Technologies for Motion Measurements in Connected Health Scenario

Pasquale Daponte, Luca De Vito, Gianluca Mazzilli, Sergio Rapuano, and Ioan Tudosa

Abstract Connected Health, also known as Technology-Enabled Care (TEC), refers to a conceptual model for health management where devices, services, or interventions are designed around the patient's needs and health-related data is shared in such a way that the patient can receive care in the most proactive and efficient manner. In particular, TEC enables the remote exchange of information, mainly between a patient and a healthcare professional, to monitor health status, and to assist in diagnosis. To that aim recent advances in pervasive sensing, mobile, and communication technologies have led to the deployment of new smart sensors that can be worn without affecting a person's daily activities. This chapter encompasses a brief literature review on TEC challenges, with a focus on the key technologies enabling the development of wearable solutions for remote human motion tracking. A wireless sensor network-based remote monitoring system, together with the main challenges and limitations that are likely to be faced during its implementation is also discussed, with a glimpse at its application.

Keywords Motion measurements · Connected health · Body area sensor network · IMU · Healthcare

1 Introduction

Healthcare challenges get increasingly complex due to the growing and aging population, the rising cost of advanced medical treatments and the severely constrained health and social care budgets. In such scenario, TEC is capable of providing cost-effective solutions such as telehealth, telecare, and telemedicine with the aim of providing care for people in convenient, accessible, and cost-effective manner.

P. Daponte · L. De Vito · G. Mazzilli · S. Rapuano (✉) · I. Tudosa
Department of Engineering, University of Sannio, Benevento, Italy
e-mail: daponte@unisannio.it; devito@unisannio.it; gmazzill@unisannio.iti; rapuano@unisannio.it; itudosa@unisannio.it

A. El Saddik et al. (eds.), *Connected Health in Smart Cities*,
https://doi.org/10.1007/978-3-030-27844-1_10

One of the most challenging features of Connected Health is related to human motion measurements. Over the last few years, several motion tracking systems and techniques have been developed in order to allow clinicians to evaluate human motion across several biometric factors or obtaining accurate postural information about sport athletes. Recent developments in human motion tracking systems, mainly due to the modern communication capabilities, led to a number of exciting applications in Connected Health scenarios, in particular in the fields of medical rehabilitation and sport biomechanics.

In recent years, medical motor rehabilitation relevance grew fast as the average population age increased, along with a surge of chronicle diseases and accidents, as those related to sport activities. The ultimate goal of rehabilitation process, which includes several stages, should be to fully recover from temporary motor impairments, or to enhance the life quality of patients with permanent motor disorder by aiming at the highest possible level of independence [1].

In the rehabilitation of motor dysfunctions, a key role is played by the Range Of Motion (ROM) measurements whose evaluation constitutes the basis of the therapist's work. ROM is defined as the amount of movement through a particular plane, expressed in degrees, that can occur in a joint. Figure 1 depicts a flexion exercise apt to determine the ROM for elbow. Most times ROM measurements are carried out under subjective scrutiny of therapists who rely on their own sensitivity and expertise about visual analysis of human body and palpation of the concerned regions. The adoption of electronic measurement methods in rehabilitation offers the outstanding advantage of automatic measurements that allow to assist qualitative analysis of therapists with objectively measured quantities. Moreover, combining measurements via electronic instrumentation with the wide area networks set rehabilitation activities free of space and time constraints.

One of the fields where the automatic measurement of ROM could provide significant improvements in the treatment process and in the cost reduction of such

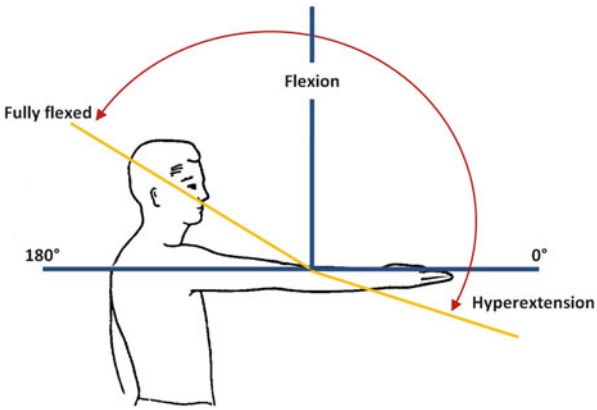

Fig. 1 Range of motion for elbow joint

treatment is home rehabilitation. Basically, home rehabilitation allows a patient to undergo treatment without the need to reach a specialized center. Apart from minimizing inconvenience and cost of commuting, a patient that has been given the opportunity of carrying out rehabilitation activities while staying at home is likely to show motivation and make progress thanks to the more comfortable conditions he/she enjoys. Moreover, avoiding for patient to share space, equipment, and therapists' attention with other people in a crowded center implies longer, and thus more effective, sessions. Ultimately, helping to improve the quality of treatment mainly means helping make recovery faster, which has a direct impact on the costs for healthcare systems [2].

Another emerging field that involves automatic human motion measurement techniques, often simply called motion tracking techniques, for studying biomechanical parameters of the human movement is sport biomechanics. In this context, the development of accurate activity monitoring techniques is performed to gain a greater understanding of the athletic performance. As an example, real-time monitoring of load and tiredness of athletes during their training sessions is important in order to maximize performance during competitions, as well as being important for the health of the athletes. Activity monitoring also plays an important role in injury prevention and rehabilitation. Due to the nature of sport activities, any monitoring device should be small and unobtrusive as possible.

Recent advancements in communication and network technologies have made possible the remote monitoring of motion tracking systems, both for home rehabilitation and sport applications. Authors in [3] describe a remote environment for athletes' training and support. By means of wireless sensors, the system provides the visualization to a remote advisor about runners' conditions, providing feedback functions to them by using kinematic feature of arm swing. A conceptual representation of a remote monitoring system for home healthcare in a Connected Health scenario is shown in Fig. 2. Small sensors, unobtrusively worn on designed clothing or accessories, are used to gather physiological and movement data. Sensors are placed according to the clinical application of interest. For instance,

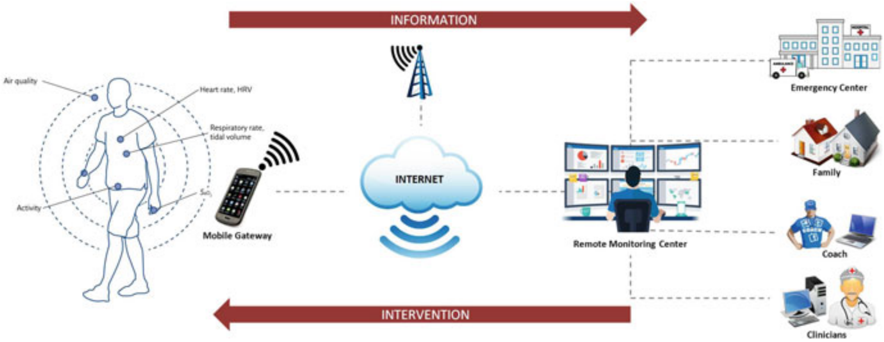

Fig. 2 Conceptual representation of a remote monitoring system for home healthcare in a Connected Health scenario

sensors for human motion measurements could be deployed on the body parts involved in a rehabilitation treatment. Wireless communication is enabled to stream health-related information to a mobile phone or an access point, forwarding them to a Remote Monitoring Center (RMC) via Internet. Warning situations are detected via dynamic data processing algorithms and an alert message is sent to an emergency center to provide immediate assistance. Caregivers and family members are alerted in case of an emergency but could also be notified in several situations when the patient requires assistance.

