ICST Transactions on Ambient Systems

Research Article ICST.ORG

FM-CW radar sensors for vital signs and motor activity monitoring

Octavian Adrian Postolache[1,*], Pedro Manuel Brito da Silva Girão[2], José Miguel Costa Dias Pereira[1], Gabriela Postolache[3]

[1]Instituto de Telecomunicações/LabIM/EST/IPS, Portugal; [2]Instituto de Telecomunicações/DEEC/IST/UTL, Av. Rovisco Pais, Lisbon, Portugal; [3]Escola Superior de Saúde, Universidade Atlântica, Oeiras, Portugal

Abstract

The article summarizes on-going research on vital signs and motor activity monitoring based on radar sensors embedded in wheelchairs, walkers and crutches for in home rehabilitation. Embedded sensors, conditioning circuits, real-time platforms that perform data acquisition, auto-identification, primary data processing and data communication contribute to convert daily used objects in home rehabilitation into smart objects that can be accessed by caregivers during the training sessions through human–machine interfaces expressed by the new generation of smart phones or tablet computers running Android OS or iOS operating systems. The system enables the management of patients in home rehabilitation by providing more accurate and up-to-date information using pervasive computing of vital signs and motor activity records.

Keywords: FM-CW Doppler radar, smart phone, smart walker, smart wheelchair

Received on 15 August 2011; accepted on 5 October 2011

doi: 10.4108/trans.amsys.2011.e5

1. Introduction

The health system all over the world has been drastically changing moving from acute health delivery to prevention, from secondary healthcare delivery to primary care and to home care, from patient healthcare delivery to wellness. Nowadays, one of the major directives in HealthCare systems is the involvement of the patient and the family environment in the management of his/her own disease or health problem. The changes are radical and have repercussions on new institutional and state planning, on new technologies, on consumption behaviours and on continuing medical education.

Many R&D projects and public administrative reforms are being conducted worldwide in order to identify issues related with the caregivers' concerns, the requirements for the efficient home telecare as well as to implement telecare around the recipient's care plan. For instance, preliminary results of European Project—Collaborative evaluation of rehabilitation in stroke across Europe—have shown large discrepancies in recovery pattern and organization of the rehabilitation centres [1]. Furthermore, recently review of randomized clinical stroke rehabilitation trials revealed that most of the studies on effectiveness of interventions for motor recovery after stroke enrolled small numbers of patients, which precluded their clinical applicability (limited external validity) [2]. These data suggest the necessity of large randomized trials for rehabilitation assessment based on information technologies approach, for technology assessment deployment and medical liability. Adding telecommunication tools to the practice of rehabilitation, especially if integrated with home rehabilitation, may provide researchers with timely access to adaptive rehabilitative processes and to design large studies with better ecological validity, lowering key constraints to timely assessment [3]. Large-scale telemedicine reports have shown good functional outcome and mortality comparable to other case series and trials of conventionally treated patients [4, 5].

One of the aims of our working group is to design and to develop a contextual-aware system that continuously assesses physiological signs and motor activity and

*Corresponding author. Email: octavian.postolache@gmail.com

stimulate the users to take actions that contribute to improve their health. Our team is currently exploring the viability of a system for in home rehabilitation combining low-cost smart sensors installed in a wheelchair, walker, bed or chair and a wearable device attached to the wrist of the patient. They are parts of a pervasive computation architecture that delivers diagnostics and decisions in autonomous form based on performance measures (process and outcomes measures) conducted with well-established instruments (questionnaire, physical examination) used in rehabilitation and also integrated with new methods and technologies that produce data on physiological and motor activity in an unobtrusive way.

The article reports on the design and implementation of smart sensors based on microwave Doppler radar technology with availability to sense subjects' vital signs and motor activity during in home rehabilitation sessions. In Section 2, we discuss the pervasive healthcare requirements, mainly for in home rehabilitation. In Section 3, we present the design of proposed smart wheelchair, smart walker and crutches for physiological and motor activity monitoring with the environment we are deploying. In Section 4 the software developed for a smart phone is described. Finally, we present conclusions and address further work in Section 5.

2. Pervasive healthcare requirements

Pervasive healthcare may be defined from two perspectives: (i) as the application of pervasive computing technologies for healthcare and (ii) as making healthcare available everywhere, anytime and to anyone [6]. It is a main tool on effort to change the healthcare delivery model: from doctor-centric to patient-centric, from acute reactive to continuous preventive, from sampling to monitoring. Pervasive healthcare applications include pervasive health monitoring, intelligent emergency management system, pervasive healthcare data access and ubiquitous mobile telemedicine. The term 'pervasive' stands for the tendency to expand or permeate, while 'ubiquity' is the property of being omnipresent. A main objective of Ubiquitous Computing (UbiComp) is physical integration and embedding of computing and communication technology into environments. In this sense, the ultimate goal of pervasive healthcare is to become a means for achieving ubiquitous health.

