FALL DETECTION AND GAIT ANALYSIS IN A SMART-HOME ENVIRONMENT

V. Bianchi, F. Grossi, G. Matrella, I. De Munari, P. Ciampolini, *Member, ISG*

Abstract— **In this paper, the development of a prototypal wearable sensor, suitable for home monitoring purposes, is described. The sensor analyzes the data stream coming from a MEMS tri-axial accelerometer to infer fall occurrences and to evaluate the gait quality. Data processing is carried out locally, to limit energy-demanding radio transmission. Smart algorithms have been implemented to extract, from a single MEMS, information concerning both the acceleration and orientation of the worn device. By combining such data, reliable detection can be obtained, avoiding false alarms. Evolution toward more compact and energy-efficient devices is foresee, by implementing monolithic motion detection chips.**

I. INTRODUCTION

Population ageing [1] is among the most demanding global challenges the world is facing. On the one hand, the increase in life expectancy is a brilliant success of science and medicine; on the other hand, it has (and will mostly have) a deep and problematic impact on many social and economical issues. The decrease of the ratio between "active" younger population and older retirees, not only threatens social security programs, but also makes more difficult to provide older persons with effective care. In fact, very often some (maybe minor) illnesses or diseases are associated to ageing, which may limit or compromise independency and self-sufficiency of older persons in attending daily living tasks. Lack of home care (either delivered by relatives or professional caregivers), in turn, may require to move frail elderlies to healthcare facilities and this calls for large expenses and may degrade the perceived quality of life. As older persons are becoming the largest fraction of the population, conventional home care approaches are becoming difficult to sustain: ICT technologies are hence expected to provide for innovation and support in this field too. Assistive Technologies are being developed to counteract sensorial, mobility and cognitive impairments [2]. Assistive devices can be deployed in the home environment, allowing older persons or people with disabilities to live as longer as possible in their home, making the home itself safer, more comfortable and capable of cooperating to the management of daily living activities. Ambient-assisted Living (AAL, [3]) techniques are expected, in the near future, to give some answers to the increasing need of home care. Basic features of such a system should necessarily include: low cost, ease of use and reliability. Moreover, needs of different persons are vastly different, and are inherently subject to changes in time. Hence, versatility, expandability and system reconfigurability are of the utmost importance as well.

Although effective assistive devices are being developed since a long time, "mainstreaming", i.e., embedding assistive functionalities into standard, widely diffused information and communication technologies, is regarded as a promising strategy to match more easily the above requirements.

A system has been developed, which accounts for home safety and security, task automation, monitoring of home activities and of health parameters. The system, described in details elsewhere [4], is fully based on standard IP communication techniques and allows for low-cost implementation of flexible and reliable home-control functionalities. The system is hierarchically organized for reliability purposes, and inherently allows for remote operations, enabling telecare functionalities. It exploits a distributed intelligence strategy, based on a peer-to-peer network of intelligent sensor controllers. Information coming from a large number of home sensors are gathered together: integration and fusion of sensor data fosters higher reliability (by cross-checking of data from different sensors) and allows for inferring richer health-related information (e.g., by indirectly metering intensity of home activities). In this paper, we describe the integration into such a system of wearable sensors, wireless-connected to the main home network, and suitable for acquiring information about the health and activity status of the persons wearing them. Additional features required in this case, with respect to wall-mounted environmental sensors, include light weight, small size and extremely low power consumption, to preserve battery life. First stages of the development of a wearable multi-sensor platform aimed at meeting such goals are described below.

In the present prototypal version, the device is exploited for motion analysis, to detect possible falls and evaluate gait quality. Such a device can be used for 24-hr monitoring of unassisted persons, for measuring progresses of rehabilitation therapies in the home environment, and for evaluating functional decline due to aging.

II. THE HOME CONTROL NETWORK

As mentioned above, a powerful and versatile home control system has been developed, fully based on standard IP communication protocol and devices. The hierarchical structure of the system actually coincides with a standard home LAN, and may be shared with home data and entertainment applications. Through gateways, the connectivity of the home control system is further expanded: WAN gateways enable control and monitoring of the home environment from an arbitrarily remote

Manuscript received May 14, 2008. This work was supported in part by Regione Emilia Romagna, Provincia di Parma, Fondazione CaRiPArma, AUSL Parma, Comune di Neviano degli Arduini, Comune di Tornolo, Comune di Borgo Val di Taro, in the framework of the Project "A nostra ca'" .

