A Wearable Multi-sensors Device for AAL Environment

Francesco Montalto, Valentina Bianchi, Ilaria De Munari and Paolo Ciampolini

Abstract MuSA (Multi Sensor Assistant) is a wearable multi-sensor device designed for elderly people monitoring. The system features healthcare services equipping a fall detector, a user alarm button, heartbeat, breathing rate and body temperature evaluation. By integrating MuSA in an ambient-assisted living framework, CARDEA, data fusion approaches can be implemented to obtain a behavioral profile which can be significant for the caregivers. The objective is to provide a set of features that integrated all together may foster a safe, independent and autonomous life to elderly in their home in accordance to the AAL (Ambient Assisted Living) paradigm. This paper describes the main concepts of MuSA and the details of the single functionalities. The suitable low-cost approach and the adequate quality of the system response, at the same time, have been proved by field tests of the device.

1 Introduction

The population is increasingly becoming older and a growing amount of people is facing weakness and disability problems. In 1999, the World Health Organization (WHO) launched a new campaign called "Active Ageing" [1]. With this initiative the WHO aims to improve the quality of life as people age, allowing people to realize

F. Montalto (✉) · V. Bianchi · I. D. Munari · P. Ciampolini
Dipartimento di Ingegneria dell'Informazione, Università degli Studi di Parma,
Parco Area delle Scienze 181/A, 43124 Parma, Italy
e-mail: francesco.montalto@unipr.it

V. Bianchi
e-mail: valentina.bianchi@unipr.it

I. D. Munari
e-mail: ilaria.demunari@unipr.it

P. Ciampolini
e-mail: paolo.ciampolini@unipr.it

S. Longhi et al. (eds.), *Ambient Assisted Living*, DOI: 10.1007/978-3-319-01119-6_12,

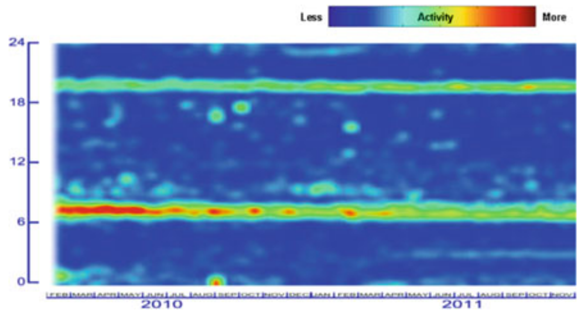

Fig. 1 Use of PIR sensors to evaluate quantity of activity

their potential for physical, social, and mental well-being throughout the life course and to participate in society, while providing them with adequate protection, security and care.

In this context the technology may play an important role both through the Assistive Technologies (AT) used to increase, maintain, or improve functional capabilities of individuals with disabilities and the Ambient Assisted Living (AAL) for an independent, autonomous and safety life at home. Exploiting the fusion of these two technologies new assistance and monitoring services can be carry out.

For example it is possible to collect the information from AT and AAL systems and process them to evaluate a person wellness and the evaluation of his health status, doing a sort of behavioral analysis.

A simple behavioral analysis can already be done using some simple information from environmental sensors used in AAL systems. Our project among the AAL environments is called CARDEA [2]. It is based on TCP/IP communication, i.e., all the system components are connected to the same Local Area Network. It features the capability of controlling a wide range of environmental sensors and home appliances and includes "assistive" interface modules (vocal, brain-computer); it also enables full web-based monitoring and control through a simple user interface. A wireless sensor network (WSN) contributes to the system architecture as well, dealing with mobile devices. Here, we shall refer to a WSN based on the IEEE-802.15.4 (ZigBee) standard protocol, exploited for the implementation of the wearable sensor described in the following.

An example of behavioral analysis obtained from environmental sensors is depicted in [3]: by tracking the activity of the PIR sensors we are able to quantify the activity of the person who lives in the room, and to outline a trend in his habits (Fig. 1).

Although this approach is simple to implement, environmental sensors have some limitations. First they are not able to distinguish which person has been detected and second they are strictly related to fixed positions.