Pervasive healthcare systems for in home rehabilitation require sensing and computing systems that permit long-term subjects' health assessment, health critical events signalling, motor activity and activities of daily living monitoring. Also, an optimal setting of pervasive healthcare should allow biofeedback therapy. This can be accomplished by using new devices that can unobtrusively monitor physiological signals and motor activity and can be easily adapted to the user's house reality and commonly used objects. Many research projects and implemented healthcare systems have shown that vital signs and other health parameters can be autonomously measured by embedding monitoring sensors in clothes, chairs, beds, toilets, bathtubs and kitchen appliances among others [7]. In addition to the information on vital signs, activities of daily living, current location, fall detection, gait and balance, and skin breakdowns, sensors and sensors networks can generate a significant amount of information and/or services to the user. What is also needed in an optimal setting of UbiComp is that technology 'disappears' so that the 'computer' and the 'human–computer interface' are hidden at least in the perception of the human. This implies that the user doing a task is not aware of operating a computer system. This scenario should be realized through non-invasive/unobtrusive sensors, identification tagging, actuators, tracking and positioning and sensors network. There are several methodologies used in monitoring motor activities such as electrical potentials from muscles, magnetic and optical motion capture systems, video recordings and questionnaires. For instance, a common way for motion sensing is the use of Passive Infrared (PIR) sensors [8]. These sensors detect changes in the heat flow in the environment and can therefore detect humans and animals moving in the sensing region of the sensor. Motion detection using PIR sensors compared to video analysis is less powerful, but by far cheaper and simpler to implement. These sensors always have a directed input and are available with different lenses offering observation angles of 30° and 180°, and ranges of 2–15 m. Inter-daily gait velocity and daily activity metrics of eight elderly living independently, monitored using a PIR sensing system, showed no correlation to clinical or daily ethnographic data [9]. The team of Walsh et al. [9] suggested that a clinical assessment does not always provide an adequate estimate of the degree of diurnal and daily variation in gait speed. The clinical measurement of gait speed may suffer from the white coat effect (i.e. the patient may walk faster in the clinic as he is being watched by a healthcare professional). Similarly, other inter- and intra-variations were found, such as deviations in the minimum and maximum number of hits per day, in activity monitoring and in the distribution of the activity [9]. However, precise measurement of motion using PIR sensing system requires advanced calibration methods that may be unsuitable for mass deployment. As an alternative for PIR sensors for motion detection can be used sensors networks based on accelerometers and gyroscopes. Accelerometers are available as integrated micro-machined devices combined with driving electronics in an IC, e.g. the ADXL202E. These sensors are fairly easy to interface to a microcontroller and their power consumption is rather small (e.g. ADXL202E 0.6 mA at 3 V). Also the device size is minimal. The changes in acceleration are reflected quickly in the sensors output, of the order of milliseconds. In the past many accelerometer-based systems for the recognition of human activity have been developed. They differ in the number of acceleration sensors used, the way sensor information is processed and the usage scenario [10]. Gyroscopes give information on angular velocity. These devices are generally more expensive, bigger in size and also need more power. They usually supply an analogue signal that represents the angular velocity in volt per degree per second. For many applications, especially when no prior knowledge about the orientation of the device is available, it can be very useful to combine three accelerometers or three gyroscopes to gain information about acceleration/motion in all dimensions. Inertial measurement units contain one or more sensors to detect motion or orientation i.e. accelerometers, gyroscopes and magnetometers. When combined with suitable RF hardware they are termed wireless inertial measurement units [11]. Such inertial measurement units can be used to efficiently record motion data [11, 12].

In areas where people object to the presence of video cameras the option of using PIR sensors, accelerometers or gyroscopes is an alternative for activities of daily living monitoring. However, the multiple capabilities of microwave radar sensors and the potential low cost of the full integration in home telecare make their use an attractive target for unobtrusive motion detection as well as for non-contact physiological parameter assessment. We designed and developed a smart sensor based on microwave radar technology for motion and health monitoring. Using radar sensors embedded on smart objects, vital signs information (for instance from the radar sensors implemented on a wheelchair) or information on gait, activities of daily living and falls (i.e. from the radar sensor embedded on a wheelchair, walker or crutches) are obtained. There is an advantage of sensing RF energy as opposed to light, infrared or thermal energy when attempting to infer people's physiological signals or movements. Visible light cameras largely depend on daylight; light and infrared do not penetrate smoke or solid non-transparent walls. Radio-frequency waves can penetrate smoke and various non-metal walls or materials, unlike light, thermal or millimetre-wave energy. We believe that by embedding low-cost, small microwave radar sensors into clothes, beds, chairs and everyday living spaces ubiquitous health monitoring can be possible.

Another requirement in pervasive healthcare is control of the smart devices, either locally by the resident or remotely by friends/family/care professionals (Figure 1). Many research laboratories are recently working on the design, development and implementation of smart sensors and multimodal interfaces related to motions/voices/image analysis and comprehension that allow residents, friends and family and/or care professionals to view the current state of the monitored person and the connected devices within the home. Also, it is very useful to automate particular tasks for the resident through context models, mixed reality systems, coordination models and proactive environments (see Figure 1).

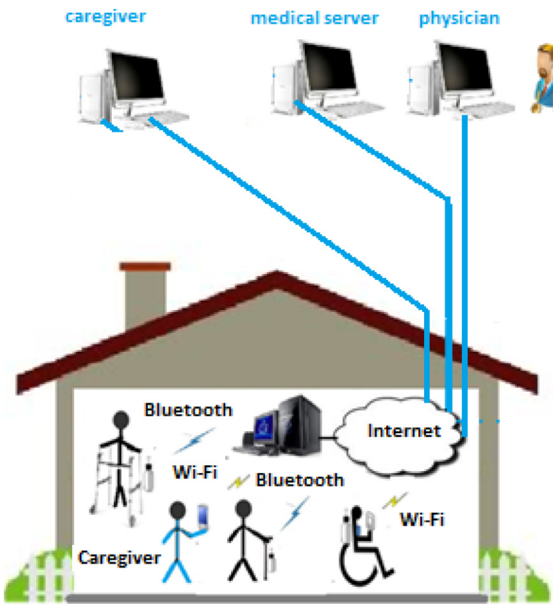


Figure 1. Diagram of patient-centred health monitoring for 'at home' rehabilitation.

A comprehensive health monitoring system should also be context-aware where the system adapts to the changing contexts, allowing better decision on person's current conditions and health. Incorporating affective reasoning into the decision-making capabilities of interactive environments can enable them to create customized experiences that dynamically are tailored to individual users, ever-changing levels of engagement, interest and emotional state.