Despite the proven benefits of the remote monitoring systems relying on body-worn sensors like those described above, there are considerable open challenges that need to be addressed before such systems can be adopted on a large scale. These challenges include not only technological barriers, such as interoperability across different platforms and security issues but also serious cultural barriers such as the dislike of the use of medical devices for home-based clinical monitoring [4].

Some of the aforementioned technical challenges have already been dealt with satisfactorily, some others are being faced and some others are still under study. This chapter presents some solutions to those challenges focusing on a remote measurement system designed for motion tracking in home rehabilitation field that can be adopted for sport biomechanics and can easily be extended to other remote health applications. The main challenges will be presented first, than the available technologies, their lacks, and some possible solutions will be discussed in the next sections. In particular, Sect. 2 provides an overview of key sensing technologies enabling the development of wearable solutions for human motion tracking and remote monitoring systems. Although the most common enabling technologies can be classified as sensing and communication hardware, the influence of signal processing and software technologies can be significant when designing a remote monitoring system for home healthcare. Of course, the role of such technologies depends on the specific application case. Therefore, the chapter presents a case study from the choice of the sensors to the architecture design and implementation to the communication and usage optimization. In Sect. 3, a remote monitoring system capable of bringing a real-time 3D reconstruction of human posture is described. Section 4 deals with the problems of realizing such system relying on a standard wireless network. Section 5 shows an example of the application of advanced software technologies to improve the scalability and the communication performance of the remote monitoring system. Finally, Sect. 6 draws conclusions.

2 Key Enabling Technologies

Systems for human motion tracking and remote monitoring consist of three main blocks: (1) the sensing hardware to collect motion data; (2) the communication interface (both hardware and software) to gather data coming from sensing devices and relay them to a RMC, and (3) dynamic data analysis algorithms to extract clinically relevant information from motion data.

The advancements of sensors based on MEMS (Micro Electro-Mechanical Systems) technology, and in particular of inertial sensors have enabled a huge development of instruments and systems for motion tracking, in particular for applications in the fields of healthcare, rehabilitation, and biomechanics. MEMS inertial sensors have been recently used to design personal and body area motion measurement systems to continuously monitor the patients during the rehabilitation treatment. Monitoring allows the doctors to be aware of the patient's progress, as well as to collect data for biofeedback systems, where the patient's motivation can be increased by looking at his/her results [5]. MEMS inertial sensors are usually composed of a 3-axial accelerometer, able to measure the static acceleration, and a 3-axial gyroscope, able to measure the angular rate, to form an Inertial Measurement Unit (IMU). Often such sensors are combined with a 3-axial magnetometer, able to measure the Earth magnetic field. In this case, the sensor unit takes the name of MARG (Magnetic, Angular Rate, and Gravity).

The values measured by the different sensors need to be combined to obtain an estimation of the orientation of the unit. Although, in order to obtain the orientation, just the 3-axial accelerometer and the 3-axial magnetometer would be needed, it is useful to merge the measurements from such sensors with those from the gyroscope, with the aims of reducing the noise on the accelerometer and magnetometer readings, and of compensating for the gyroscope offset, that causes a drift of the orientation estimation. Moreover, the magnetometer is often prone to disturbances coming from external magnetic fields and ferromagnetic materials in the environment.

A motion capture suit composed of inertial sensors has been presented in [6]. The suit has been specifically introduced for home and hospital rehabilitation, with the aim of providing real-time support to health assessment by supplying motion-related quantities. The embedded sensors communicate with a personal computer via CAN bus at 1 Mb/s. In their latest revision, authors replaced CAN interface with a Bluetooth module.

Sensor nodes must be noninvasive to be accepted by the patient, and they have to avoid restraining the movements that the patient does in normal conditions, otherwise the measurement results will be altered by the system itself. For this reason, wireless technologies have been recently adopted in many health applications because of the flexibility offered by reduced wiring, which gets costs lower and patient more friendly to instruments he/she has to interact with. Furthermore, wireless equipment is usually based on low-power consumption technologies enabling long-term monitoring. A review of wireless-based solutions for health applications is available in [7].

Authors of [8] experimented with a wireless system using an accelerometer to monitor vital signs of people staying at home. Post analysis unveiled that different types of human movements (i.e., walking, falling, jumping, and so forth) generate different patterns in acceleration data, and that information can be used to recognize abnormal activities and warn against them. Patients with Parkinson disease were monitored during everyday activities to evaluate their in-home mobility [9]. To capture the whole-body motor function and identify movement patterns in scripted and unscripted tasks, inertial units were attached to body parts and communicated with a laptop computer in the range of action. Results obtained with principal component analysis showed a wide variability across tasks for several subjects, and within subjects for each task. IMUs have also been integrated into consolidated equipment accompanying rehabilitation treatment, like those applied to forearm crutches being used in lower limb rehabilitation [10] to sense the force applied by patient, the crutch tilt and the handle grip position. These parameters have been proven to deeply affect the recovery rate, thus, monitoring them and giving biofeedback can help the patients to adjust their crutch walking to the proper way.

Several studies can be found in the literature addressing the use of wireless IMUs in sport applications. The speed and energy expenditure of athletes over ground running can be obtained through the use of wearable accelerometers [11]. Authors in [12] combined a suite of common, off-the-shelf, sensors with body sensing technology and developed a software system for recording, analyzing, and presenting sensed data sampled from a single player during a football match. Readings are gathered from heart rate, galvanic skin response, motion, respiration, and location using on-body sensors.

Although they are not the most accurate instrument to track human movements [13], wireless IMUs have long turned out comfortable for home rehabilitation applications, as they can work under the most common circumstances, without any particular constraint on lighting or space. Many approaches to motion tracking have been introduced over the years based on wearable motion sensors, whose measurements have mostly been validated against well-known camera-based systems with markers. A wearable wireless sensor network able to keep track of arm motion in sagittal plane was proposed in [14]. Two nodes, equipped with a biaxial accelerometer, were used as inclinometer and sensed the orientation of the upper and lower arm while extending and flexing the limb. The angle estimate error due to misalignment of nodes along the arm was modeled, and a calibration to determine accelerometer offsets was carried out by mounting the sensor on a high-precision rotary motor. Furthermore, system accuracy was evaluated by making the motor produce swinging motion with different oscillation speeds.

Motion tracking applications by means of wearable systems most often employ multiple sensors typically integrated into a Body Area Sensor Network (BASN). An example of this technology is the motion tracking system described in [15, 16]. The described home rehabilitation system produces, by means of a BASN, ROM measurements for patients performing rehabilitation exercises. A set of wireless nodes (or motes) constitutes a wearable device that keeps track of orientation produced by different body segments. Given a joint to monitor, both of the involved limb segments are equipped with a mote embedding an IMU, so that the ROM is determined from the absolute orientation of two motes. The primary functions of the sensor nodes in a BASN are (1) to unobtrusively sample motion signals and (2) to transfer relevant data to a personal gateway by means of a wireless connection. A personal gateway, implemented on a smartphone or a personal computer, sets up and controls the BASN, transferring health-related information to the RMC through the Internet.

The availability of mobile telecommunication networks (e.g., GRPS, 3G, 4G) allows pervasive user monitoring when he/she is outside the home environment. During the last few years, several communication standards for low-power wireless communication have been proposed in order to fulfill three main requirements: (1) low cost; (2) small size of transmitter and receiver devices; and (3) low-power consumption. The recent developments of IEEE 802.15.4 (ZigBee) and IEEE 802.15.1 (Bluetooth) have the major focus on increasing network throughput. Moreover, network lifetime has a greater importance in BASNs since devices are expected to perform over long periods of time [17].

