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A High Reliability Wearable Device for Elderly Fall Detection

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***Abstract*—Falls are critical events among elderly people that requires timely rescue. In this paper we propose a fall detection system consisting of an inertial unit that includes triaxial accelerometer, gyroscope and magnetometer with efficient data fusion and fall detection algorithms. Starting from the raw data, the implemented orientation filter provides the correct orientation of the subject in terms of Yaw, Pitch and Roll angles. The system is tested according to experimental protocols, engaging volunteers who performed simulated falls, simulated falls with recovery and Activities of Daily Living (ADL). By placing our wearable sensor on the waist of the subject, the unit is able to achieve fall detection performance above those of similar systems proposed in literature. The results obtained through commonly adopted protocols show excellent accuracy, sensitivity and specificity, improving the results of other techniques proposed in the literature.**

***Index Terms*—Accelerometer, Fall detection, Gyroscope, Magnetometer, MARG sensor, MEMS, Wearable sensors.**

I. Introduction

POPULATION ageing is unprecedented in the history of humanity and started in the western world during the 20th century. At the world level, the number of older persons is expected to exceed the number of children for the first time in 2045 [1]. This phenomenon was also made possible by the advances in health care sector. The shift in age structure associated with population ageing has a deep impact on a broad range of economic, political and social processes. For example, increasing longevity results in rising medical costs and increasing demands for healthcare services.

Falls are the leading cause of injury-related hospitalization among people 65 years and older in society [2] and two thirds of all severe injuries in the elderly are caused by falls [3]. The major underlying causes for fall-related hospital admission are hip fracture, traumatic brain injuries and upper limb injuries [4]. Previous studies report that the consequences of a fall depend on the sex and age of subject [5] and on the direction [6] and type [7] of fall. Data from 3,628 falls of 12 different retrospective studies about the percentage of occurrence of types of fall among older persons living in a variety of settings were summarized by Rubenstein [7]. According to this study, environment-related falls are the most frequently occurred with a mean percentage of 31%. The category of gait disorders causes falls for 17% of cases. Syncope and dizziness (falls in which the subject is generally able to sit) have been the attributable cause of about 13% of falls. Drop attacks (sudden falls without loss of consciousness) have been reported in 9% of falls. Other minor causes of falls are confusion, postural hypotension, visual disorder. Furthermore O'Neill *et al.* [6] reported that most of falls in elderly people occur forwards, backwards or sideways. Many studies examining the locations where falls occur in real life were reviewed by Lord *et al.* [8]. Most falls (56%) occur in public areas due to pavement cracks and misalignments, steps, uneven ground and slippery surfaces. In older community-dwelling people, 44% of falls occur within their homes and immediate home surroundings. Most falls occur on level surfaces within bedroom, lounge and kitchen, comparatively few falls occur in the bathroom, on the stairs, or from stools. A fall occurred at home can be very dangerous among elderly people living alone since they might be unable to seek help. It has also been found that more than 20% of patients admitted to hospital as a result of a fall had been on the ground for an hour or more [8]. Furthermore falls do not only cause physical, but also severe psychological effects [9]. Tinetti *et al.* [10] found that up to 47% of non-injured fallers are not able to get up off the floor without assistance and when an elderly person experiences a lack of ability to stand up after a fall while living alone, the consequences can be quite serious. In particular, half of those who remain on the ground for more than an hour following a fall, die within 6 months even if no direct injury from the fall has occurred [11] thus indicating a deterioration in general health. As a consequence, science today is looking for automatic fall-detection devices and applicable algorithms in order to notify nursing personnel or EMS (Emergency medical services) [12].

During the last decades, many solutions have been proposed for elderly fall detection. Such solutions can be categorized into three types. One of the earliest solutions involved ultrasonic sensor network system; such a system continuously monitors the elderly people in a nursing room and, when it detects a fall, caregivers are notified about the occurrence of such an event [13]. The main disadvantage of this solution is the need to place a series of spatially distributed sensors within the environment in which the elder lives.

Video and audio detection systems are commonly used solutions at present [14]. However, also this kind of solution is limited to a given space under observation and it can not achieve ubiquitous monitoring.