3. Smart wheelchair, smart walker and crutches for in home rehabilitation

To transform objects used in rehabilitation into smart objects, embedded processing and communication devices must be added. Considering the necessity to sense the motor activity of a patient during the training session, we propose the use of a FSK/FM-CW Doppler radar (IVS-162 from InnoSenT) as one of the main components of smart objects that integrate an assistive environment for the people with less mobility or people with long-term health condition. The range and the velocity of the moving target, that is to say, the patient during the rehabilitation using walkers or crutches, can be achieved using the features of this radar.

Additionally, the respiration and cardiac activity monitoring of a patient resting on a wheelchair is achieved through the use of the 24GHz FM-CW radar sensor. Since the change of the displacement is small compared to the wavelength (12.5 mm at 24 GHz), the demodulated signal is proportional to the periodic displacement of the target, allowing accurate detection of respiratory and cardiac motion. We achieved good Heart Rate (HR) information even with signals passing through the wheelchair backrest (polyester material) and through wheelchair user's clothes. Depending on the direction of the motion, the polarized electromagnetic waves from the radar sensor are 'compressed' or 'diluted' producing frequency variation called the Doppler frequency. According to Doppler theory, a target with a time-varying position, but no constant velocity, will modulate the reflected signal's phase in proportion to the target's position. For instance, a stationary person's chest has a periodic movement with no constant velocity, and a Continuous Wave (CW) radar with the chest as the target will receive a signal similar to the signal it transmits, but with its phase modulated by the time-varying chest position. The received signal has a time-varying phase. In other words, the reflected signal is modulated by the periodic displacement of the heart and the respiration. The displacements by the heart beat and the respiration are assumed to be 0.05–0.15 mm and 1–2 mm, respectively.

The used FM-CW Doppler radar sensor architecture includes two antennas: Transmit Antenna (TX), that is associated to the body incident microwave signal; Receive Antenna (RX), that is associated to microwave signal reflected by the body. The received signal coming from RX is amplified by a low-noise amplifier and applied to two mixers M1 and M2 together with the transmitted signal, provided by splitter devices connected to a Voltage-Controlled Oscillator (VCO) through a preamplifier circuit. The VCO signal frequency depends on the value of the tuning voltage (Vtune) (Figure 2).

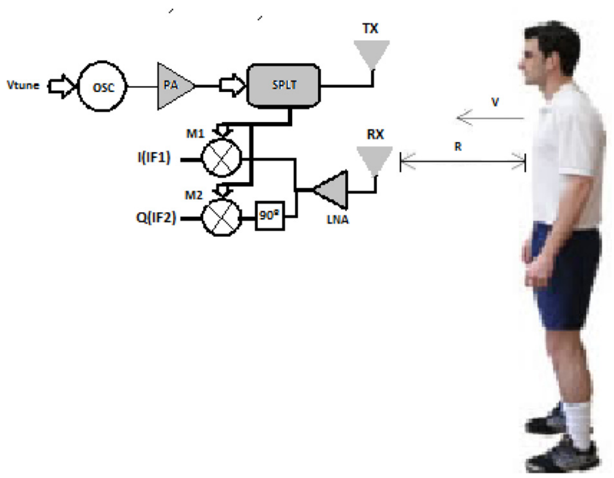


Figure 2. FM CW Doppler radar block diagram (Vtune = tuning voltage; OSC = voltage-controlled oscillator; M1, M2 = analogue mixers; I(IF1) = in phase intermediary frequency signal output; Q(IF2) = in quadrature intermediary frequency signal output; PA = preamplifier; SPLT = signal splitter; TX-transmit antenna; RX-receive antenna; LNA = low-noise amplifier.

The M1 and M2 mixer outputs expressed by intermediate frequency IF1 and IF2 signals, correspond to signal in Phase I and signal in quadrature Q. We used IF1 and IF2 to extract by appropriate signal processing not only the velocity (v) of the user, but also the motion direction that can be useful to estimate the posture and physical activity of the wheelchair, walker or crutches user. Particularly for the walker and crutches, the radar sensor is used to estimate the gait type and also the rehabilitation evolution during the training period [13, 14].

Embedding a radar sensor on the backrest of the wheelchair (DRS1) (Figure 3) the information on respiration and cardiac activity was obtained. Although the sensor has a reduced sensing range, this is not critical considering that the sensor antennas are located at 5–15 cm from the target.

Experimental work regarding wheelchair user's clothes—materials such as 100% cotton, 100% polyester and even E-textile—was carried out showing good sensitivity of the implemented device for non-contact heart and respiratory rate estimation.

The wheelchair backrest radar sensor can also be used to obtain the information on low amplitude motion of the wheelchair user when the wheelchair is stopped, when the user controls the wheelchair motion himself or when a caregiver manually operates the wheelchair. Complete information about the motion of the wheelchair is obtained mounting a second radar sensor (DRS2) near the wheel that can obtain the information of the travelling distance through the detection of a conductive tape on the spoke wheel.