The large amount of data gathered using wearable systems for user's status monitoring has to be managed and processed in order to derive clinically relevant information. Signal processing, data mining, and pattern recognition are examples of data analysis techniques that enable remote monitoring applications that would have been otherwise impossible. Although an exhaustive discussion of the various data processing algorithms used to process and analyze wearable sensor data is outside the scope of this chapter, one cannot emphasize enough the fact that data processing and analysis techniques are an integral part of the design and development of remote monitoring systems based on wearable technology.

3 A Remote Monitoring System for Home Rehabilitation

An example of joint adoption of the key technologies introduced in the previous section can be found in [18], proposing an integrated wireless system gearing toward the human motion tracking in home rehabilitation. The study described in [18] deals with the design and implementation, from scratch, of a remote monitoring system allowing the real-time 3D reconstruction of the patient's motion. The key contribution of the proposal, in addition, to help improving treatment conditions and to reduce healthcare costs, lies in producing outputs that can be evaluated both qualitatively and quantitatively by an operator. The system has been designed in order to reduce costs, as well as occupancy, of home-side instrumentation. In such a scenario, a subject in treatment may stay at home performing rehabilitation exercises while wearing small motion sensors, which are included in a BASN. Of course, nothing prevents the same system from being used also within the rehabilitation centers, where many patients could be contemporarily accommodated.

Being properly strapped to the body segments of interest, the sensor nodes provide information about their own respective motions. Through a network connection, sensed data are delivered to a dedicated server (Posture Reconstruction Server—PRS), housed at the RMC, that processes the raw measurements to determine the corresponding human posture. The evolution of human body part orientation and posture in time is afterwards stored in a database so that the motor behavior can be replayed for post analysis. The patient's motor behavior is projected at the RMC on a 3D digital representation.

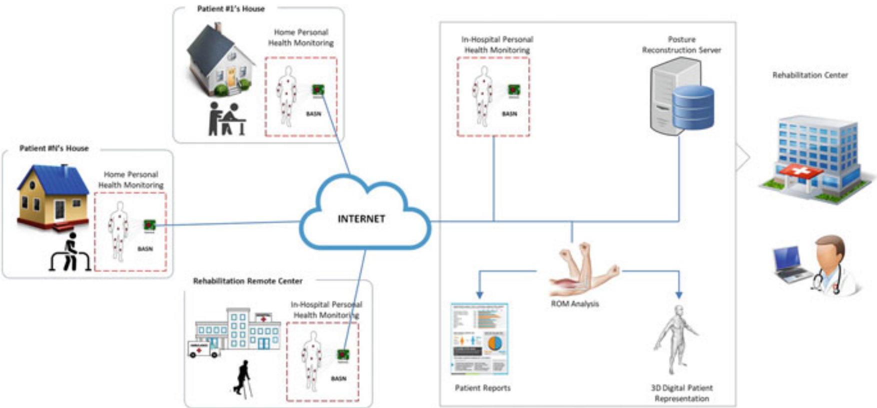

Fig. 3 System architecture of the human motion tracking system proposed in [18]

By interacting with a ROM analysis graphical user interface, the clinical staff can watch, without leaving the workplace, the movements of several subjects under analysis as they are executed at the same time. Augmenting the observation experience of physiotherapists with objective ROM measurements may stand for an unprecedented way to evaluate functional recovery, both between and within subjects.

The components of the remote monitoring system are detailed in the following subsections (Fig. 3).

3.1 Body Area Sensor Network

The proposed BASN (Fig. 4) includes as many sensor nodes as body segments to track, in addition to a gateway node. Each sensor node is responsible for providing the data needed to determine the absolute orientation in the space of the body segment. All the motes taking part in the BASN are Zolertia Z1 modules, having the size of $34.40 \times 57.00 \times 11.86$ mm^3, and transmitting data via IEEE 802.15.4 interfaces to the gateway node. Each of them is programmed with TinyOS, and equipped with a 9 degrees of freedom IMU. Such an IMU comprises three sensors connected by I2C bus to a Texas Instruments© MSP430 microcontroller: a 3-axis accelerometer measuring linear acceleration with 12-bit resolution, a 3-axis gyroscope measuring angular rates with 16-bit resolution, and a 3-axis magnetometer sensing the magnetic field with 16-bit resolution, all being sampled at 50 Hz along the same local reference system. Apart from size and weight of motes being limited, the fact that the whole communication relies exclusively on wireless technology goes a long way toward getting the usage as tidy and comfortable as possible. Consequently, the patients may enjoy more mobility than wearing a wired

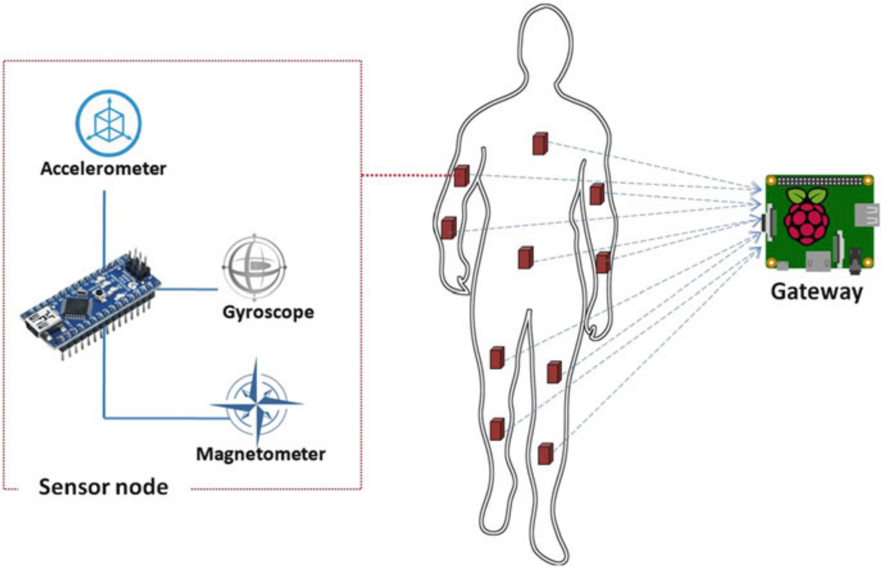

Fig. 4 Body area sensor network

measurement system, which may play an essential role in motivating patients. The gateway node consists of a mote, wirelessly receiving data from sensor nodes, that is attached via USB to a Raspberry Pi, a very cheap banknote-sized single-board computer, having TCP/IP capabilities and being connected to the power grid. The single-board computer, equipped with a 32-bit ARM 700 MHz processor and 512 MB RAM, gathers and handles raw sensed data from IMUs that are then streamed to the PRS via Real-time Transport Protocol (RTP).

3.2 Posture Reconstruction Server

The PRS, housed in the RMC, is a processing unit that is in charge of three different functions: (1) it handles raw sensed data from several BASNs to obtain absolute orientation of single body segments and, as a result, the whole body orientation and posture of multiple patients tracked at once; (2) it runs a Real Time Streaming Protocol (RTSP) server offering to the users the possibility of controlling the 3D representation playback; and (3) it operates a database storing the patient's posture as it evolves in time, thus making up a sort of personal motor history. The PRS represents a powerful resource that allows both for offline analysis of progresses made by a given subject over time and for comparison of quantities concerning the same rehabilitation stage in a given treatment from different patients. The RTSP server can be required by the user to stream either “live” playback, directly from a BASN, or some content stored in the database.