Our purpose is to extend the behavioral analysis to wearable sensors in order to evaluate more information about people status. Wearable sensors are useful for early risk detection and continuous health monitoring that play an important role among

Fig. 2 MuSA

the assistive functions in the home environment. Many technological solutions have been developed in order to monitor personal activities and vital signs. In this area, Wearable Monitoring Health Systems (WHMS) realize consumer operated personal prevention and early risk detection [4]. A variety of prototypes and commercial products have been designed with the aim of providing real-time information about a person's health, either to the user himself or to a specific caregiver.

In this paper, MuSA, Multi Sensor Assistant, will be described (Fig. 2). It has been conceived for personal activity and vital parameters continuous supervision [5]. MuSA has been specifically developed to be embedded in CARDEA even if it is able to communicate with any Ambient Assisted Living (AAL) systems. Our aim is to extract useful information from the raw data obtained from the sensors implemented on MuSA. By processing these data on-board we send only significant information to CARDEA. Finally, from the vast availability of information coming from wearable sensors and environmental sensors, data fusion can be performed in order to obtain reliable behavioral analysis and hence a good awareness of people status.

2 MuSA

MuSA is a wearable multisensor platform, specifically designed with assistive purposes. It is compliant with ZigBee 2007 PRO standard protocol, and the Home automation standard profile thanks to a CC2531 SoC [6]. MuSA is designed to be worn at belt or at chest: it is quite small ($78 \times 48 \times 20$ mm), and lightweight (about 70 g, Li-Ion battery included). Different functions can be implemented on the same platform, basic configuration of MuSA includes a call button and automatic fall detection. MuSA can be extended with further functions, hosted by the same hardware platform: a single-lead ECG system is used to evaluate heart rate and respiration rate using EDR technique [7] and a NTC thermistor is included to evaluate body temperature. All of the signal acquisition and processing is carried out by MuSA on-board circuitry: detection of abnormal behaviors or deviation of vital signs from their "normal" range is carried out by this device. Radio communication is hence kept at a bare minimum (alarm messages and network management), saving battery energy.

Two basic building blocks can be identified: a IEEE 802.15.4 radio transceiver, and a microcontroller taking care of ZigBee stack management. The same microcontroller is exploited for digital signal processing. The board also includes sensors and analog front-end circuitry needed to acquire vital signs.

2.1 Fall Detection

Fall movements can be quite different, depending heavily on the actual situation. In literature three different kinds of most common falls for an older adult can be found: fall during sleep, from the seated position and from standing up to lying on the floor. Whereas the first two can be somehow monitored by means of bed- or chair-occupancy sensors the last one (also being the most frequent kind) requires a smarter automatic detectors. Basic fall detection algorithms exploit threshold comparison [8]: since falls are often associated to acceleration peaks, current acceleration (the Euclidean norm of the acceleration vector, actually) is checked against a given threshold, which depends on personal physical features (height, weight, etc.). However, tuning such a threshold is critical: hence a more reliable detection strategy is exploited: MuSA correlates acceleration pattern with postural information.

A tri-axial MEMS accelerometer, LIS331DLH [9], has been chosen here to evaluate human body position and orientation. The implemented algorithm detects, at first, specific acceleration peaks and then evaluates the eventual variation of the body orientation. Observing Fig. 3, the CC2531 reads the acceleration components from the accelerometer every 16 ms, then MuSA computes the acceleration norm and compares it to a particular threshold. If this condition takes place, it is necessary to look for the tilt angle computed just before and after the acceleration peak. The scalar product of the static acceleration components, before and after the acceleration peak, is used to evaluate the orientation by comparing this value to a suitable threshold, in order to detect an actual fall.

2.2 Heart Rate

Heart activity monitoring is necessary to promptly identify a person's abnormal heart rate rhythms (i.e. arrhythmia, tachycardia, etc.). Moreover this analysis can be useful to combine heart information with motion data, in order to classify human activities [10, 11].