Authors are with the Dipartimento di Ingegneria dell'Informazione and Centro di Collaborazione sulle Tecnologie Assistive (Centro TAU) dell'Università degli Studi di Parma, Viale G.P. Usberti 181/a, 43100 Parma, Italy. Phone: +39-0521-905828; fax: +39-0521-905822; e-mail: paolo.ciampolini@unipr.it.

location and provide the basis for tele-care services.

Gateways can be deployed for including a wireless sensor network (WSN) into the system architecture as well, needed for mobile devices to communicate among themselves and with the supervising layer of the structure. Here, we shall refer to a WSN based on the IEEE-802.15.4 (ZigBee) standard protocol, exploited for the implementation of motion sensors described in the following.

III. THE WEARABLE SENSOR

Falls are among the first causes of injuries and death for older adults, and the fear of falls is often among the causes that contribute to make the home environment perceived as unsafe by older adults and their relatives [5].

Furthermore, recovering the standing position after an inoffensive fall may be a critical problem for an unassisted older person; emergency call buttons can be deployed in the rooms, or even worn (wireless wrist button or necklace pendant) can be used but they are ineffective if the wearer is unable or impeded to activate them. An automatic fall detector is hence more reliable, although it requires smarter devices at the user side.

Among the risk factors of falls are abnormal balance and gait [6]. Gait analysis can thus be used for prefiguring a possible fall, as well as for gauging the stage of some diseases (e.g. Parkinson) [7].

A sensor, capable of gait evaluation and fall detection has been developed, integrated into the assistive smart-home system previously mentioned.

The complete system should be light and small, in order to be worn daily with no significant burden: several placement can be exploited [8], or even multiple sensors distributed over the body [9], to provide more accurate motion information. Aiming at an everyday use, to limit the burden, we opted for a single sensor.

Reliability is a key issue: the device function is critical for the safety, and the device is likely to experience non negligible stresses while worn.

In [10] it is reported a study to determine a threshold associated with a fall based on accelerometers placed at four different locations of the body (trunk, thigh, waist and wrist). The results of this study was that the optimum sensor location was the trunk, between the chest and waist. Accordingly to such findings, we have chosen a belt-mounted device.

Wireless communication is mandatory: low-power solution are needed to allow for long lifetime of light batteries. Power-saving strategies should be envisaged both at the system and the circuit levels. All of these reasons make appealing the development of solid-state, miniaturized ASIC devices; a single-chip, or a single-package, implementation of the sensor would allow for fine tailoring of the functions and performance and for accurate power budget management. However, to effectively design an hardwired ASIC unit for fall detection, we need to validate fall-detection algorithms in advance: to this purpose, we designed and built a first prototype, based on more conventional implementation technologies. It consists of a small PCB board, which includes a MEMS tri-axial accelerometer [11] and a wireless transceiver [12], compliant with the ZigBee-/IEEE802.15.4 standard. In order to preserve the battery life, power-hungry radio transmission should be avoided whenever possible. Hence, analysis of the data flow coming from the accelerometer should be carried out on-board, to detect the fall, limiting the radio activity to the actual broadcast of an alarm signal. To this purpose, we use the same microcontroller exploited for the the ZigBee stack management.

The resulting device is shown in Fig. 1; it weight about 78 grams (with batteries) and measures 5cm x 5cm x 3cm: even if still to be optimized, it is already suitable for being worn on the belt and therefore adapt for validation.

Fig. 1. The wearable sensor prototype.

Two simple algorithms have been implemented on this platform. A "smart" fall detection algorithm and a gait quality analyzer. As explained later, raw acceleration data are not sufficient for reliable evaluations, and additional information is needed about the actual device orientation. Assessing the sensor orientation, in principle, may have required a gyroscope. However, including such a device would negatively impact on the overall sensor cost and power performance. On the other hand, relative assessment of the orientation change is enough for our purposes, and we may extract such an information from further processing acceleration data themselves. We hence compensated the lack of native gyroscopic information and used a single sensor for both purposes. In the following paragraphs, the orientation estimate is introduced and the algorithms exploiting it are presented.

A. *Sensor Orientation Evaluation*

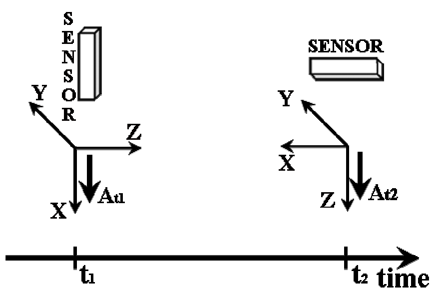

Fig. 2. Schematic view of sensor orientation

MEMS accelerometers are actually sensible to both the "dynamic" acceleration, directly due to the sensor movement, and the gravity 1g, which can be regarded as a "static" (i.e., invariant) component of the acceleration. Static acceleration can be extracted from the sensor output stream by proper filtering, to provide an estimate of the sensor orientation.