3.3 ROM Analysis Software

The software application for posture and ROM analysis runs at the physician’s workstation and offers several analysis interfaces to the medical staff by interacting with the PRS. For example, patient reports including data and statistics on current treatment can be composed and displayed by the software upon accessing the history database in the PRS. Intra-subject analyses can be conducted by aggregating data from that source as well. The digital reconstruction of human posture is realized by means of a free 3D engine. The application can be set to feed the animation either with the data from one of the operating BASNs (real-time playback), or with stored posture information (delayed playback). It is worth adding that the operator is given the possibility of defining a set of joint angles he/she is interested to watch. The 3D animated model can be observed in Fig. 5 while set for measuring right upper limb motion. In this way, while the 3D animation is going on, objective quantities about those angles are displayed in virtual labels. The labels also show the maximum value reached since the therapy session has started, giving highly valuable support for immediate ROM assessment.

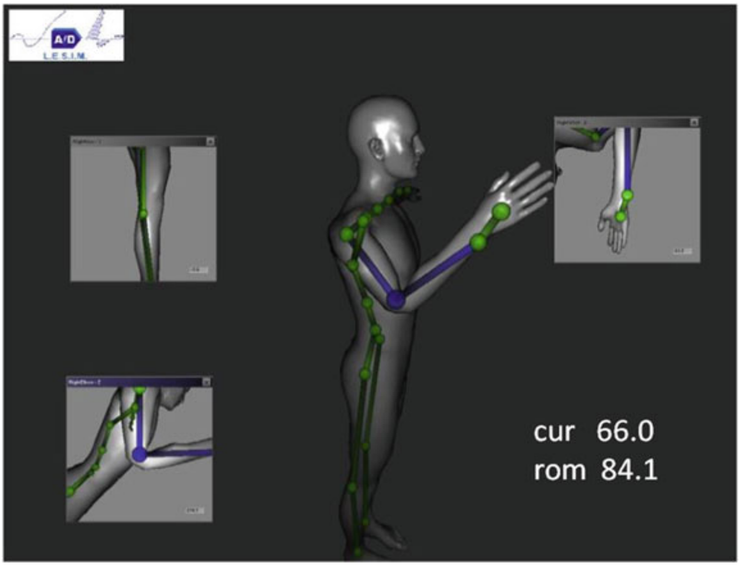

Fig. 5 A screenshot from the 3D animation of the right upper limb in action. The joint under analysis is the blue node in the screen

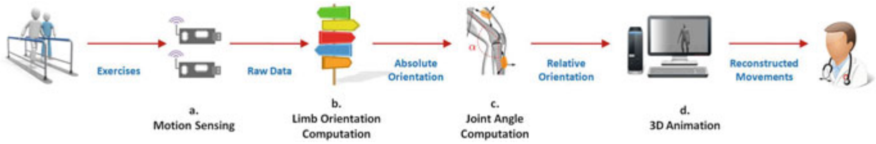

Fig. 6 Stages of real-time processing to animate the 3D reconstruction

3.4 Stages in Processing the Measurement Signals

Figure 6 outlines the stages that the real-time 3D reconstruction goes through, from home to the RMC. At the first stage (a), the movements produced by the patient are captured by the IMUs, whose raw data are collected and sent by the gateway to PRS. Subsequently (b), the PRS filters the compensated sensor outputs to determine, in real time, the orientation of the several body segments in the Earth's coordinate frame. The segment orientations are then combined to compute relative orientations and joint angles for reconstructing the posture of the subject (c). In the final stage (d), limb orientation and posture feed the ROM analysis application running on clients that show a 3D real-time animated model representing the patient. A therapist working at the rehabilitation center can finally observe from his/her workstation the movements as they are executed, maximizing productivity by observing multiple subjects at once.

3.5 Quaternion-Based Processing

Avoiding to engage them in any orientation computation lets the nodes of the BASN spend most of their working time in low power consumption mode, thus preserving battery life. Therefore, the PRS turns raw sensor data into body segment orientation and posture.

The orientations are expressed with quaternions $\mathbf{q} \in \mathbb{R}^4$ as representations based on Euler angles (i.e., pitch, roll, and yaw) suffer well-known singularity problems [19]. Although angular rates produced by a 3-axis gyroscope suffice to sense movements in the three planes, bias drift affecting the measurement prevents the accuracy necessary in human motion tracking applications. This is why the adopted algorithm uses data from accelerometer and magnetometer to estimate and compensate the gyro drift. On the other hand, external acceleration and magnetic disturbance usually make outputs from those two sensors noisy. To tackle these problems, step b of Fig. 6 is carried out by a quaternion-based implementation of extended Kalman filter [20]. Before an orientation estimation might be produced by a filter, a quaternion corresponding to each set of accelerometer (a) and magnetometer measurements (m) $y_m = [a\ m]^T$ should be computed. This is done by the Factored Quaternion Algorithm (FQA) [21], which offers good performance by avoiding to compute trigonometric functions. Moreover, since magnetic disturbance might be remarkable in indoor environments such as home and medical settings, the adoption of FQA is significant for the application as it limits the influence of magnetometer and, consequently, of disturbance to one plane of motion. The computed quaternion, along with angular rate from gyroscope, represents the input of the Kalman filter. Relative orientation quaternions necessary to the 3D representation are obtained at step c of Fig. 6 from global coordinate orientations through a reference system conversion. For example, let $\mathbf{q}_u$ and $\mathbf{q}_f$ be, respectively, the quaternions providing the absolute orientations of the upper arm and forearm segments, then $\mathbf{q}_f^u$ is the forearm orientation expressed in the upper arm's local reference system and is given by:

$$\mathbf{q}_f^u = \mathbf{q}_u^* \bigotimes \mathbf{q}_f \tag{1}$$

where $\bigotimes$ is the quaternion multiplication and $\mathbf{q}_u^*$ represents the conjugate of $\mathbf{q}_u$. Relative quaternions are also used to determine the joint angles that the operator requires to measure. For example, elbow joint angle θ can be expressed as pitch angle of the forearm segment in the upper arm's reference frame, that is:

$$\theta = \arcsin\left(2wy - 2xz\right) \tag{2}$$

with $\mathbf{q}_f^u = [\ w\ \ x\ \ y\ \ z\ ]^T$.

4 Orientation Estimation in BASN Affected by Packet Loss

In order to achieve battery life extension, leading commitment in designing a BASN, a node is generally equipped with a low-power radio transceiver implementing IEEE 802.15.4 communication [22]. After all, extended battery life comes at a price: the less power is used, the lower is the communication reliability, meaning that the probability of packet loss may be significant. In most of wireless sensor network applications, communication occurs once in a while and retransmission is a viable way to overcome losses. Unfortunately, the strict time constraints on sampling, processing, and sending in real-time systems do not allow to broadcast once again a packet supposed to be not delivered. This happens any time a processing task cannot be postponed due to the needs for immediate feedback to provide. For instance, augmented reality applications have to adapt their outputs according to the change of spatial position and orientation as it happens [23].

In those cases, the only action one can take to face loss is to deal with it: loss tolerance countermeasures must aim at the reduction of the relative effects on the system outputs. Packet loss in real-time motion tracking applications basically results in a temporary decrease of the sampling rate, whose value is essential to capture a subject's movement adequately. In particular, for remote monitoring systems like the one described in the previous section, it can seriously harm the capability of the system to provide the user with accurate real-time measurements (e.g., a 3D model in motion tracking may happen to pose incorrectly). The problem is even bigger in applications with tens of nodes jointly working to trace the whole-body motion.