The third kind of solution employs wearable devices with integrated Micro Electro-Mechanical Systems (MEMS) such as several motion sensors [15] in order to automatically detect

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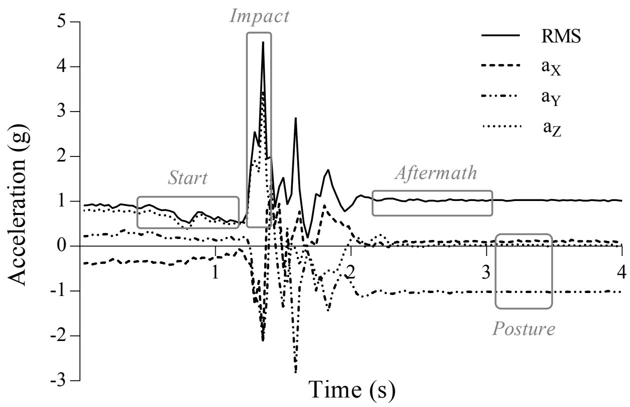

Fig. 1. Acceleration changes during an accidental fall.

a fall and generate an alarm. Non-obtrusive wearable devices have been realized [16], [17] using a single accelerometer attached on the body of the subject. In this class of systems a fall is detected by observing changes in acceleration measurements provided by 3-axis accelerometers. Typical changes in acceleration during a fall can be identified and valued by appropriate algorithms in order to detect the event [17].

As shown in Fig. 1 the acceleration changes occurring during an accidental fall can characterize the following four phases:

1) Start: In this phase the subject loses the contact with the ground and then starts the descent towards the ground experiencing the weightlessness. Attracted by the force of gravity, the body accelerates reaching maximum speed just before impact to the ground. During the free fall, the root mean square (RMS) of acceleration will tend to 0 g or otherwise will be substantially less than 1 g.

2) Impact: After experiencing weightlessness, the subject impacts the ground or other objects. In this phase the RMS rapidly increases until reaching a peak greater than 2 g.

3) Aftermath: After an impact, the subject usually remains nearly motionless [17], [18] for a very short period even if the fall is without serious consequences. In this phase the RMS presents a flat trend. After this period of immobility, the conscious subject starts to move trying to get up.

4) Posture: After a fall, the subject's body will be in a different orientation than before the impact. Therefore the acceleration values of the individual axes will be different from those measured before the fall. This phase is placed two seconds away from the moment of impact and is characterized by the fact that the subject is in supine or prone position [17].

Many algorithms proposed in literature take into account two or more of these phases in order to detect a fall. Kangas *et al.* [17] proposed three algorithms for fall detection. The first algorithm detects a fall if an impact occurred and then the posture is horizontal (*Impact* and *Posture* phases). The second algorithm additionally requires the detection of *Start* phase of fall event within a second before impact (*Start*, *Impact* and *Posture* phases). The third algorithm further requires that velocity before impact is above the threshold value of 0.7 ms^{-1} (*Start*, *Impact* and *Posture* phases). These kinds of algorithms are all based on the detection of the *Posture* phase whereas do not take into consideration the *Aftermath* phase although it is crucial to identify if a subject remains motionless on the floor after a fall.

In this study we wish to evaluate performance of a new fall detection algorithm that takes into account the *Aftermath* phase too and therefore the risk factors related to it [10]. The advantage of this approach will be evident in Section VI, where we will compare it against a reduced version where the detection of the Aftermath phase is not expected.

As shown by Kangas and many other studies, the detection of *Posture* phase becomes crucial for the functioning of the fall detection system. Data from a single 3-axis accelerometer are generally employed for tilt sensing and then for *Posture* phase detection. However, information provided by a single 3-axis accelerometer has some limitations when used for posture determination and therefore also for the purpose of fall detection. In fact, if the user is trembling or rapidly moving the accelerometer, the computed orientation data could be unreliable because sensor suffers from external accelerations and vibrations [19]. Therefore, for the purpose of fall detection it is necessary to obtain an accurate estimation of orientation of the subject which is not always easy to derive from the information provided by a single 3-axis accelerometer.

In this paper we propose a wearable fall detection device in which is incorporated a MARG (Magnetic, Angular Rate, and Gravity) sensor [20] to overcome the limitation of a single accelerometer. In order to provide the proper orientation of the subject wearing it, this device combines information from 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer using a suitable algorithm known as orientation filter [21]. In this work we shall show a performance comparison between the proposed device and the system employed by Kangas *et al.* [17] and based on data provided by just one accelerometer.

The inclusion of the gyroscope in a fall detection device was proposed by several studies [22], [23] in which, however, an orientation filter was not implemented to compute the properly orientation of the subject. Conversely Wu *et al.* [24] proposed a preimpact fall detector apparatus that embeds 3-axis accelerometer and 3-axis gyroscope and implements an orientation filter based on Kalman solutions. This technique for orientation sensing demands a high computational load that may not be supported in real-time applications with limited processing resources [18].

