A Proposal of a Fall Detection Algorithm for a MultiDevice Personal Intelligent Platform

Miguel A. Estudillo-Valderrama, Laura M. Roa, Javier Reina-Tosina and David Naranjo-Hernández

***Abstract*— In this paper methodological and design issues about the development of a personal platform for the control and processing of data acquired from intelligent biomedical sensors are presented. This platform is designed in the context of a telehealthcare system for the elderly with chronic diseases, and one of its objectives is to monitor and detect fall events. The main feature of the device is its on-line personalization to the patient through adaptive knowledge generation in real-time, which will result in special time execution requirements. As a result a fall detection algorithm proposal is described and analyzed.**

I. Introduction

THE patient-doctor interaction model classically represented by the teleconsultation process and considered the telemedicine paradigm is being overtaken by the needs of new medical care context. Advances in diagnostic and therapeutic techniques and better health-social conditions of the population are serving to sustain the increasing incidence of chronic diseases due to the progressive ageing of population. The benefits that telemedicine and in general the Health Information Technologies (HIT) can provide to the attention of these patients pretend to overcome the classical centralized model [1] by considering heterogenous health information besides Electronic Health Record (EHR).

The authors have recently shown the advantages of a methodology bound to the teleassistance domain based on the knowledge generation concept. By means of this paradigm, HIT are capable of providing personalized and adaptive biomedical knowledge for a patient in such a way that cannot be carried out by current telehealthcare models, which results in an increase of his/her quality of life. The idea and principal innovation of this paradigm is its capacity of creating real-time personalized knowledge in opposition to other monitorization devices that make an off-line data process. This methodology shows advantages, for example, in fall detection [2]. We employ a multilayer process architecture, whose first layer is defined by a platform of several intelligent sensors that send captured and processed data to a second layer, which creates a computational image of patient's state, centered in the desired biomedical domain and processed by a set of distributed subsystems.

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M. Estudillo, L. Roa and D. Naranjo are with the Biomedical Engineering Group, University of Seville, Spain, m.estudillo@gmail.com, lroa@us.es, davidazuaga@gmail.com.

J. Reina-Tosina is with the Dept. of Signal Theory and Communications, University of Seville, Spain, jreina@us.es.

It is important to highlight the multimodal nature of the intelligent platform because it is able to manage and process heterogenous signals from various devices, ranging from those given by classical biomedical sensors (ECG, EEG, etc.) to vocal sounds, which is the case of a therapeutic-prosthesis for stuttering based on adaptive auditive feedback [3].

From the point of view of movement monitoring and falling detection, the ability to measure the movement in an objective manner at low cost is a fundamental requirement. For this purpose different types of sensors fixed to the body have been used [4]-[5], like accelerometers, gyroscopes or goniometers. Accelerometers are the most advantageous: they respond to frequency and intensity movement, some types can be used to measure the tilt and movement of the body, and technical advances in the field of MEMS systems have made possible the existence of commercial miniature accelerometers, cheap and reliable.

Other monitoring systems based on acceleration measurements are constrained in their application domain to the subject's home, leaving him/her unprotected when he/she leaves home or in case of being undressed [6]. The last situation is more dangerous because it usually occurs in moments when the subject is in the bathroom or in the bedroom, with a high probability of suffering a fall [7]. In addition to this, the importance of an appropriate emplacement of the device in the body must be taken in account. This location is near the center of gravity of the subject, that is, in the back, in the median plane at the height of the sacrum [5]-[6], which is a requirement not fulfilled by all monitoring systems [8].

The above limitations are overtaken by the movement monitor that the Biomedical Engineering Group has patented [9]-[10]. In this work we present a first approach to the design and functional aspects of a falling detection algorithm integrated in what we refer to as Multidevice Personal Intelligent Platform.

II. System Description

The design of our portable monitor pursues a 24/7 supervision of the user in- and outdoors. It permits patient's monitoring in high risk situations and eliminates acceleration components due to the relative movement in the human body-sensor interface. The monitor architecture does not restrict the emplacement of the sensor on the body so as to permit an easy access to its interface by the user. The monitor is embedded in a wireless personal network (WPAN) and it is composed by a Multidevice Personal Intelligent Platform (PIP) and a set of sensors as shown in Fig. 1.

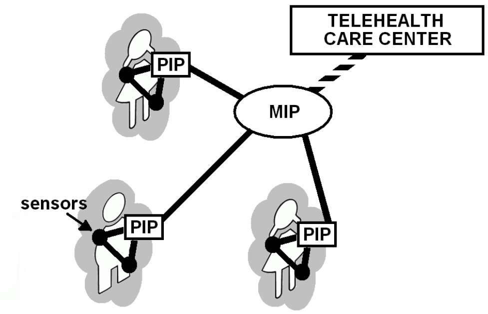

Fig. 1. Scheme of the proposed Multidevice Personal Intelligent Platform.