The problem of tracking and reconstructing the subject's movements can be modeled as the problem of finding out the spatial orientations, at any given time, of each of the segments the body is composed of. Theoretically, two main approaches are possible in order to estimate an orientation: either integrating the angular rates or referring to the projections of the Earth's gravity and magnetic field onto the sensor frame. In the former case, estimation relies exclusively on gyroscope data, in the latter accelerometer and magnetometer measurements are used as the inputs. Integrating angular rates means keeping an internal state (*stateful*) relying on the history of gyroscope data, while one sample of acceleration and magnetic field suffices to find orientation (*stateless*). In practice, both approaches, when working separately, fail to come up with a result being fit to represent human motion accurately. Gyroscope data are affected by bias that changes unpredictably in time, leading to an integration error that drifts remarkably in a few seconds. On the other hand, accelerometer and magnetometer data are basically noisy, and so are the resulting orientations, in addition, to suffering from interference caused by external acceleration and magnetic perturbations.

Every time a packet gets lost, a gap in the history of angular rates some of the body segments of the 3D model fall behind the actual movement, and in some cases awkward postures may show up. Figure 7 shows the ideal humerus pitch angle obtained when a loss occurs after 40 s, against the humerus pitch angles produced by single-frame algorithm (red line) and data-fusion algorithm (blue line). As can be seen, the ideal pitch angle grows linearly with time, while single-frame trajectory gets back on its track reacting to the same loss faster than what happens for data-fusion trajectory. A trade-off has to be found between choosing single-frame or data-fusion algorithms that could cause lower orientation accuracy and/or better loss resilience. In order to deal with that problem, a method based on the interpolation of quaternions computed by two algorithms, as depicted in Fig. 8, has been proposed in [24].

Having two unit quaternions representing rotations, an intermediate rotation can be found by interpolating them. Linear interpolation is not the best solution since a rotating joint is expected to move along a smooth curve. *Spherical Linear IntERPolation* (*SLERP*) is defined as a linear interpolation performed on the surface of a unit sphere, used in the field of computer graphics to obtain smooth motion. Analytically, let $\mathbf{q}_{\mathrm{A}}$ and $\mathbf{q}_{\mathrm{B}}$ be two unit quaternions, θ be the rotation angle, and $\mu \in [0, 1]$ be a real scalar value, the *SLERP* resulting from

$$\mathbf{q}_C = SLERP\left(\mathbf{q}_A, \mathbf{q}_B, \mu\right) = \frac{\sin\left(1-\mu\right)\theta}{\sin\theta}\mathbf{q}_A + \frac{\sin\mu\theta}{\sin\theta}\mathbf{q}_B \tag{3}$$

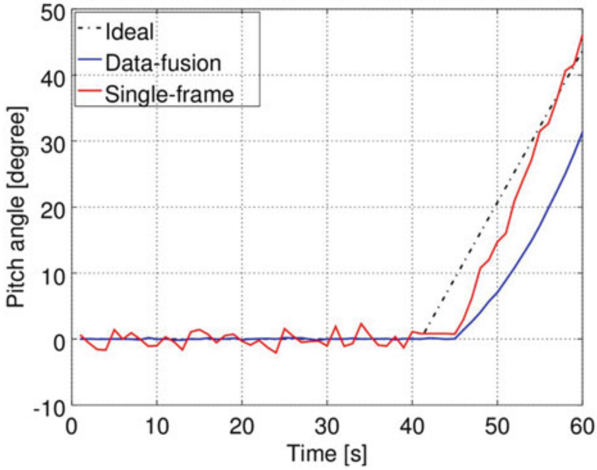

Fig. 7 Humerus pitch angle trajectories

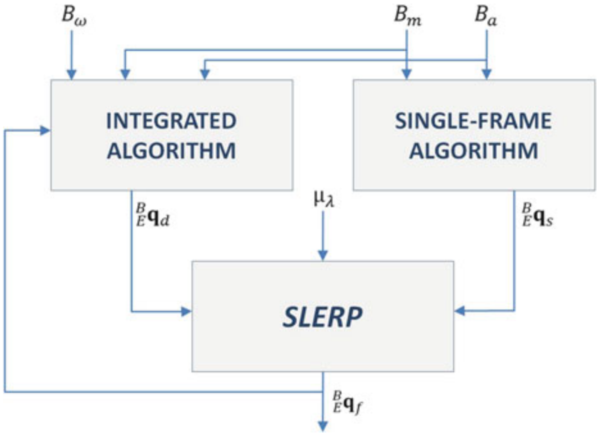

Fig. 8 Interpolation between data-fusion and single-frame quaternion

carries out a spherical interpolation between $\mathbf{q}_A$ and $\mathbf{q}_B$ by an amount μ, with $\mathbf{q}_C$ determined as a point along the circle arc on the surface of the unit sphere.

Early experiments have been carried out and their results have been presented in [24]. The sensor platform used in experiments consists of the same Zolerzia Z1 described above. The raw data have been organized in 6-sample packets, collected by a personal computer from a sensor via wired serial communication in order to get continuous lossless sequences of samples. These sequences then have been artificially injected with several profiles of loss, so as to create artificial lossy sample sequences and analyze the algorithm performance under different conditions of network reliability. In order to assess effects not only on the single node orientation, but also on joint angle measurement, sequences from two adjacent nodes have been acquired. In particular, raw data related to a 90° arm extension have been acquired and the pitch angles of humerus and forearm have been analyzed. The raw data sequence of the humerus trajectory has been injected with a loss of four packets right after 80 samples.

Figure 9a reports the performance of the data-fusion algorithm proposed in [24]. It can be seen that the occurrence of packets loss results in humerus pitch angle (red line) different from forearm one (blue line). As reported previously, this results in a growing elbow joint angle (black line). Moreover, the slow convergence rate causes a considerable deviation of the elbow joint angle for more than 2 s (about 100 samples), which is not desirable in human motion capture. The noisy single-frame orientations are shown in Fig. 9b to reduce the upper bound of elbow joint error below 20°, even though they return trajectories being unacceptably jerky. The performance of the interpolation method is shown in Fig. 9c, where the error of elbow joint angle reaches 10° for about 1 s only. It is worth remarking that these