In order to provide a continuous monitoring and a non-obtrusive design at the same time, a simple electrocardiogram (ECG) has been implemented on MuSA by using a single-lead (I Einthoven) derivation using an elastic strap belt. An analog front-end circuit has been implemented on-board. It mainly consists of a differential instrumentation amplifier and an analog low-pass filter; moreover a feedback op-amp integrator has been used to keep to a constant value the DC component, in order

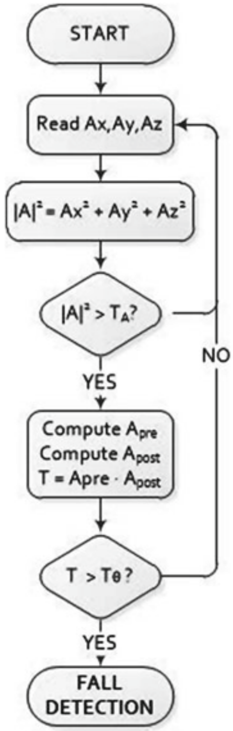

Fig. 3 Fall detection algorithm

to avoid skin-electrode resistance dependence. The acquired ECG signal is then properly filtered by the CC2531 for the purpose of emphasizing the QRS complexes.

Heart rate is measured detecting and counting every R-peaks in the ECG filtered signal. It is done by detecting the local maximum, observing when the ECG derivative passes through zero (Fig. 4).

2.3 Respiration Rate

Healthy people's respiration depends on both age and physical activity. Monitoring breathing activity allows the evaluation of abnormalities such as apnea, hyperpnea, tachypnea, etc.

In a first time, respiration signal was obtained from a piezoelectric sensor attached to the elastic chest belt. Unfortunately, the non-perfect signal periodicity and even more the motion-induce artifacts, makes the algorithm unreliable.

A sensorless solution, based on the fact that the respiration is highly correlated to heart activity, has been studied and implemented. Hence, the EDR (ECG Derived Respiration) method has been chosen [7]: small ECG morphology variations during

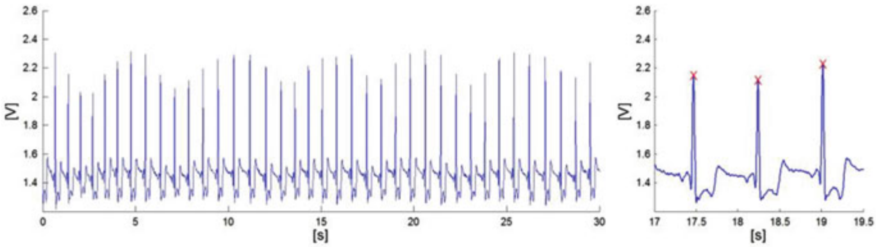

Fig. 4 ECG signal and R-wave peaks detection

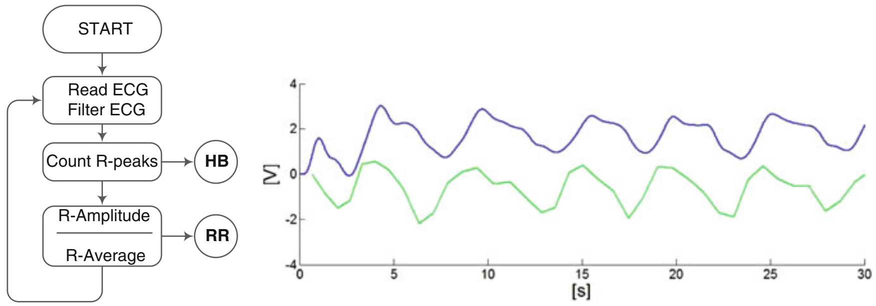

Fig. 5 ECG and EDR routine (**a**); respiration waveforms: piezo (*blue*) versus EDR (*green*) (**b**)

the breathing cycle happen due to the movement of the heart position in relation to the chest electrodes and the mutation of the lung volume that causes a dielectric changes. Here, the EDR method focus on the amplitude modulation of the ECG signal: heart's apex move towards the abdomen while inspiring, and it relaxes during expiration.

