters for a given smart object assigned (e.g. smart walker) to the user. The data from the contextual interpreter is transmitted to the information compositor module using XML format that will provide complete information (users, smart object localization, and adapted HMI needed for a given context). The information obtained on the compositor side is provided to the Web server that will provide the information according with the human machine interface and refreshed every time when the user is detected for the first time using a smart device (e.g. smart wheelchair), or when a specific sensor make a measurement. It also happens every time when an observer is detected in front of a situated display. A simplified materialization of above presented hardware and software architecture is presented in Figure 16. Thus the user is using a smart walker which communicates the data through Bluetooth to a smartphone (which software can be considered on the user layer too). The data received on the smartphone from the walker (values measured by the walker sensors) is delivered through the Wi-Fi/3G-UMTS Internet to the server side (ambient layer) where the data is processed and sent to the contextual interpreter and information compositor software modules. The Web server receives the appropriate information to be presented to the patient or caregiver when using the elements of the display layer. Tests on reliability were realized through the progress of design and deployment of the system and we are going to publishe the results.

A smartphone application for indoor air quality and respiratory function monitoring was also implemented by the authors (see Figure 15). By utilizing community sensing technologies with mobile telephone, public health research can exploit the wide penetration of mobile devices to collect data that can give information on impact of environment on health. For instance, projects such as the PEIR project from the University of California (UCLA) used sensors in phone to build a system that enables personalized environmental impact reports, which track how the actions of individuals affect both their exposure and their contribution to problem such as carbon emission [96]. By aggregating the data from mobile phone of different users, from *personal sensing* and from distributed sensing nodes for indoor air quality, more insight on environmental impact on human health can be obtained and public health policy shall be able to craft initiatives to mitigate risk associated with indoor and outdoor air pollution. Integrating use of GIS and GPS with mobile technologies adds a geographical mapping component [97] that is able to "tag" voice and data communication to a particular location or series of locations. These combined capabilities have been used for emergency health services as well as for disease surveillance, health facilities and services mapping, and other health-related data collection.

There is a paucity of studies that evaluate effectiveness of mHealth application. Gurman et al. [98] analysing the evidences on effectiveness of mHealth behaviour change communication (BCC) interventions in developing countries have shown that studies did not consistently demonstrate significant effects of exposure to BCC mHealth interventions on the intended audience. Although most publications described interventions that used two-way communication in their message delivery design, less than half described tailoring the content or targeting [99]. Moreover, evaluation of efficacy of a mHealth campaign using SMS as a platform to disseminate and measure HIV/AIDS knowledge and to promote HIV/AIDS testing at clinics in rural Uganda has shown that only one fifth of the mobile subscribers responded to any of the questions. The campaign had proportionately limited success in increasing knowledge levels on a mass scale [99]. A variety of techniques are designed recently for mHealth that can motivate a change of behaviour or a habit as: the use of games, competitions among groups of people, sharing information within a social network, or goal setting accompanied by feedback. We are working on design and deployment of a serious games model, taking into account elements such as the use of RFID for game playing, tablets for interaction and patient's physiological vital signals monitoring, personalization and adaptation issues. The first prototype is a type of a memory and mahjong based game designed for a tablet PC attached to the wheelchair. It is directed to address therapeutics activities in aphasia and alexia, the most common speech and language disturbance in stroke and head trauma [55].

Understanding which types of metaphors and feedback are most effective for various persuasion goals is still an open issue. Building mobile phone sensing systems that integrate persuasion requires interdisciplinary research that combines behavioral and social psychology theories with computer science, sensors and communication network engineering.

Withal privacy and security of data stored and transmitted through mobile phone will remain a significant problem in the foreseeable future. Although there are approaches that can help with these problems (e.g. cryptography, privacy-preserving data mining) they are now insufficient [100,101]. While this research field can leverage evidence and insight from data mining, machine learning, standard on communication of data, best clinical practice and ethical issue, health information system policy it present challenges is not addressed by this present work.

5 Pervasive Computing

Over the past decade, miniaturization and cost reduction in semiconductors have led to computers smaller in size than a pinhead with powerful processing abilities that are affordable enough to be disposable. Similar advances in wireless communication, sensor design and energy storage have meant that the concept of a truly pervasive 'wireless sensor network', used to monitor environments and objects within them, has become a reality. Ubiquitous computing means network connectivity everywhere, linking devices and systems as small as a drawing pin and as large as a worldwide product distribution chain [102]. Pervasive computing (the term used in some recent literature with the same meaning of ubiquitous computing) relies on the convergence of wireless technologies, advanced electronics and the Internet. The pervasive computing abilities may allow continuous monitoring of human health in any environment, be it home, hospital, outdoors or the workplace.