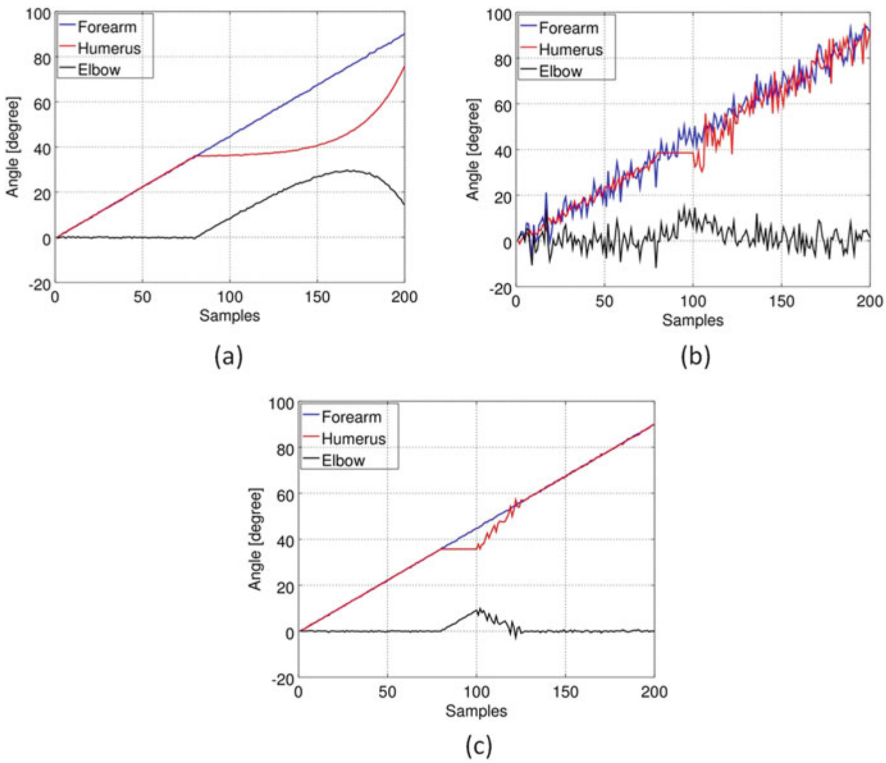

Fig. 9 (**a**) Trajectories produced by data fusion deviate remarkably from real motion due to loss. (**b**) Single-frame algorithm produces jerky trajectories. (**c**) Interpolation algorithm preserves the smoothness and limits the maximum deviation

early results seem to confirm that quaternion interpolation is a viable way to reduce the packet loss effects.

5 Remote Health Monitoring Systems and IoT

The example shown above follows a general paradigm based on a three-layer architecture. The first layer of the architecture is composed of the sensing nodes of the BASN. Each mote receives initialization command and responds to queries from its coordinator, also called gateway. The network nodes continuously sample and process raw information, sending data to the gateway. The operative frequencies for sampling, processing, and communicating are established according to the nature of the application. The second layer is the gateway that interfaces the BASN sensor nodes and communicates with services at top level. Typically, the gateway is responsible for the following tasks: (1) sensor node registration (number and type of sensors), (2) initialization (e.g., specify sampling frequency and operational mode), and (3) setup of secure communication. Once the network is configured, the gateway manages the BASN, taking care of channel sharing, time synchronization, data retrieval, and processing. At top level, a wide area network of several computers receives user' electronic health data and provides several services, such as data storage, user authentication, data pattern analysis, and recognition of serial health anomalies.

In addition to technology for data collecting, storage and access, healthcare-related information analysis and visualization are critical components of remote health monitoring systems [25]. Dealing with huge amount of data often makes their analysis quite frustrating and error prone from the clinician point of view. A solution for the aforementioned challenges can be found in data mining and visualization techniques [26]. The integration of Internet of Things (IoT) paradigm into remote monitoring systems can further increase intelligence, flexibility, and interoperability [27]. A device adopting the IoT scheme is uniquely addressed and identifiable anytime and anywhere through the Internet. IoT-based devices in remote health monitoring systems are not only capable of sensing tasks but can also exchange health information with each other. As exemplified in [28], IoT-enabled remote monitoring systems are able to provide services such as automatic alarm to the nearest emergency center in the event of a critical accident for a supervised patient.

A paradigm that breaks the rigid layered architecture shown above can be helpful when human motion of multiple users is simultaneously monitored by multiple observers. In such cases, a solution that takes advantages from the IoT and the Publish-Subscribe communication paradigm has been proposed in [29]. According to this last paradigm, the information produced by users, also known as *publishers*, is delivered to one or multiple observers, as a function of their interests. To this aim, the user labels the information with a topic before publishing it. The subscription

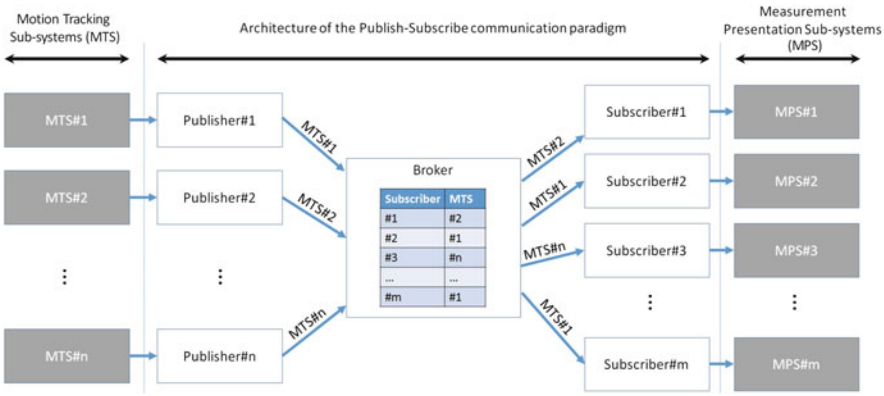

Fig. 10 Architecture of the remote health monitoring system based on IoT and Publish/Subscribe communication paradigm

of the interest to a certain topic enables the observers, also called *subscribers*, to receive notification when publications on such topic occur.

In Fig. 10, a different architecture of the remote health monitoring system based on IoT and Publish/Subscribe paradigms is shown. It is made of several Motion Tracking Sub-systems, devoted to acquire measurement information about the body segments of a single user (i.e., the BASNs described previously) and several Measurement Presentation Sub-systems, devoted to display the results to the clinicians. Among them the communication is ensured by software modules called publishers, subscribers, and broker. Differently from traditional human motion tracking systems, in the proposed one: (1) many Motion Tracking Sub-systems operate simultaneously and (2) each Motion Tracking Sub-system does not send the measurement information directly to the Measurement Presentation Sub-system but to the publisher. The publisher, once received the measurement information, labels it with a topic, e.g., the identification number of the subject being monitored and sends it to the broker by means of Internet. The broker reads the label of the received measurement information and sends it, using Internet, to further the subscribers that have previously declared their interest in that topic. Each subscriber operates in two successive phases: (1) it declares its interest by sending a message with the topic in which it is interested to the broker, and (2) it receives the measurement information in which it is interested from the broker and sends them to the Measurement Presentation Sub-system.

In the proposed solution, the human motion measurements coming from several Motion Tracking Sub-systems are published onto topic-based channels. A topic can refer to measurement information concerning a single user, multiple users, a body part of one or more users. Subscribers express their interest in one or more topics and then receive all information published to such topic.

In order to manage the information delivery, the Message Queue Telemetry Transport standard (MQTT) protocol has been selected. It was designed for networks with low bandwidth and high-latency, as in the case of Internet. The reduced size of header and payload in MQTT messages makes it useful for the transmission of data in a real-time mode. Further advantages of using MQTT relate to hiding the implementation details about networking aspects and to confine the difficulties in the data recruitment only to a topic identification. In this way, different subscribers can easily access data from different publishers. To this aim, MQTT makes use of different components, as described in the following:

- The publisher software module: (1) Creates a message, (2) labels the message with a topic, and (3) sends the message to the broker.
- The subscriber software module: (1) Subscribes to receive messages that it is interested in, (2) unsubscribes to remove a request for messages, and (3) receives from the broker the messages labeled with the topic in which it is interested in.
- The broker software module routes the messages from publishers to subscribers according to each message label and the topic in which each subscriber is interested in.

The novelty of such a paradigm lies in the fact that a client will no longer need to contact the server periodically to check new data availability. Instead, the server sends the specific data requested by the client, as soon as it has them available.