Referring to the respiratory and cardiac information, an analogue processing scheme, expressed by active filters and amplifiers, was associated to DRS1. Thus, a second-order active low-pass filter, characterized by a cutoff frequency f_c = 0.3 Hz, was designed and implemented to extract the respiratory wave, while a second-order active

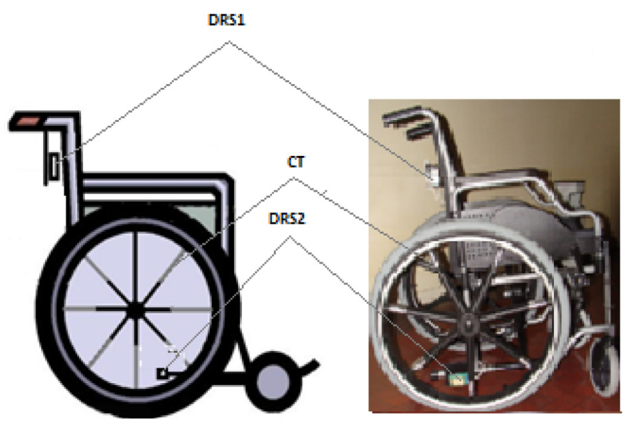


Figure 3. The architecture of a smart wheelchair with Doppler radar for vital signs and motor activity monitoring: (DRS1, DRS2 = Doppler radar sensors; CT = conductive tape).

high-pass filter, f_c = 0.9 Hz, was designed and implemented to extract the cardiac wave, denominated ballistocardiography wave. Additionally, two programmable gain amplifiers (PGA1 and PGA2) based on INA122 and CD4052 were implemented to assure the gain necessary to provide Acquisition and Communication Module (ACM) input signals in the 0–5 V range. The ACM was designed to be used with all smart objects (wheelchair, walker and crutches).

To improve the gait recovery assessment, we designed and implemented a smart walker and smart crutches that

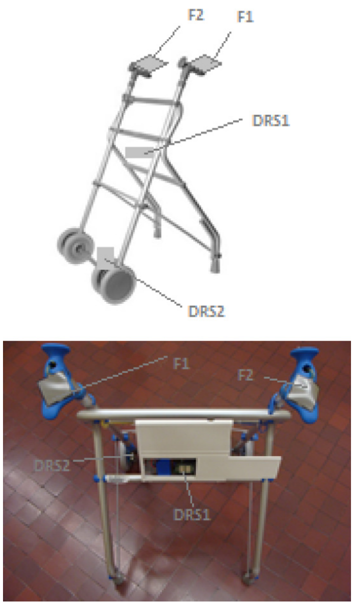


Figure 4. Smart walker architecture and prototype (DRS1, DRS2 = Doppler radar sensors; F1, F2 = piezoresistive force sensors).

include the Doppler radar sensor for motion sensing. The smart walker and smart crutches prototypes are presented in Figures 4 and 5.

As the conditioning circuit for Doppler radar signal are mentioned a second-order low-pass filter, f_c = 0.5 Hz, and an instrumentation amplifier INA122 that permits one to filter the noise, including the power line signal interference, but also to amplify the signal considering the dependence of the DRS1 output signal on the distance between the radar antenna and the target (the walker's user legs) during the rehabilitation training. Considering the analogue 0–5 V input range of the used ACM, an auxiliary DC voltage is applied to the inverter input of the instrumentation amplifier and adjusted in order to obtain values of the filtered and amplified Doppler radar signal in the range of 0–5 V range for different kinds of gaits.

To provide a general solution for all implemented smart objects, a data acquisition and Bluetooth data communication module was considered. It performs an analogue-to-digital conversion using a 16-bit ADC (ADS8344) that communicates through the SPI bus with a 16F673 PIC microcontroller. Figure 6 presents the ACM block diagram for the particular case of smart walker setup. Figure 6 shows that no conditioning circuit follows DRS2. However, several tests were done using a comparator and a Schmidt trigger to assure a rectangular-shaped signal characterized by TTL level according to the wheel position.

Referring to the force conditioning circuit, it includes a reference voltage (Vref = 1VDC) and a two-channel non-inverter amplifier scheme whose input resistances are the force sensors resistance. The signals from the aX, aY and aZ channels of the 3D accelerometer are analogue filtered

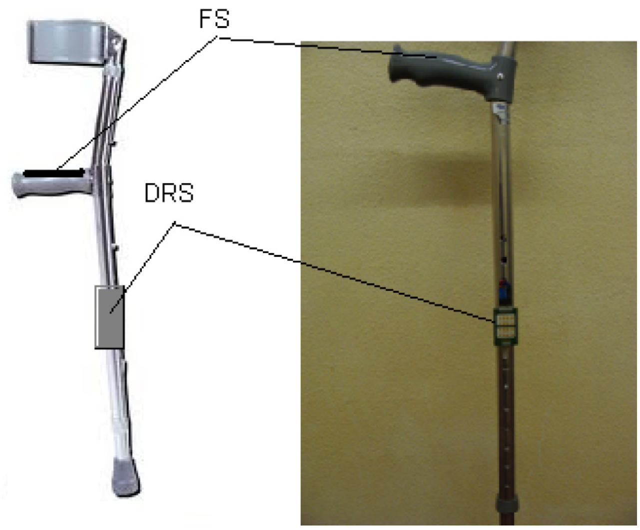


Figure 5. Smart crutches architecture and prototype (DRS = Doppler radar sensor; FS = piezoresistive force sensor).

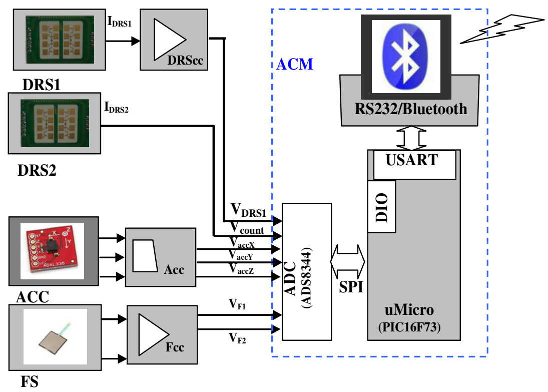


Figure 6. Sensing, acquisition and communication block diagram (DRS1, DRS2 = Doppler radar sensors; FS = piezoresistive force sensors; DRScc = Doppler radar sensor conditioning circuit; Fcc = force conditioning circuit; ACC = accelerometer ADXL335; ACM = acquisition and data communication module.