With reference to Fig. 2, let's assume a coordinate reference system connected to the sensor and changing orientation between time instants t_1 and t_2. We can extract the static acceleration components A_{t1} and A_{t2} in both cases, and compute the angle θ (on the common plane) between the two reference systems looking at the dot product between A_{t1} and A_{t2}:

$$T = A_{t1} \cdot A_{t2} = A_{t1\_x}A_{t2\_x} + A_{t1\_y}A_{t2\_y} + A_{t1\_z}A_{t2\_z} \quad (1)$$

$$T = |A_{t1}||A_{t2}| \cos\vartheta = G^2 \cos\vartheta \quad (2)$$

Each acceleration is expressed by a finite precision, 12-bit triplet of values. Hence, results may be affected by round errors, depending on the actual orientation. Simple analysis, however, lead to the relative errors shown in Table I below:

Table I

Val_V	Val_M	E%	Val_v	Val_m	E%
0°	0°	0	120°	118,6166°	1,15
30°	30,0809°	0.27	135°	133,4785°	1,13
45°	44,4583°	1,2	150°	148,9246°	0,72
60°	59,6062°	0,66	180°	178,6480°	0,75
90°	88,9904°	1,12	270°	269,9076°	0,03

The error is limited to a 1.2% maximum, which is more than acceptable for the applications at hand. We hence implemented the angle estimation engine, to be exploited by the algorithms described in the following.

B. Fall Detection Algorithm

A first-order approach to fall detection could be looking for abrupt accelerations: the fall actually implies an acceleration peak, which can be easily distinguished from those observed during normal activities, such as walking or standing. A simple threshold comparison could hence be used to this purpose: in [13], a 3g threshold is suggested. However, such a simple peak analysis does not ensure a reliable enough detection: the variability of such parameter is large, and comparable accelerations are not infrequent in unharmful activities, such as fast-pace walking, stair climbing, stumbling. Hence, to avoid false alarms, validation should be obtained by further analysis. An effective strategy may supplement the acceleration peak detection with a check for body tilt [13]. To implement such a solution, we need to evaluate the orientation of the sensor with respect to the upright position. Such a figure is a relative one, since it depends on the actual orientation of the worn sensor: nevertheless, this is sufficient for the differential measure needed to verify the fall and the strategy suitable for orientation change estimation can thus be used.

Whenever an acceleration peak exceeding the threshold is observed, a comparison between the orientation before and after the peak occurrence is carried out. The algorithm is illustrated by the flow chart below:

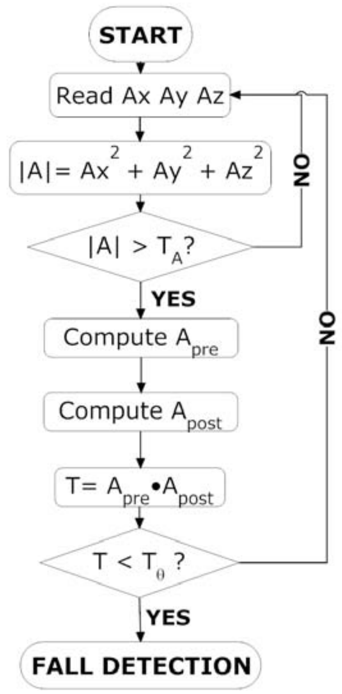

Fig. 3. Fall detecton algorithm.

In practice, current static acceleration components are periodically read and their intensity is computed. When the intensity threshold comparator is triggered, the acceleration stream is averaged on a relatively long period (say, 1 second) to make it independent on the actual sampling time. Two streams are averaged: one (A_{pre}) refers to the period which immediately preceding the peak trigger, the other (A_{post}) to the period which follows. The dot product between pre- and post-peak average accelerations is then computed, to extract the actual tilt angle. Such an angle is compared with a suitable threshold (T_θ) to validate the fall inference.

Data analysis is carried out on-board, and the transceiver remains in off-state until an actual fall is detected and an alarm signal has to be sent.

The algorithm has been implemented in the microcontroller, allowing for functional tests. In Fig.4, the response of the sensor is illustrated; the acceleration intensity is reported in two different cases: first, an actual fall has been taken into account, and the combined two-thresholds (acceleration and angle) approach properly detects the fall. Then, different situations which may possibly lead to sensor misbehaving have been considered, by running and jumping while wearing the sensor. Although even larger accelerations are found, the angle check avoids false alarms. A more comprehensive set of lab test has been carried out, under a wide range of different conditions, with positive results.