The implemented algorithm used to estimate the respiration signal from the ECG, described in detail in [12], has its main advantage in being a real-time operation, suitable for our low-power CC2531 SoC. Shortly, we can describe the ECG signal as a composite R-wave amplitude, consisting of the sum of the amplitude modulation due to breathing activity of the chest and various noise components. After the ECG is properly filtered, the algorithm identifies every R-wave peak, stores the value of its amplitude and computes the current and previous amplitudes running average. By evaluating the ratio of the current amplitude and the running average we obtain the estimation of the respiration signal.

This method has been validated comparing a piezo-sensor outcome and an EDR signal of the same respiration activity (Fig. 5b). It is important to emphasize that the EDR technique does not aim to provide an highly accurate respiration waveform, but rather to give a precise respiration rate measure. Moreover this solution allows to reduce the overall cost and increase the user's comfort by removing the piezo-sensor from the system. From the EDR-inferred signal has been possible to realize the respiration cycles count algorithm by simply counting waveform maximums.

2.4 Body Temperature

Body temperature is another important indicator for health status monitoring. Since changes during the day can be related to actual activity, a combination of the above information and the body temperature might be relevant. A value around 37 °C is considered to represent healthy status and the temperature setpoint is defined as the level which the body try to maintain, if this value rises we speak of fever status. However this value varies during the day for each person.

Here a temperature probe capable of measuring in a range between 35–45 °C, with a 0.1 °C accuracy, has been implemented on MuSA. An inexpensive NTC thermistor has been chosen here as the sensing element. From its temperature-resistance relationship, a multi-stage analog circuit has been designed to provide a linear characterization of the voltage-temperature relationship in the desired range. Power consumption issues have been taken into account to prevent the thermistor self-heating. As it was done before, the successful validation of the temperature system has been conducted by comparison with a mercury thermometer, as reference instrument.

2.5 Behavioral Analysis

As stated in the beginning of this article, our vision is to extend the process of the information coming from the previous algorithms in order to obtain meaningful analysis.

A first example of what we could do about is showed in Fig. 6. From the filtered accelerations, we already use for the fall detection routine, we examine a person quantity of movement. In particular by calculating the discrete norm of the three accelerations component and comparing this value with proper thresholds, it is possible to distinguish static from active situations and, at the same time, still detect fall events.

Furthermore, from the same acceleration components, we are able to measure the body orientation (tilt angle) and so discriminate is a person is sitting/standing or lying.

Although this approach needs improvements, this is a first interesting step towards behavioral analysis.

3 Results and Discussion

In this article we presented an AT solution called MuSA. It was at first conceived as a fall detector. MuSA has been later enhanced with more health monitoring functionalities. Our vision is to fuse the most of the data available in order to obtain reliable behavioural analysis. This can be done exploiting MuSA itself but even more by correlating MuSA and CARDEA's environmental sensors information.