Pervasive computing shares many application fields in common with mobile computing such as mobile networking, mobile information access, adaptive applications, location sensitivity. However it addresses four key issues expressed by smart spaces, invisibility, localized scalability and masking uneven conditioning [103]:

- *Smart Spaces*: embedding computing infrastructure in building infrastructure brings together two worlds that have been disjoint until now. The fusion of these worlds enables mutual sensing and control of these worlds.
- *Invisibility*: the ideal expressed by Weiser is complete disappearance of pervasive computing technology from a user's conciousness. In practice, a reasonable approximation to this ideal is minimal user distraction. If a pervasive computing environment continuously meets user expectations and rarely presents him with surprises, it allows him to interact almost at a subconcious level.
- *Localized Scalability*: as smart spaces grow in sophistication, the intensity of interactions between a user's personal computing space and its surroundings increases. This has severe bandwidth, energy and distraction implications for a wireless mobile user. Scalability, in the broadest sense, is thus a critical problem in pervasive computing. Like the inverse square laws of nature, good system design has to achieve scalability by severely reducing interactions between distant entities. This directly contradicts the current ethos of the Internet, which many believe heralds the "death of distance."
- *Masking Uneven Conditioning*: uniform penetration, if it is ever achieved, is many years or decades away. In the interim, there will persist huge differences in the "smartness" of different environments – what is available in a well-equipped conference room. This large dynamic range of "smartness" can be jarring to a user, detracting from the goal of making pervasive computing technology invisible. One way to reduce the amount of variation seen by a user is to have his personal computing space compensate for "dumb" environments. As a trivial example, a system that is capable of disconnected operation is able to mask the absence of wireless coverage in its environment.

Pervasive computing devices should be completely connected and constantly available. Hence, pervasive computing stimulates and reinforces deployment of smart products that communicate unobtrusively. The smart sensors for pervasive heath monitoring and care may be connected to the Internet and the generated data may be easily available. Therefore pervasive health monitoring and pervasive healthcare systems may generate a wealth of information for the healthcare provider above and beyond what is currently available. How this information will be acquired, stored and interpreted, and how healthcare systems will respond to adverse events and to improve quality of care must all be considered. It is important to appreciate that at present while much patient information is collected by continuous monitoring, for example during hospital admission, most of this information is lost. As pervasive health monitoring systems will collect a vast amount of information, separating this into 'important' and 'non-important' is going to require very accurate context sensing and data mining. Reacting to this information is going to require major process automation and structural change to existing healthcare systems. Traditional approaches for handling data are often based on large dedicated computer systems which store all required data at one single location and handle all incoming requests from applications and their users. While this is a valid approach for limited amounts of data, it is no longer functionally and economically viable for large scale pervasive health monitoring and care. The apparent solution is to distribute both data and requests onto multiple computers. In this case, a method to create coherence between computers is required, designed to make the distributed appear like a single large units to its users [104]. The Cloud Computing [31] that is a specialized form of distributed computing that introduces utilization models for remotely provisioning scalable and measured information technology resources. Analyzing the main characteristics of the cloud computing such as on-demand self-service, broad network access, resource pooling and rapid elasticity can be underlined that the usage of this kind of technology fit well with the pervasive healthcare. Thus smart object as patient assistants can access to the cloud computing capabilities in order to obtain the processed metrics associated with the values measured by the sensors that can used to generate warning up message translated in audio and/or video signaling forms. Based on cloud computing models the computing resource are pooled to serve multiple consumers using multi-tenant model [105] with different physical and virtual resource dynamically assigned and reassigned according with smart object demand or mobile platform demand. Taking into account the reliability requirements for the healthcare systems the cloud computing provides increased reliability through the use of multiple redundant sites, which makes Cloud Computing suitable for health system continuity and disaster recovery. The first steps in Cloud Computing technology application for healthcare are already done especially related to the usage of cloud storage facility; however fewer steps were done in the healthcare data analysis side where the usage of computational intelligence and semantic Web technologies represent the next step in the future of healthcare system. Computational Intelligence (CI) [106] is a set of nature-inspired computational approaches that primarily includes Fuzzy Logic Systems (FLS) [107], Evolutionary Computation (EC) [108] and Artificial Neural Networks (ANN) [109]. The Evolutionary Computation may deal with the vastness and tractability issues in storing, querying, reasoning and mapping semantic data in pervasive health monitoring, Fuzzy Logic may effective for management of vagueness and uncertainty in pervasive healthcare while Artificial Neural Network may improve the learning capacity of the pervasive health system and solve inconsistent issues with regards to data mapping and the data alignments in pervasive health monitoring and care.