Field test (i.e., long-running experimentation in the home control system pilot site) are hence starting. Radio communication enables the system supervisor to issue alarm messages within 3 seconds from the fall, forwarding alerts to caregivers or family members through LCD panels, wireless PDA's or cell phones, or over the internet.

Lab test have also allowed for estimating the actual power consumption. At a 3.3V power supply, an average 18.4 mW power consumption (RF transmitter off) has been worked out.

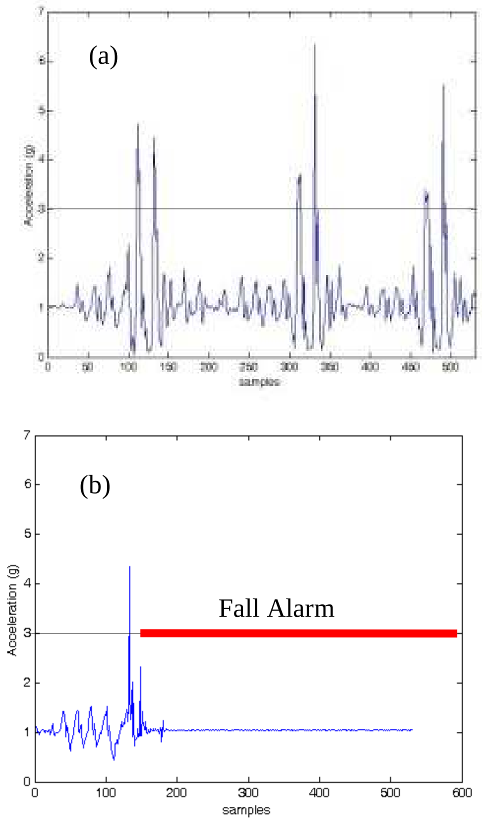

Fig. 4. Response of the sensor. Walk and jump acceleration(a), actual fall acceleration(b).

Assuming a battery capacity in the order of 2000 mAh, this yields a battery lifetime in the order of one month. If a better figure is needed (a six-month target lifetime, for instance, seems more reasonable for the application at hand), different implementation technologies should be used, as mentioned in the introduction.

C. Gait Quality Analysis

Although its fall-detection function is already definitely relevant, the device introduced so far is conceived to act as a platform for a wider set of services. Further functions can be worked out by smart processing of available data, and additional information can be obtained by introducing more sensors.

A first example is the evaluation of gait quality, which can be obtained by exploiting the strategy for sensor orientation assessment introduced above. As introduced in [14], by looking at the trunk sway the actual gait quality can be inferred. The sway can be evaluated by sampling trunk angles or trunk transverse accelerations; in the former case, the sway assessment is often made with angular velocity transducers [15], while in the latter accelerometers are used and less accurate results are obtained. In this case too, however, estimating the relative angle range is enough, and the methodology introduced above can still be used. In this case too a differential approach is used to get rid of absolute sensor positioning issues: sway is obtained by averaging on a suitable timeframe the maximum detected angle range, along the three available axes. Long-term monitoring of the sway can be useful for health-status assessment, whereas threshold comparison allows for detection of harmful staggering, which may be interpreted as a symptom of an incoming fall.

In Fig. 5 the outcome of trunk sway analysis is shown: the plots refer to the estimated sways along three orthogonal directions. After 30 seconds standing, the person wearing the sensor walks normally for 1.5 minutes, then begins to stagger (along Y-axis) and eventually (at 4.5 minutes) falls. Extracted warning signals are shown.

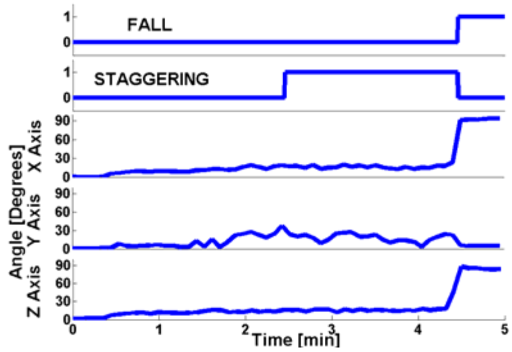

Fig. 5. Monitoring of trunk sway angle

IV. FURTHER DEVELOPMENTS

A monolithic version of the sensor integrates several devices and services together with dedicated control circuitry is being studied. It will allow for a significant leap in device size and power consumption and will be used as the core of a multi-functional wearable platform, fully integrated into a monitoring and assistive home system.