The PIP takes the master role in the WPAN and processes in real-time data captured by the biosensors, which take the role of slave in this topology. The PIP manages the communications between the portable monitor and the Multi-person Intelligent Platform based on standards (MIP), which is an access point to the Telehealthcare Center. The monitor interface is integrated into the PIP and thus is separated from the Intelligent Accelerometer Unit (IAU), which is the main sensor in the case of patient movement monitoring, and has been designed to be worn as an adhesive patch on the back of the patient at the height of the sacrum. Wireless technologies used in the IAU-PIP and PIP-PIM links are Zigbee ant Bluetooth respectively, which selection is motivated in [11].

Acceleration signals are analyzed in a distributed manner between the IAU and the PIP. The IAU realizes a preprocessing of the sampled signals at a frequency higher than needed in order to estimate the kinetic and postural parameters. This previous analysis is performed so as to detect signal properties which suggest falling event occurrences and postural transitions. Detected events and properties together with accelerometer signals are sent to the PIP. The latter realizes the real-time process of the acceleration signal. With this distributed methodology we are able to decrease the process load in the PIP and consequently the data flow between devices, which reduces power consumption.

A. PIP Functions

The main functions to be met by the PIP operating system embedded in a DSP are:

- Managing the communications with peripherals: it must be able to meet the demands from different peripherals, mainly in terms of inter-device communications standards like I2C, SPI, etc.
- Managing the internal PIP operation: it should be responsible for tasks such as device re-programming and updating the mathematical model; reviewing and diagnosing device status; managing the admission of new sensors in the WPAN or the revision of the state of both PIP and sensors.
- Processing bio-signals from sensors in real time and operating accordingly. As an example, and for our particular case of detecting falls functionality, this processing should allow to adapt the parameters of the implemented algorithm in the IAU to user and context.

A modular design has been followed for the PIP software development, in which the different applications are integrated into a set of threads that correspond to the main functionalities of the PIP as explained below.

III. Material and Methods

A. Methodology

A concurrent application design has been implemented through threads, in a way that maximizes its robustness and can reduce the DSP processing load as much as we can, which should be available as long as possible to execute the real-time thread processing during normal operation. Three main threads are executed that correspond to the previously described functionality: Peripherals Management Thread, PIP Management Thread, and Signal Processing Thread. When none of the threads is running or if processing thread terminates, the energy saving module runs, resulting in a decrease in the switching frequency of the state logic in the DSP CMOS circuitry and a state of inactivity in the CPU, pending on an interruption that removes from this state [12]. More details of the hardware of the PIP and IAU are contained in [13]-[14].

The 24/7 system availability is crucial, which requires us to oversee the battery state. For this reason a specific module has been developed that, in conditions of low power battery, makes a safeguard of the instant, event, last captured data and other state data together with system identifiers, with the aim of returning the PIP to the same state after it recovers the power.

B. Development Tools

In order to meet the mentioned functions, some software modules have been implemented by using a set of development tools [15]. On the one hand, Code Composer Studio v3.1 together with a TI Development Kit (TMS320C6713 DSK) allow us to program the DSP both with assembly and high-level programming languages. They also provide several management utilities for the internal processor and Kit's embedded peripherals using the DSP / BIOS tool. On the other hand, we are using Matlab and more particularly the Embedded Tools for TI C6000 DSP and Real Time Workshop packages, that make possible to compile and run optimized C code in the DSP for the development of the thread of accelerometric signals processing. In addition, the Link for Code Composer Studio package allows us to communicate with the DSP development board as well as to perform a parallel processing of the data between the board and Matlab.

C. Fall Detection

In order to comply with the real time requirements, we propose an algorithm for accelerometric data processing based both on frequency and time analysis separately. This kind of analysis pursues a double objective detailed in relevance order:

- First, to make a precise detection in terms of sensivity and specifity [16] and in a short time. This way we can

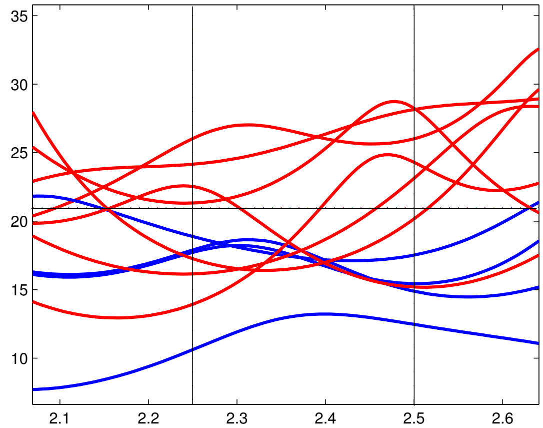

Fig. 2. Magnitude Threshold (horizontal axis in hertz, vertical axis in dB).