The performance of the previously described remote health monitoring system has been evaluated by considering the one-way delay from publisher to subscriber. In order to characterize such packet delays in the IoT scenario, multiple instances of MQTT publishers and subscribers have been executed providing multiple message flows from publisher to broker and from broker to subscriber. Figure 11 depicts the architecture of the test bench. Several instances of MQTT publishers have been executed on a dedicated computer (PC#1 in Fig. 11). One instance of the MQTT broker has been running on a further computer (PC#2 in Fig. 11). Several instances of MQTT subscribers have been executed on another computer (PC#3 in Fig. 11). Finally, a delay measurement system has been installed on a further computer (PC#4 in Fig. 11), in order to analyze the network traffic. It consists of an open-source network analyzer tool, *Wireshark*, able to capture network packets in real time, filtering them, and displaying the acquired information in human-readable format. It is worth noting that the packets are time stamped by *Wireshark* having as reference the same clock, i.e., the one of PC#4. This solution avoids the use of protocols to synchronize the clock of the PC sender and the clock of the PC receiver in order to evaluate the packet delay [30]. All computers in the test bench are connected together to a network hub. This choice allows to capture each packet as soon as it is sent by PC#1 and PC#2 and then to consider the behavior of the broker as function of the message flows, only. In the test scenario of this preliminary experimental analysis, a computer has been used for all the publishers and a further computer for all the subscribers. This does not happen in actual applicative scenario, where a dedicated machine is typically used for each publisher and subscriber. The usage of a single computer, however, represents a worst case, for two main reasons: (1) all the publishers/subscribers, share the same computational resources, and (2) the messages sent by all the publishers are queued to the same network interface.

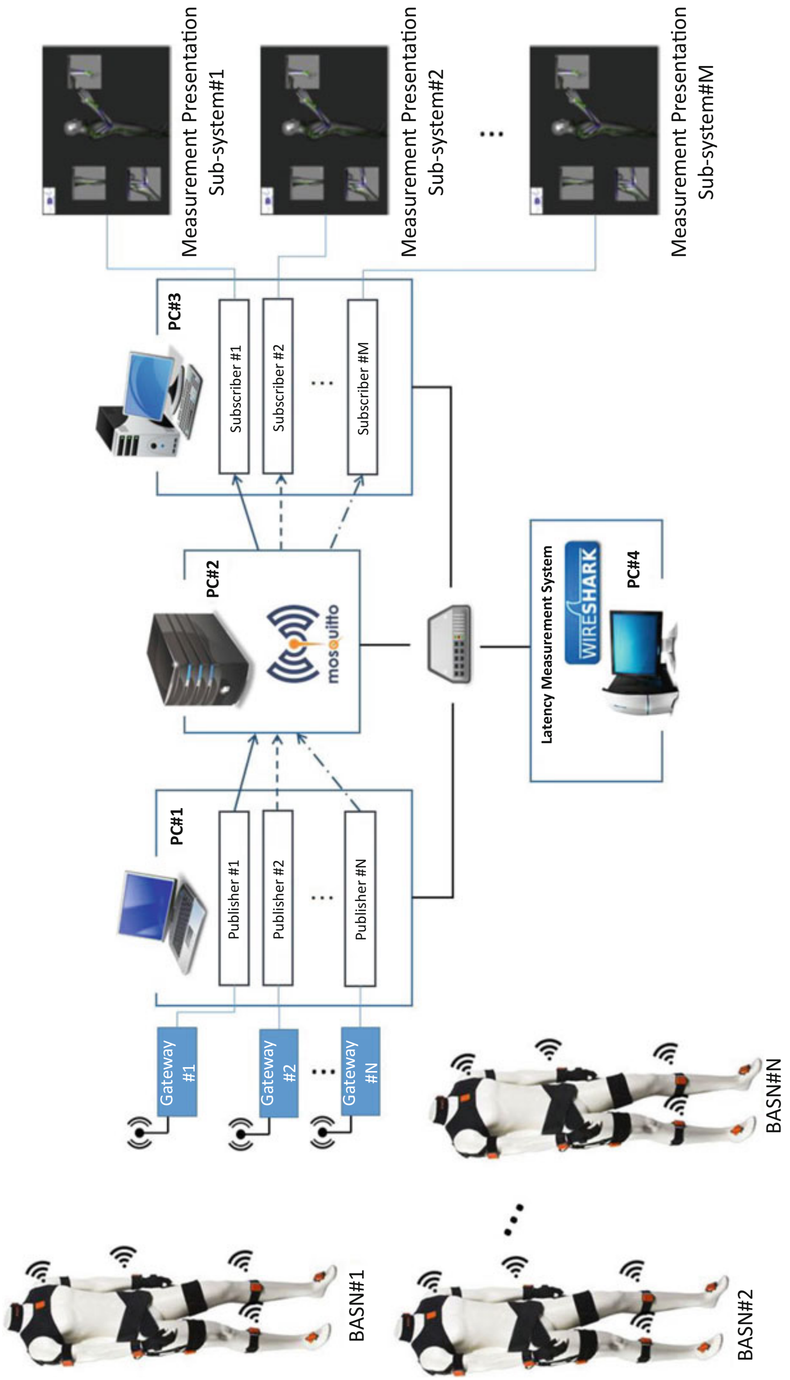

Fig. 11 The architecture of the experimental test bench

Table 1 Packet delays with respect to multiple publishers and subscribers [29]

# Publisher	# Subscriber	Max. (ms)	Min. (ms)	μ (ms)	σ (ms)
1	1	14.54	0.01	0.08	0.96
1	3	13.45	0.01	0.05	0.63
3	3	13.29	0.01	0.41	2.05
5	5	55.33	0.01	9.98	7.47
5	10	24.53	0.01	3.61	4.48
10	5	21.16	0.01	5.29	4.40
10	10	20.49	0.01	7.38	6.28

Table 1 shows the results of the experimental test bench considering different numbers of message flows produced by the publishers and received by the subscribers. As expected, the values of mean and standard deviation increase by increasing the number of message flows. No strict requirements are needed about the end-to-end delay, as the streaming is one way from the Motion Tracking Subsystems to the Measurement Presentation Sub-system. About the delay variation, requirements are related to the capability of a jitter buffer of removing such variation. This can be easily done until values of the variation in the order of 50 ms, therefore, the obtained results, reporting a maximum standard deviation of less than 8 ms, are fully acceptable for the 3D movement reconstruction application.

6 Conclusions

Driven by the widespread adoption of information and mobile communication technologies for health-related applications, the healthcare system could see a radical changing from current professional centric healthcare system to a distributed networked and mobile healthcare system. In such a context, the pervasive access to health-related data will be essential for diagnosis and treatment procedure in healthcare system. Wearable sensors, particularly those equipped with IoT capabilities, are the key players of such challenge. In this chapter, an unobtrusive sensing solution based on MEMS technologies with the aim of providing human motion measurement has been presented, together with motion measurement related research field and open issues. In particular, technological solutions related to packet loss in wireless networks, network scalability, and remote control in existing network infrastructures have also been discussed. It is easy to imagine extending the type and number of measurements by embedding other kinds of sensors in the wireless motes, like EMG electrodes and force sensors, in order to monitor and process vital signs related to motor activity.