In order to evaluate the performance of the fall detection system, the proposed algorithm has been tested in an experimental protocol in which volunteers performed simulated falls, simulated falls with recovery and Activities of Daily Living (ADL). Backward falls ending in sitting position and syncope (leaning against a wall and then slipping vertically ending up sitting) have been included according to the experimental protocol proposed by Noury *et al.* [25]. These latter types of fall are not considered in Kangas' experimental protocol as well as in almost all past studies on fall detection [18], [22], [23], [24] even if they represent a statistically significant percentage of falls in the elderly population. [7], [26]. However the Kangas experimental protocol was taken into consideration

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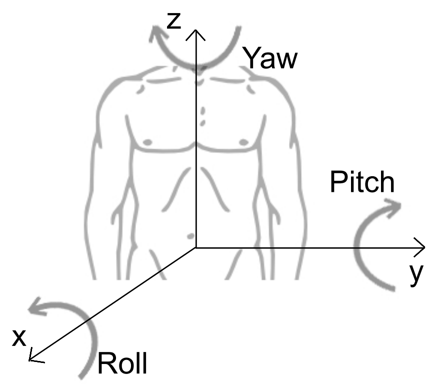

Fig. 2. Reference system for the Yaw, Pitch and Roll angles.

in order to assess the performance of the fall detection system in the same test situations. This experimental protocol is similar to those commonly adopted in literature. Therefore, the activities and the test situation of this experimental protocol is comparable to those used in previous studies on fall detection.

II. Three-Dimensional Orientation Measurement of Human Body

The accurate measurement of orientation plays a critical role in human motion analysis as well as in a range of fields including navigation and robotics. In order to describe the posture of the human body we adopt Euler angles [27] formalism (also known as Yaw, Pitch and Roll angles) for representing the spatial orientation. This type of formalism describes the current orientation of a body as a composition of three elemental rotations (the angles Yaw, Pitch and Roll) starting from a fixed reference frame which is the world frame. The axes of fixed reference frame are denoted in Fig. 2 as X, Y and Z and are supposed to be rigidly attached to a rigid body. Yaw, Pitch and Roll angles are identified as the rotations around the Z, Y and X axis, respectively. Thus, in the following Yaw, Pitch and Roll angles will be used to represent the actual orientation of human body.

A single 3-axis accelerometer placed on the waist of a subject provides an incomplete estimate of the orientation of the body. In fact, the output of a three axis accelerometer can be used for tilt sensing of subject by computing Pitch and Roll angles but it is not possible to have an information on the Yaw angle. Yaw is defined as the angle between a fixed heading point (e.g., Earth North) and the X axis of the device. This is a consequence of the fact that, using only gravity as reference vector, any rotation of the device around the gravity vector will not produce any difference in the output of the accelerometer. The method for tilt determination only using an accelerometer also suffers from errors caused by external accelerations and vibrations which adding to gravity make this device unreliable.

In order to sensibly increase the reliability of the orientation sensing capabilities it is possible to exploit information from different sensors using an appropriate algorithm called orientation filter [21]. In this type of system MARG sensors are used to measure rotational and translational movements in three dimensions [20]. The orientation filter combines accelerometer, gyroscope and magnetometer data obtained by the MARG sensor to provide a complete measurement of orientation relative to the direction of gravity and the Earth's magnetic field.

The task of an orientation filter is the optimal fusion of sensor measurements for providing an estimate of orientation based on the available processing resources. The Kalman filter [28] is widely adopted by the majority of orientation filter algorithms and commercial inertial orientation sensors. Kalman-based solutions demand a large computational load for implementation and need a high sampling rate for human motion capture applications.

Starting from the work of Mahony *et al.* [29], Madgwick *et al.* [30] introduced an orientation filter applicable to MARG sensor arrays which employs a quaternion representation of orientation [31]. A quaternion $\hat{q}$ is a four-dimensional complex number that is defined by equation:

$$\hat{q} = [q_1 \ q_2 \ q_3 \ q_4] \tag{1}$$

where q_1 is the scalar part of the quaternion whereas q_2, q_3 and q_4 represent the vector part components.

Madgwick's filter estimates the quaternion orientation at time t, $q_{est,t}$, via the fusion of two different orientation calculations, $q_{\bigtriangledown,t}$ and $q_{\omega,t}$, defined by:

$$q_{est,t} = \gamma_t \ q_{\bigtriangledown,t} + (1-\gamma_t) \ q_{\omega,t}, \ 0 \leq \gamma_t \leq 1 \tag{2}$$

where $q_{\bigtriangledown,t}$ is the orientation provided from accelerometer and magnetometer data and calculated using the gradient descent algorithm, $q_{\omega,t}$ is the orientation computed from angular rate measured by the gyroscope and γ_t determines the weights given to each orientation calculation.