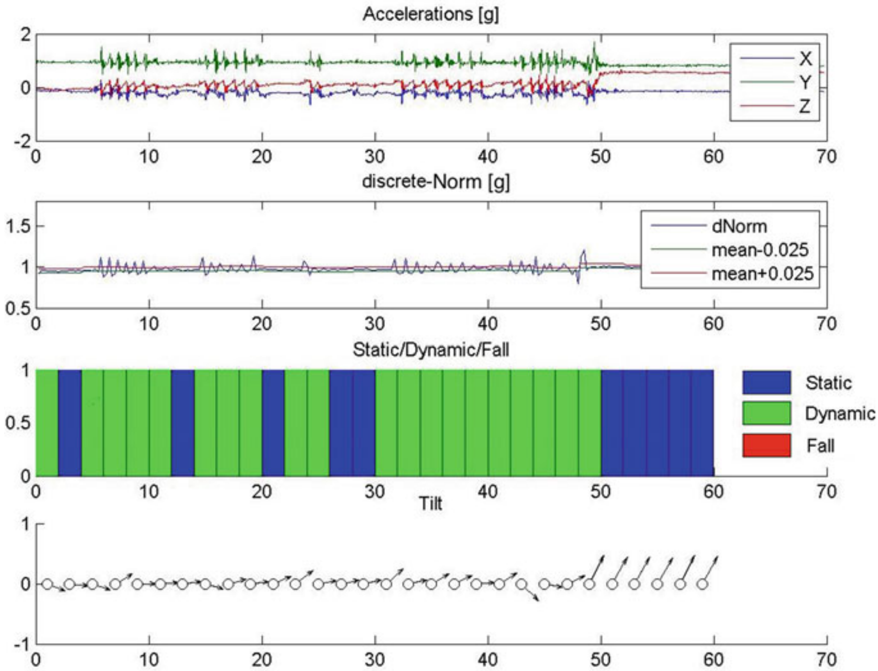

Fig. 6 Acceleration components (**a**); discrete Norm and thresholds (**b**); Quantity of movement analysis, static (*green*), dynamic (*blue*), fall (*red*) (**c**); body orientation evaluation (**d**)

Concerning the singular functionalities of our wearable device, preliminary tests on people have been conducted in laboratory. For the fall detection, by considering the number of True Positives and the number of False Negatives, the algorithm assesses 99 % of sensitivity and 97.8 % of specificity [5]. Heartbeat and respiration rate have been tested together on ten healthy volunteers. The relative error of both algorithms has been estimated as the difference between the counted rates by the user and the ones by the algorithms themselves in a one-minute window. First results state a mean relative error about 0.56 % for the heart-rate and about 12.5 % for the respiration rate. It is clear that if the ECG has a typical generic waveform for every person, the respiration signal changes due to different body characteristics and respiration mechanism. Nevertheless, the attained accuracy is adequate to the application at hand. As mentioned before, the body temperature system provides an accuracy lower than 0.1 °C.

In this work a multi-sensor wearable device has been expanded toward low-cost healthcare functionalities. The medium-term target is to combine all the kinetic and physiological parameters in order to lead data-fusion strategies and obtain user's behavioral analysis and health-status profile. The integration of this device into the AAL system CARDEA provides an innovative solution in the assistive technologies.

References

1. World Health Organization. Active ageing, a policy framework. http://www.who.int/ageing/active_ageing/en/index.html (2002)
2. Grossi, F., Bianchi, V., Matrella, G., De Munari, I., Ciampolini, P.: An assistive home automation and monitoring system. In: ICCE 2008 Digest of Technical Papers, pp. 341–342 (2008)
3. Losardo, A., Grossi, F., Matrella, G., De Munari, I., Ciampolini, P.: Exploiting AAL environment for behavioral analysis. In: Assistive Technology: From Research to Practice. Assistive Technology Research Series, vol. 33, pp. 1121–1125 (2013)
4. Pantelopoulos, A., Bourbakis, N.G.: A survey on wearable sensor-based systems for health monitoring and prognosis. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. **40**, 1–12 (2010)
5. Bianchi, V., Grossi, F., De Munari, I., Ciampolini, P.: Multi sensor assistant: a multisensor wearable device for ambient assisted living. J. Med. Imaging Health Inf. **2**, 70–75 (2012)
6. Texas Instruments. www.ti.com
7. Mazzanti, B., Lamberti, C., de Bie, J.: Validation of an ECG-derived respiration monitoring method. IEEE Proc. Comput. Cardiol. (2003). doi:10.1109/CIC.2003.1291230
8. Chen, J., Kwong, K., Chang, D., Luk, J., Bajcsy, R.: Wearable sensors for reliable fall detection. In: Proceeding 27th Annual International Conference of the Engineering in Medicine and Biology Society (2005)
9. STMicroelectronics. http://www.st.com/
10. Fujimoto, T., Nakajima, H., Tsuchiya, N., Marukawa, H., Hata, Y.: Human activity classification by ECG and accelerometers aided by fuzzy logic. In: IEEE International Conference on Systems, Man, and Cybernetics, Seoul, 14–17 Oct 2012
11. Tapia, E.M., Intille, S.S., Haskell, W.: Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. In: Proceedings of the 2007 IEEE International Symposium on Wearable Computers, pp. 37–40, 11–13 Oct 2007
12. Arunachalam, S.P., Brown, L.F.: Real-time estimation of the ECG-derived respiration (EDR) signal using a new algorithm for baseline wander noise removal. In: Proceedings of IEEE Engineering in Medicine and Biology Society Conference, pp. 5681–5684 (2009)