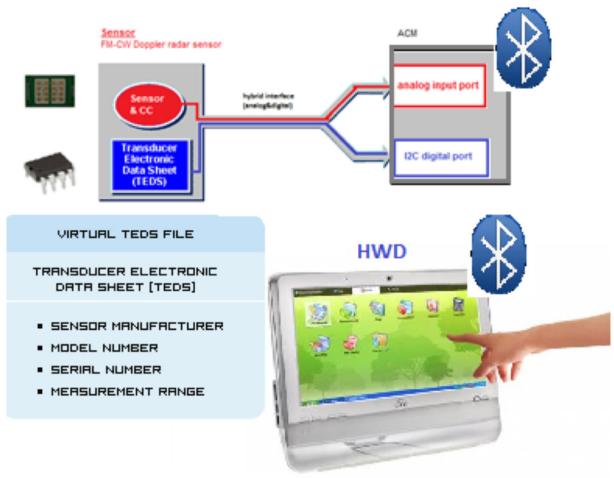


Figure 7. Smart sensor IEEE1451.4 compatible architecture (ACM = acquisition and data communication module; HWD = healthcare window device).

using a set of first-order, Butterworth low-pass filters, f_c = 45 Hz, used to remove the power line interference.

After signal acquisition and data coding by the ACM, the data are wireless transmitted through Bluetooth connection to a smart phone or tablet computer that runs Android OS software developed to assure the acquisition control, data storage, data synchronization and Graphical User Interface (GUI).

Regarding the ACM architecture, an advanced solution that includes a sensor identification reader was developed. This solution assures the IEEE1451.4 compatibility [15] for the measurement channel characterized by analogue input and embedded in the smart objects. For each of the sensing channels (e.g. DRS1 channel) attached to the daily used object is associated two-wire serial communication (I2C) EEPROM (24LC256) where specific information about the sensor is stored (Figure 7).

According to the above-mentioned standard, the main information about the sensor is materialized by the BASIC TEDS (TEDS, Transducer Electronic Data Sheet), whose components, bit length and allowable range are expressed in Table 1 [16].

In order to extend the information about the sensor, a combination between the hardware TEDS (the sensor characteristics are stored in the EEPROM memory) and Virtual TEDS (the sensor characteristics are stored in a database) represents an interesting solution.

Table 1. Basic TEDS content.

	Bit length	Allowable range
Manufacturer ID	14	17–16381
Model number	15	0–32767
Version letter	5	A–Z (data type Chr5)
Version number	6	0–63
Serial number	24	0–16777215

One of the healthcare LabVIEW software implementations developed by the authors includes a Virtual TEDS database and is installed in a touch panel compact computer (Eee Top from Asus) that was denominated Healthcare Window Device (HWD) in the present defined architecture. The application is accessed by the accompanying person and/or caregiver and performs the following tasks: (i) control of Bluetooth data communication between the HWD and ACM associated with the smart sensors embedded in the daily used objects (e.g. walker, wheelchair), (ii) smart sensor identification through Bluetooth MAC stored in the Virtual TEDS database, (iii) data logging and signal processing of the signals acquired from the sensor and (iv) GUI, including personalized front panels based on user's identification through a password or through the use of RFID tags. In the case of RFID technology use, an additional low-cost RFID reader from Phidget is attached to the HWD using the USB communication interface.

Referring to the signal processing, analogue filtering, amplification and digital signal processing algorithms implemented on the HWD were considered to extract the vital signs and motor activity information. Several results concerning the cardiac activity detected by radar sensors after analogue and signal processing based on active high-pass filtering are presented in Figure 8. Additionally, a reference ECG signal obtained from Medlab P-OX 100 is included in order to highlight the cardiac detection capability of the implemented measurement channel. Thus the baseline wandering and artefact removal based on DWT and ICA [17], adaptive peak detection for heart rate (HR) and respiration rate (Resp) calculation, and DWT for heart rate variability estimation [18, 19] can be mentioned.

The radar output signal is highly dependent on the position of the user body and on its involuntary motion on the wheelchair. Using appropriate adaptive filtering techniques [20, 21] the low amplitude artefacts that characterize the low amplitude involuntary motion of the wheelchair user can be removed. However, during high amplitude motions of the user sitting on the wheelchair the acquired radar signal can be used exclusively to estimate the user motor activity.

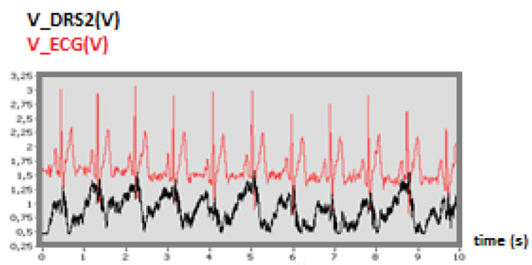


Figure 8. The evolution of the DRS2 and ECG voltage signals, after analogue and digital signal processing.

Considering the mobility requirements, the caregiver or physiotherapist is planned to interact with the smart objects used for rehabilitation using mobile devices such as smart phones or tablet computers.

The motor activity, mainly sensed by the Doppler radar sensors mounted on the walker or crutch, is monitored through the evolution of the acquired signal by ACM but also through the values of statistical parameters (e.g. variance, kurtosis) used as input features for gait recognition algorithms [22–24].

In the walker and crutches case a study concerning the correlation between the measured forces by embedded piezoresistive sensors, the body posture and radar wave pattern is underway. The cross-correlation between the piezoresistive sensors signal and the signal from radar sensors can give important information on the rehabilitation progress. The signals acquired from the radar sensors attached to the wheelchair wheel or walker can be processed to extract the information on the distance and the average velocity associated with the user motion during the rehabilitation session. Some results obtained on the wheelchair case, where the signals associated to the wheel motion are acquired using the Doppler radar sensor and processed and visualized at the HWD level, are presented in Figure 9.