In the early sixties, the concept of Semantic Network was firstly introduced as a knowledge representation model by cognitive scientists Allan M. Collins, linguist M. Ross Quillian and psychologist Elizabet F. Loftus [110]. In 1998, the term Semantic Web (SW) was coined by Web inventor Tim Berners-Lee as an extension of the current Web [111]. It was described as a giant global semantic network of data that is directly consumable and understandable to machines. In contrast to a hypertext Web that indicates texts linked to other texts in other places by hyperlinks, the Semantic Web projects a hyperdata Web that indicates data objects linked with other data objects across the Web through formal semantics and ontologies [112]. It enables the formation of a global web of data or open linked data [113] that interlinks distributed data at a Web-scale. The Semantic Web is led by the World Wide Consortium (W3C) as an international collaborative movement [114]. According to Tim Berners-Lee et al. [111] the Semantic Web will bring structure to the meaningful content of Web pages, creating an environment where software agents roaming from page to page can readily carry out sophisticated tasks for users as clinical diagnosis advice. Regarding the principle of "how" Semantic Web is defined [115] a layered architecture expressed in Figure 22 was proposed by Tim Berners-Lee.

In Figure 22 *Unicode* represents the standard for computer character representation, and *URIs*, the standard for identifying and locating resources (such as pages on the Web*); XML* form a common means for structuring data on the Web but without communicating the meaning of the data; *RDF (Resource Description Framework)* represents a simple metadata representation framework; *Ontologies* represents a richer language for providing more complex constraints on the types of resources and their properties; *Logic and Proof* represents an (automatic) reasoning system provided on top of the ontology structure to make new inferences ; *Trust* represents the final layer of the stack addresses issues of trust that the Semantic Web can support.

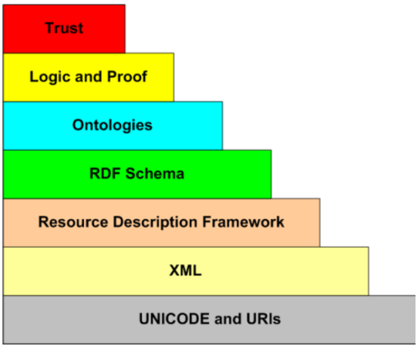


Fig. 22. Semantic Web layered architecture

Like the Web architecture, the pervasive healthcare is going to be decentralized, vast, uncertain, and incomplete. Generally, manually configuring and operating large-scale distributed systems that potentially comprise thousands of nodes is no longer feasible. Self-organizing distributed systems are able to operate autonomously [116]. The approaches developed for handling vast Web data may be adapted for pervasive health monitoring and care taking into account the specificity of data store and communicated. For instance, new approaches are recently proposed for handing with vast data: the eRDF (electronic *Resource Description Framework)* that provides the evolutionary algorithms for querying, and a swarm algorithm for logical entailment computation [117]; swarm intelligence model to store and analyze the massive amounts of semantic data and collective behavior of swarm individuals for reasoning over a fully decentralized and self-organized storage system [118]; tractable reasoning services for ontology application using tractable profiles in OWL2 (*Web Ontology Language*) and some of their fuzzy extension and reusable reasoning infrastructure called TrOWL for mashup, process refinements validation, software engineering guidance for tractable applications of fuzzy and crisp ontologies [119]; use of cloud infrastructure for scalable reasoning on top of semantic data under fuzzy pD* semantics (i.e. an extension of OWL pD* semantics with fuzzy vagueness) [120].

6 Conclusion

Driven by quality and cost metrics, the healthcare systems will change radically in the near future from current healthcare professional-centric systems to distributed networked and mobile healthcare systems. In this movement, the leading part is attributed to the pervasive technologies. Pervasive healthcare tries to change the healthcare delivery model: from doctor-centric to patient-centric, from acute reactive to continuous preventive, from sampling to monitoring.

The pervasive or ubiquitous access to healthcare data is essential for diagnosis and treatment procedure in healthcare system of the future. It requires unobtrusive sensing and convenient on-demand network access to a shared group of configurable computing resource. We describe in this chapter unobtrusive sensing solutions based on optical sensors, microwave Doppler radar, or MEMS technologies as well as Android OS software applications. The smart objects, characterized by the unobtrusiveness of sensing and computing in a pervasive system for health monitoring may deliver information to mobile platforms such as smartphone or tablet computers programmed to locally process the received data and to perform data synchronization with Web healthcare servers as Cloud computers components. These computer resources expressed by networks servers, storage applications and Web services might be rapidly provisioned and released with minimal management effort or service provider interaction, by using computational intelligence and Semantic Web.

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