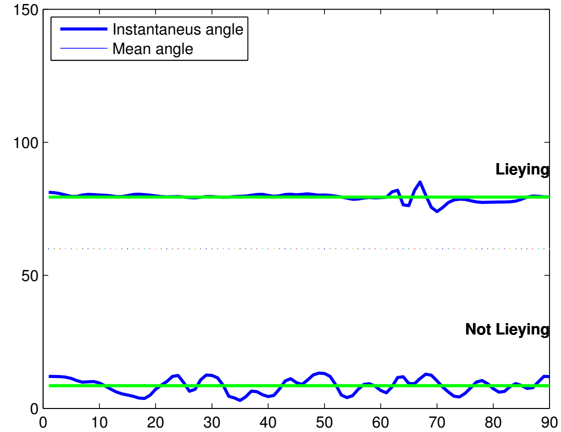

Fig. 3. Angle Threshold (horizontal axis in number of samples, vertical axis in degrees).

avoid the latency time common in algorithms based on a lack of movement basis.

- Second, and directly related to the foregoing, to implement a light computational algorithm in order not to overload the PIP, which has to manage, control and process data from several biosensors. As a consequence, code size and execution time are parameters to be minimized in our algorithm.

We employ a frequency technique for impact detection based on Linear AR-Burg spectrum estimate of small temporal segments. We have chosen AR modeling because of its simplicity to obtain the spectrum and also because this model provides the maximum spectral estimate [17]. In fact, AR-Burg modeling has been successfully applied in similar contexts of application, like tremor detection in Parkinson patients [18].

The time analysis is based on the outcomes of [2] to find the posture of the patient employing a triaxial accelerometer. They classified the posture of the patient by means of calculating the vertical angle variation in segments of time. By this way we can estimate almost instantly the posture without delaying the algorithm process.

IV. RESULTS

A. Fall Detection Algorithm

In terms of filtering, it must be said that acceleration data provided by the IAU are filtered by means of the filters detailed in [2] so as to estimate the vertical angle of the patient in step number 3. Data used to find the thresholds as well as to validate the algorithm have been taken from the set of laboratory experiments carried out by our group [10]. The steps followed by the algorithm to estimate the possible falls can be divided into two parts:

- In the first part our goal is to find the most general possible thresholds to be used in our algorithm. For this reason we calculate the sixth order AR-Burg model of the entire acceleration signal for each axis and each activity, and then we obtain the frequency spectrum of these models. We have observed that the majority of risky fall activities signals have frequency components over a threshold of 21 dB in the frequency range of $2.25 - 2.5$ Hz, as depicted in Fig. 2.
- The second part of the algorithm covers the following, for each accelerometer axis:
  1) Segmentation of the signal in 90-sa segments, what implies a temporal window of 7.425 s.
  2) Calculation of the sixth order AR-Burg model for each segment and corresponding spectrum.
  3) Obtain the mean angle M_a for each segment.
  4) Calculation of the number of samples that exceed 21 in each segment, together with the percentage of axis that goes above the cited threshold.
  5) If this percentage is greater than 2 per cent, we fill a binary vector V_b with a one. Otherwise we put a 0 in the vector component of the axis.
  6) If V_b has one or more components with value 1, i.e. one or more axis exceed the previous threshold, and the mean angle for this segment is greater than 60^o, which corresponds to a *lieying* posture (see Fig. 3), we determine that a fall has occurred in this segment.

B. Size and Execution Time Estimates

Our DSP has a memory ROM that starts the main application and hosts the basic not modifiable management modules, which are primarily responsible for activation and initial configuration of peripherals and launch of threads. The current size of the configuration code is 35% of 384 KB of ROM memory size.

Moreover, the PIP's Flash memory will store the code amount associated with the algorithm as well as captured data and other system state indicators so as to recover itself if the battery wears out. The algorithm code, yet at the stage of debugging and optimizing, is less than half of the configuration code, which represents less than 7% the size of the Flash Memory. This code can be executed in the 2100 MFLOPS DSP in just a few tens of microseconds.

V. Conclusions and Future Works

A. Conclusions

In this paper we have presented the functional and design characteristics of a falling detection algorithm proposal integrated into a multidevice Intelligent Personal Platform for the monitorization of intelligent biosensors, whose principal feature is its capacity of processing and real-time personalized knowledge generation by using a distributed architecture. Owing to this reason, execution time and size code have been fundamental implementation aspects.

The design and preliminary results obtained until now suggest that the platform can meet the functional specifications defined above, and therefore its feasibility within the layer of intelligent sensors cited.

B. Future Works

Future advances in the platform will take into account the optimization of the presented algorithm and the improvement of its personalization according to the monitorized patient and the influence of the variation of the thresholds, as well as the incorporation of new wireless communication technologies [3].

Besides, there are several outcomes [19]-[20] in the estimate of energy expenditure related to the activity of the monitored patient by means of accelerometters. To the best of our knowledge and owing to the fact that our accelerometer biosensor is attached at the back, we consider to follow Bouten results [5], who states a proportional relation between this consumption and the signal magnitude area of triaxial accelerometer data.

On the other hand, the estimation of the kind of activity performed by the patient will determine the threshold values to be sent to the IAU for its processing. A first approach of this determination has been made in our group by means of ROC curve analysis taken from a set of laboratory experiments involving different subjects and contexts of study (hard floor and soft floor). In addition to this line of research, we are considering other approaches like the study of the Fourier Transform of the vertical accelerometer signal [21], or wavelet transforms [22].

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