Regarding the objects used in the rehabilitation tasks, some tests were done with people using the smart crutches that include the microwave Doppler radar sensor to extract information about the leg motion during the crutches usage. In order to highlight the relation between the signal associated with the leg motion and the crutches acceleration, a MEMS acceleration sensor (ADXL335) was mounted on the crutches. In Figure 10 is presented the evolution of intermediary frequency radar signal (Vrad_n) and the acceleration (AX_n) in normalized values.

Taking into account the future work of gait recognition during the rehabilitation session, several statistical parameters, such as variance and kurtosis, were calculated. For the particular case of kurtosis evolution during two particular tests (2 crutches—2 points (2c2p) and 2 crutches—3 points (2c3p)) are presented in Figure 11.

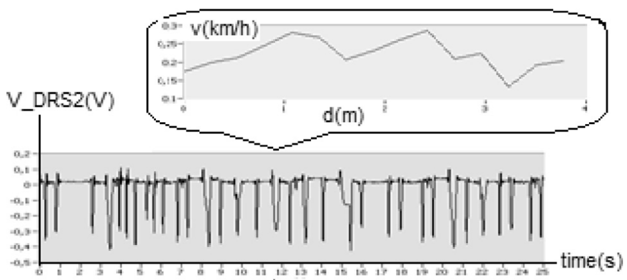


Figure 9. The evolution of the normalized voltage signal acquired from DRS2 measuring channel of the wheelchair and the corresponding velocity variation.

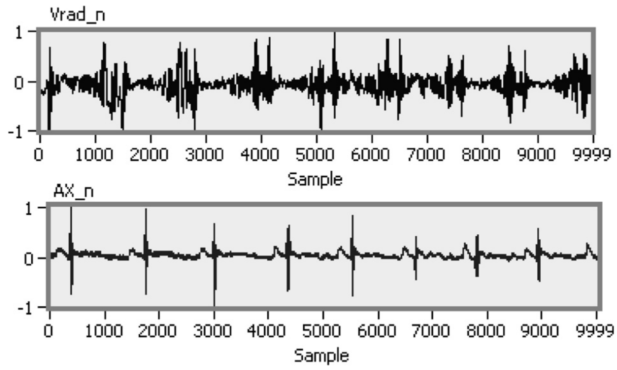


Figure 10. The correspondence between the Vrad_n and AX_n during 2 point gait with two crutches.

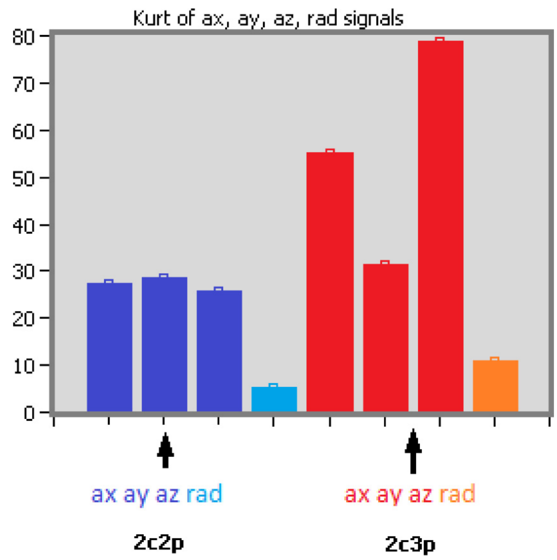


Figure 11. Radar and accelerometer signal kurtosis evolution for 2c2p and 2c3p gait tests.

It can be observed that the Kurt parameter associated with the radar signal is different from one type to another gait type, a characteristic that can be used as a feature for gait recognition [25] after a validation for an extended number of tests will include also 2 crutches—4 point gait tests.

4. Mobile software

Mobile solutions, such as smart phones and tablet computers, were considered appropriate as interfaces between physiotherapist, caregiver or even patient and the smart objects equipped with FM-CW Doppler radars. One of the implementations developed by the team was targeted on the use of a HTC Desire smart phone that runs the Android 2.2 mobile OS. Android SDK and Java [26, 27] were used to develop a general application related to smart object monitoring during the utilization by the users with motor disabilities. The main tasks implemented

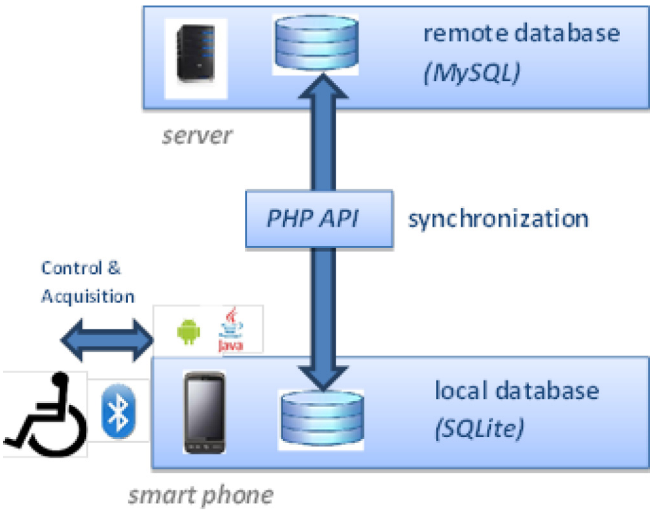


Figure 12. System physical architecture.