References

1. P. Daponte, J. De Marco, L. De Vito, B. Pavic, S. Zolli, Electronic measurements in rehabilitation, in: *Proceedings of 2011 IEEE International Symposium on Medical Measurement and Applications (MeMeA)*, Bari, Italy, May 2011, pp. 274–279
2. S.F. Jencks, M.V. Williams, E.A. Coleman, Rehospitalizations among patients in the medicare fee-for-service program. New Engl. J. Med. **360**(14), 1418–1428 (2009)
3. N. Gotoda, K. Matsuura, S. Otsuka, T. Tanaka, Y. Yano, Remote training-support of running form for runners with wireless sensor, in: *2010 Proceedings of International Conference on Computers in Education*, Putrajaya, Malaysia, pp. 417–421
4. S. Patel, H. Park, P. Bonato, L. Chan, M. Rodgers, A review of wearable sensors and systems with application in rehabilitation. J. Neuroeng. Rehabil. **9**(12), 1–17 (2012)
5. L. De Vito, O. Postolache, S. Rapuano, Measurements and sensors for motion tracking in motor rehabilitation. IEEE Instrum. Meas. Mag. **17**, 30–38 (2014)
6. S. Sessa, M. Zecca, Z. Lin, T. Sasaki, K. Itoh, A. Takanishi, Waseda bioinstrumentation system #3 as a tool for objective rehabilitation measurement and assessment—development of the inertial measurement unit, in *Proceedings of 2009 IEEE International Conference on Rehabilitation Robotics*, Kyoto, Japan, June 2009, pp. 115–120
7. E. Zubiete, L. Luque, A. Rodriguez, I. Gonzalez, Review of wireless sensors networks in health applications, in: *Proceedings of 2011 Annual International Conference on in Engineering in Medicine and Biology Society*, Boston, MA, USA, September 2011, pp. 1789–1793
8. C. Chen, C. Pomalaza-Raez, Design and evaluation of a wireless body sensor system for smart home health monitoring, in *Proceedings of IEEE Global Telecommunications Conference*, Honolulu, HI, USA, December 2009, pp. 1–6
9. F. Rahimi, C. Duval, M. Jog, C. Bee, A. South, M. Jog, R. Edwards, P. Boissy, Capturing whole-body mobility of patients with Parkinson disease using inertial motion sensors: Expected challenges and rewards, in *Proceedings of 2011 Annual International Conference in Engineering in Medicine and Biology Society (EMBC)*, Boston, MA, USA, 2011, pp. 5833–5838
10. G.V. Merrett, M. Ettabib, C. Peters, G. Hallett, N. White, Augmenting forearm crutches with wireless sensors for lower limb rehabilitation. Meas. Sci. Technol. **21**(12)
11. J. Neville, A. Wixted, D. Rowlands, D. James, Accelerometers: An underutilized resource in sports monitoring, in *Proceedings of 2010 International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*, Brisbane, Australia, December 2011, pp. 287–290
12. A.F. Smeaton, D. Diamond, P. Kelly, K. Moran, K.T. Lau, D. Morris, N. Moyna, N.E. O'Connor, K. Zhang, Aggregating multiple body sensors for analysis in sports, in *Proceedings of 5th International Workshop on Wearable Micro and Nanosystems for Personalised Health*, Valencia, Spain, May 2008, pp. 1–5
13. M.A. Brodie, A. Walmsley, W. Page, The static accuracy and calibration of inertial measurement units for 3d orientation. Comput. Methods Biomech. Biomed. Engin. **11**(6), 641–648 (2008)
14. G.X. Lee, K.S. Low, T. Taher, Unrestrained measurement of arm motion based on a wearable wireless sensor network. IEEE Trans. Instrum. Meas. **59**(5), 1309–1317 (2010)
15. P. Daponte, L. De Vito, C. Sementa, A wireless-based home rehabilitation system for monitoring 3D movements, in *Proceedings of 2013 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Gatineau, Canada, 4–5 May 2013, pp. 282–287
16. P. Daponte, L. De Vito, C. Sementa, Validation of a home rehabilitation system for range of motion measurements of limb functions, in *Proceedings of 2013 IEEE International Symposium on Medical Measurement and Applications*, Gatineau, Canada, 2013, pp. 288–293
17. S. Movassaghi, M. Abolhasan, J. Lipman, D. Smith, A. Jamalipour, Wireless body area networks: A survey. IEEE Commun. Surv. Tutor. **16**(3), 1658–1686 (2014)

18. P. Daponte, L. De Vito, M. Riccio, C. Sementa, Design and validation of a motion-tracking system for rom measurements in home rehabilitation. Measurement **55**, 82–96 (2014)
19. J.B. Kuipers, *Quaternions and Rotation Sequences : A Primer with Applications to Orbits, Aerospace, and Virtual Reality* (Princeton Univ. Press, Princeton, NJ, 1999)
20. J.L. Marins, X. Yun, E.R. Bachmann, R. McGhee, M.J. Zyda, An extended kalman filter for quaternion-based orientation estimation using Marg sensors, in *Proceedings of 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Maui, HI, USA, 2001, pp. 2003–2011
21. X. Yun, E.R. Bachmann, R.B. McGhee, A simplified quaternion-based algorithm for orientation estimation from earth gravity and magnetic field measurements. IEEE Trans. Instrum. Meas. **57**(3), 638–650 (2008)
22. P. Daponte, L. De Vito, G. Mazzilli, S. Rapuano, C. Sementa, Investigating the on-board data processing for IMU-based sensors in motion tracking for rehabilitation, in *Proceedings of IEEE International Symposium on Medical Measurement and Applications*, Torino, Italy, May 2015, pp. 645–650
23. J. Grubert, T. Langlotz, S. Zollmann, H. Regenbrecht, Towards pervasive augmented reality: Context- awareness in augmented reality. IEEE Trans. Vis. Comput. Graph. **23**(6), 1706–1724 (2017)
24. L. De Vito, G. Mazzilli, M. Riccio, C. Sementa, Improving the orientation estimation in a packet loss-affected wireless sensor network for tracking human motion, *in Proceedings of 21st IMEKO TC4 International Symposium on Understanding the World through Electrical and Electronic Measurement*, Budapest, Hungary, September 2016, pp. 184–189
25. M. Hassanalieragh, A. Page, T. Soyata, G. Sharma, M. Aktas, G. Mateos, B. Kantarci, S. Andreescu, Health monitoring and management using Internet-of-Things (IoT) sensing with cloud-based processing: Opportunities and challenges, in *2015 Proceedings of IEEE International Conference on Services Computing*, pp. 285–292
26. L. Wei, N. Kumar, V. Lolla, E. Keogh, S. Lonardi, C. Ratanamahatana, H. Van Herle, A practical tool for visualizing and data mining medical time series, in *Proceedings of 18th IEEE Symposium on Computer-Based Med. Sys.*, June 2005, pp. 341–346
27. M. Bazzani, D. Conzon, A. Scalera, M. Spirito, C. Trainito, Enabling the IoT paradigm in e-health solutions through the VIRTUS middleware, in *Proceedings of IEEE 11th International Conference on Trust, Security and Privacy in Computing and Com. (TrustCom)*, June 2012, pp. 1954–1959
28. N. Bui, M. Zorzi, Health care applications: A solution based on the internet of things, in *Proceedings. of 4th International Symposium on Applied Sciences in Biomed. and Com. Tech.*, New York, USA, 2011, pp. 1–5
29. L. De Vito, F. Lamonaca, G. Mazzilli, M. Riccio, D.L. Carnì, P.F. Sciammarella, An IoT-enabled multi-sensor multi-user system for human motion measurements, in *2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Rochester, USA, May 2017, pp. 210–215
30. L. De Vito, S. Rapuano, L. Tomaciello, One-way delay measurement: State of the art. IEEE Trans. Instrum. Meas. **57**(12), 2742–2750 (2008)