Further functions can be worked out by smart processing of available data, especially when combined with environmental data coming from the home monitoring system. Additional information can also be obtained by introducing more sensors.

For instance, the radio transceiver can be exploited for transferring vocal messages: a microphone can be easily integrated into the sensor chip to this purpose.

Another example could be the heartbeat monitoring, which is useful for controlling several diseases. By coupling heartbeat monitoring to motion analysis, much more accurate information can be extracted: from the one side, wearable ECG devices are often based on simple derivation schemes; single-lead sensors [16,17] however, are mostly sensitive to EMG interference (i.e., noise coming from skeletal muscle activity). By combining motion and heartbeat monitoring, the risk for misinterpretations can thus be reduced. On the other hand, correlation between motion and heartbeat could allow for a more accurate evaluation of the actual effort or fatigue status, as well as for smart detection of heartbeat anomalies.

REFERENCES

[1] Population Division, Department of Economic and Social Affairs, United Nations. World Population Ageing: 1950-2050. Available:http://www.un.org/esa/population/publications/worldageing19502050/.

[2] Fanucci L., Giusti D., Roncella R., Scebba A., "Platform based design of technical aids for independent living", IEEE International Conference on Industrial Technology (ICIT), Hammamet (Tunisia), 2004, pp. 1052-1056

[3] Sun H., De Florio V., Blondia C., "A Design Tool to Reason about Ambient Assisted Living Systems", Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06), Jinan, Shandong, China, 2006.

[4] F. Grossi, V. Bianchi, G. Matrella, I. De Munari, P. Ciampolini, "An assistive home automation and monitoring system", ICCE 2008, Digest of tecnical papers.

[5] Laurence Z. Rubenstein, "Falls in older people: epidemiology, risk factors and strategies for prevention", Age and Ageing 2006, Vol 35(Supplement 2) : pp ii37-ii41.

[6] Tinetti ME, Speechley M, Ginter SF, "Risk factors for falls among elderly persons living in the community", New England Journal of Medicine 1988, 319, pp. 1701-1707.

[7] Roniger L. R.., "Trunk sway may predict Parkinson's balance problems", Biomechanics, Online Magazine, 2006, 13(1).

[8] Maurer, U.; Smailagic, A.; Siewiorek, D.P.; Deisher, M., "Activity recognition and monitoring using multiple sensors on different body positions", Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on, 3-5 April 2006 Page(s):4 pp.

[9] Rocha, L.A.; Correia, J.H., "Wearable Sensor Network for Body Kinematics Monitoring", Wearable Computers, 2006 10th IEEE International Symposium on, Oct. 2006 pp. 137 – 138.

[10] A. K. Bourke, C. Ni Scanaill, K. M. Culhane, J. V. O'Brien, G. M. Lyons, "An optimum accelerometer configuration and simple algorithm for accurately detecting falls, Proceedings of the 24th IASTED international conference on Biomedical engineering", Innsbruck, Austria, Pages: 156 – 160, Year of Publication: 2006, Publisher ACTA Press Anaheim, CA.

[11] LIS3LV02DQ Datasheet: available online at www.st.com/stonline/products/literature/ds/11115.pdf

[12] MRF24J40 datasheet, www.sagitron.es/data_sheet/mc06017.pdf

[13] Chen J., Kwong K., Chang D., Luk J., Rumena B., "Wearable Sensors for Reliable Fall Detection", Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference September 2005.

[14] Adkin AL, Allum JHJ, Bloem BR, "Trunk sway measurements during stance and gait tasks in Parkinson's disease, Gait and Posture, 22, pp. 240-249, 2005.

[15] Jasper E. Visser, Nicol C. Voermans, Lars B. Oude Nijhuis, Martijn van der Eijk, Renate Nijk, Marten Munneke, Bastiaan R. Bloem, "Quantification of trunk rotations during turning and walking in Parkinson's disease", Clinical Neurophysiology 118 (2007) 1602–1606

[16] Thakor N., "Ground free ECG recording with two electrodes", IEEE transaction on Biomedical Engineering, December 1980,Vol BME27, pp. 699-704.

[17] Kaniusas E.,Maier T., Weiser H.,Varoneckas G., Zackarevicios L., "Embedded Elettrocardiographic Amplifier without reference electrode", Intelligent Solutions in Embedded Systems, 2006 International Workshop on Publication Date: June 2006 pp. 1-7