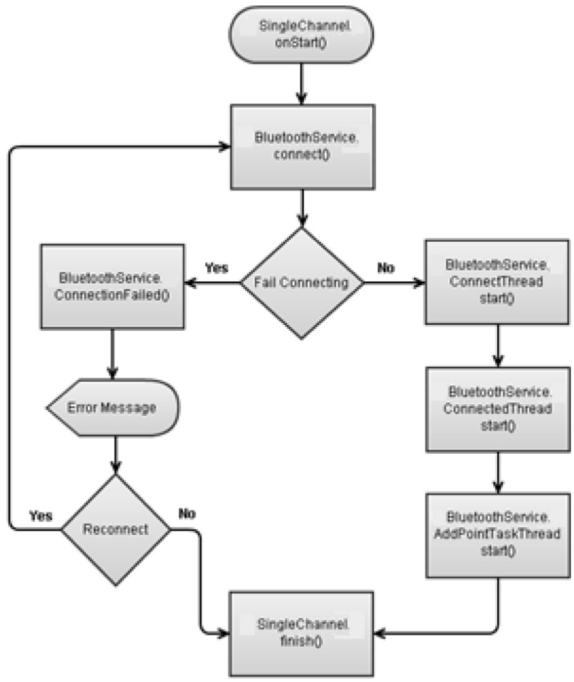


Figure 13. Flowchart associated with mobile GUI.

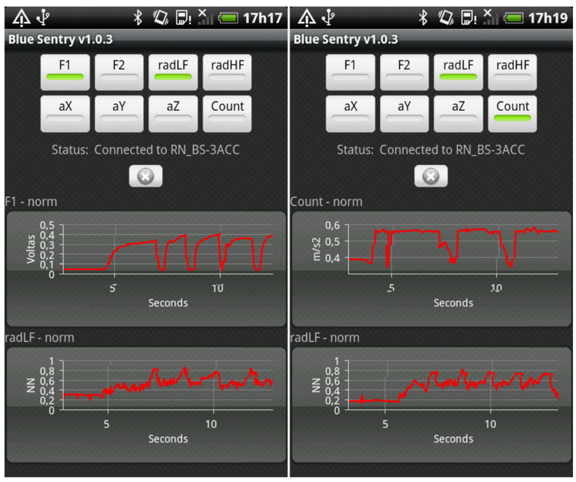
by the mobile application are: Bluetooth communication between the mobile device and the smart object, embedded data processing and graphical representation as well as data management including data storage and synchronization between a smart phone local database and a remote database associated with a web-based server application. The system physical architecture is presented in Figure 12.

To develop the present mobile software prototype, a set of activity classes were implemented: *ServerSync.java* that permits one to manage all the information regarding the application; *SingleChannel.java* that assures the graphical representation of individual waves associated with vital signs or motor activity measurement channels (e.g. gait wave from radar channel); *MultipleChannel.java* that assures multiple graphical representation of clinical status. A flowchart associated to the *SingleChannel.java* and *MultipleChannel.java* activities classes' interaction with Java methods of Bluetooth service is presented in Figure 13.

The GUI for mobile applications corresponding to force and radar response during the training session is presented in Figure 14(a).

The application permits one to visualize the motion pattern detected using the Doppler radar sensor during the physiotherapy training session using smart objects such as walkers or crutches. At the same time, the caregiver or physiotherapist can visualize the evolution of the force applied on the walker or crutch hand support (when F1 or F2 button is selected) for a specific gait during the rehabilitation session.

The mobile interface can also provide information concerning the motion of the wheelchair or walker. For the particular case of the particular case of walker, the detected motion of the wheels is sensed by (DRS2) mounted in the wheel and pressing the *Count* button, the number of turns performed by the wheel for a given



(a) **(b)**

Figure 14. Graphical user interface of the application for force and radar response during physiotherapy training session.

period of time is presented (e.g. Figure 14(b)). At the same time, in Figure 14(b) is presented the Doppler radar signal after low-pass filtering for specific gait during the physiotherapy training session.

Additional functionalities characterize the developed mobile application. Thus, the user of mobile device can perform the data synchronization between the local database and the remote database manually or automatically from time to time according to the selected time intervals between two synchronizations.

5. Conclusion

This paper describes a prototype implementation of a mobile healthcare information management system for in home rehabilitation based on pervasive computing and Android OS operating system. The prototype can improve the management of patients in home rehabilitation by providing more accurate and up-to-date information using pervasive computing of vital signs and motor activity records. It is a promising patient-centred management approach that can provide accurate and reliable data, empowers the patients, influences their behaviour and potentially improves their medical condition. It also has potential to save time and cost by reducing the visits and travel of physiotherapists or occupational therapists, and reducing hospital admission in health hazardous situations. Future research will be carried out in order to establish the relations between data from sensors used in our prototype and rehabilitation progress assessment.

Acknowledgement. The work was supported by Fundação para a Ciência e Tecnologia project RIPD/APD/109639/2009.

References

[1] Collaborative evaluation of rehabilitation in stroke across Europe, http://www.ist-world.org/ProjectDetails.aspx?ProjectId=82a07b52f7f74bdfbfb6a9fd7dcbaa86&SourceDatabaseId=9cd97ac2e51045e39c2ad6b86dce1ac2.

[2] Rabadi, M.H. (2011) Review of the randomized clinical stroke rehabilitation trials in 2009. *Med. Sci. Monit.* **17**(2): RA25–RA43.

[3] Winters, J.M. (2002) Telerehabilitation research: emerging possibilities. *Annu. Rev. Biomed. Eng.* **4**: 287–320.

[4] Audebert, H.J., Kukla, C., Vatankhah, B., Gotzler, B., Schenkel, J., Hofer, S., Furst, A. *et al.* (2006) Comparison of tissue plasminogen activator administration management between Telestroke Network hospitals and academic stroke centers: the Telemedical Pilot Project for Integrative Stroke Care in Bavaria/Germany. *Stroke* **37**: 1822–1827.

[5] Schwab, S., Vatankhah, B., Kukla, C., Hauchwitz, M., Bogdahn, U., Furst, A., Audebert, H.J. *et al.* (2007) Long-term outcome after thrombolysis in telemedical stroke care. *Neurology* **69**: 898–903.

[6] Korhonen, I. and Bardram, J.E. (2004) Guest editorial introduction to the special section on pervasive healthcare. *IEEE Trans. Inf. Technol. Biomed.* **8**(3): 229–234.

[7] Postolache, O., Girão, P., Pinheiro, E. and Postolache, G. (2010) Unobtrusive and non-invasive sensing solution for on-line physiological parameters monitoring. In Lay-Ekuakille, A. and Chandra Mukhopadhya, S. [eds.] *Wearable and Autonomous Biomedical Devices and Systems for Smart Environment: Issues and Characterization* **75**: 277–314.

[8] Hayler, S., Austin, D., Hayes, T.L., Kaye, J. and Pavel, M. (2010) Unobtrusive and ubiquitous in-home monitoring: a methodology for continuous assessment of gait velocity in elders. *IEEE Trans. Biomed. Eng.* **57**(4): 813–820.

[9] Walsh, L., Greene, B.R., Burs, A. and Scanaill, C.N. (2011) Ambient assessment of daily activity and gait velocity. In *Proceedings of the 5th ICST Conference on Pervasive Computing Technologies for Health Care*, Dublin, Ireland, May, 1–8.

[10] Czabke, A., Marsch, S. and Lueth, T.C. (2011) Accelerometer based real-time activity analysis on a microcontroller. In *Proceedings of the 5th ICST Conference on Pervasive Computing Technologies for Health Care*, Dublin, Ireland, 1–7.

[11] Gaffney, M., Walsh, M., O'Connell, S., Wang, B., O'Flynn, O. and Mathuna, C.O. (2011) A smart wireless inertial measurement unit system. Simplifying and encouraging usage of WIMU technology. In *Proceedings of the 5th ICST Conference on Pervasive Computing Technologies for Health Care*, Dublin, Ireland, May, 1–2.

[12] Zhang, J., Markovic, S., Sapir, J. and Wagenaar, R.C. (2011) Continuous functional activity monitoring based on wearable tri-axial accelerometer and gyroscope. In *Proceedings of the 5th ICST Conference on Pervasive Computing Technologies for Health Care*, Dublin, Ireland, May 2011, 1–4.

[13] Postolache, O.A., Girão, S.P.M., Pinheiro, E.C., Pereira, J.M., Madeira, R., Postolache, G., Mendes, J.G. *et al.* (2011) Multi-usage of microwave Doppler radar in pervasive healthcare systems for elderly. In *IEEE International Instrumentation and Measurement Technology Conference, IMTC 2011*, Hangzhou, China, May, 1–5.

[14] Postolache, O., Madeira, R., Girão, S.P. and Postolache, G. (2010) Microwave FMCW Doppler radar implementation for in-house pervasive health care system. In *IEEE Workshop on Medical Measurements and Applications Proceedings (MeMeA)*, Ottawa, Canada, May 2010, 47–52.

[15] Ulivieri, N., Distante, C., Luca, T., Rocchi, S. and Siciliano, P. (2006) IEEE1451.4: a way to standardize gas sensor. *Sens. Actuators, B* **114**(1): 141–151.

[16] Wobschall, D. (2008) Networked sensor monitoring using the universal IEEE 1451 Standard. *IEEE Instrum. Meas. Mag.* **11**(2): 18–22.

[17] Pinheiro, E.C., Postolache, O.A. and Girão, S.P. (2011) Cardiopulmonary signal processing of users of wheelchairs with embedded sensors. In *IEEE Workshop on Medical Measurements and Applications (MeMeA 2011)*, Bari, Italy, 1–6.

[18] Postolache, O., Girão, S.P., Joaquim Mendes, G. and Postolache, G. (2009) Unobtrusive heart rate and respiratory rate monitor. In *IEEE Workshop on Medical Measurements and Applications (MeMeA 2009)*, Cetraro, Italy, May 2009, 83–88.

[19] Postolache, O., Girão, P.M., Postolache, G. and Dias Pereira, J.M. (2007) Vital signs monitoring system based on EMFi sensors and wavelet analysis. In *Proceedings of IEEE Instrumentation and Measurement Technology Conference (IMTC 2007)*, Warsaw, Poland, May 2007, **1**: 1–4.

[20] Myung, H.I., Soo, Y.L., Tae, S.P., Tae, S.K., Min, H.C. and Young, B.A. (2006) Ballistocardiogram artifact removal from EEG signals using adaptive filtering of EOG signals. *Physiol. Meas.* **27**: 1227–1240.

[21] Chan, K.W. and Zhang, Y.T. (2002) Adaptive reduction of motion artifact from photoplethysmographic recordings using a variable step sze LMS filter. In *Proceedings of IEEE Sensors*, **2**: 1343–1346.

[22] Moustakas, K., Tzovaras, D. and Stavropoulos, G. (2010) Gait recognition using geometric features and soft biometrics. *IEEE Signal Processing Letters* **17**(4): 367–370.

[23] Yanmei, C., Qing, W., Jingping, J. and Rongchun, Z. (2006) A novel human gait recognition method by segmenting and extracting the region variance feature. In *ICPR 2006 Proceedings of International Conference on Pattern Recognition*, **4**: 425–428.

[24] Junping, Z., Jian, P., Changyou, C. and Fleischer, R. (2010) Low-resolution gait recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* **40**(4): 986–996.

[25] Sprager, S. (2009) A cumulant-based method for gait identification using accelerometer data with principal component analysis and support vector machine. In *Proceedings of the 2nd WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science*, 94–99.

[26] Burnette, E. (2009) Hello, Android: Introducing Google's Mobile Development Platform. In *Pragmatic Bookshelf (Pragmatic Programmers)*, November, 3rd ed.

[27] Meier, R. (2010) Professional Android 2 Application Development. *Wrox Ed.*