Through a suitable choice of optimal value of γ_t [30], equation (2) can be simplified to equation (3):

$$q_{est,t} = \hat{q}_{est,t-1} + \dot{q}_{est,t} \ \Delta t \tag{3}$$

where $\hat{q}_{est,t-1}$ is the previous estimate of orientation, $\dot{q}_{est,t}$ is the estimated orientation rate and Δt is the sampling period. The estimated orientation rate, $\dot{q}_{est,t}$, is calculated as the gyroscope orientation rate minus the magnitude of gyroscope measurement error in a direction based on the data provided by accelerometer and magnetometer.

Subsequently, Yaw, Pitch and Roll angles are computed directly from quaternion data to describe the coupled nature of orientation in three-dimensions. The Yaw, Pitch and Roll angles starting from the components of a quaternion, $q_{est,t}$, can be expressed by the equations:

$$Yaw = atan2 \ (2q_2q_3 - 2q_1q_4, \ 2q_1^2 + 2q_2^2 - 1) \tag{4}$$

$$Pitch = -sin^{-1} \ (2q_2q_4 + 2q_1q_3) \tag{5}$$

$$Roll = atan2 \ (2q_3q_4 - 2q_1q_2, \ 2q_1^2 + 2q_4^2 - 1) \tag{6}$$

Further details about the mathematical derivation of orientation estimation by means of Madgwick's filter can be found in [30]. Madgwick's orientation filter provides compensation for

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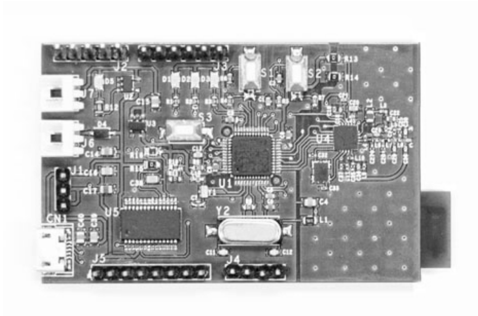

Fig. 3. Photo of the assembled device.

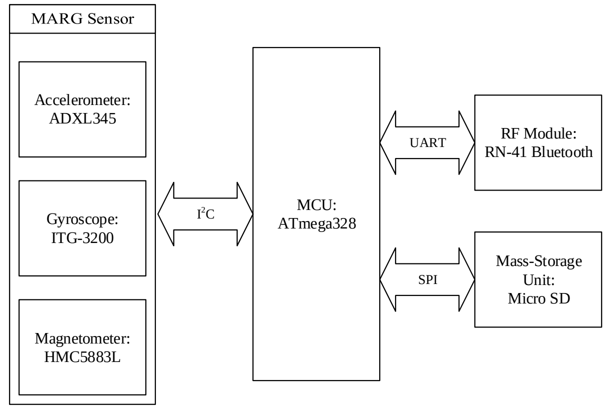

Fig. 4. Block diagram of wireless sensor node.

magnetic distortion and gyroscope bias drift. It significantly reduces the computational load associated with conventional Kalman-based approaches, even up to one order of magnitude in sampling rate reduction. This orientation filter is particularly well suited for real-time applications where limited processing resources may be available.

The device proposed in this paper contains a MARG sensor in order to provide a complete measurement of orientation of the subject wearing it. A Madgwick orientation filter has been implemented on the embedded MCU (Micro Controller Unit) allowing to compute Yaw, Pitch and Roll angles by fusing data coming from 3-axis accelerometer, gyroscope and magnetometer. Using accurate and fast Madgwick algorithm, it has been possible to implement a real-time orientation filter even in a low cost 8-bit microcontroller like the one used in the device proposed in this paper.

III. Design of wireless sensor node

This study proposes a wireless wearable device for fall detection integrated within a compact module allowing the owner to move unrestricted. The dimensions of this custom prototype device are 70 x 45 x 30 mm (62 x 41 x 11 mm without plastic housing and battery). A picture of the assembled device is shown in Fig. 3.

The device contains a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer realizing a MARG sensor. Madgwick's orientation filter has been implemented on the MCU of the device in order to provide a complete measurement of orientation of the subject wearing it. Such a filter computes orientation data in term of Yaw, Pitch and Roll angles with a high level of accuracy (RMS error less than one degree) [30]. On the MCU has also been implemented an automatic fall detection algorithm handling acceleration and orientation data sampled at 50 Hz, a bandwidth adequate for human motion sensing. This real-time algorithm is able to generate an alarm when a fall has been detected. Raw data, orientation or just the fall alarms can be stored in a microSD card or sent to external devices such as a smartphone, PC or tablet via Bluetooth transceiver. The current consumption of the proposed device is about 34 mA during Bluetooth transmission of raw and orientation data (15 mA during normal operation mode where just the alarms are sent).

The developed device consists of MARG sensor, MCU, RF module and mass-storage capability. A block diagram of the system is shown in Fig. 4 and the hardware used is described in the following.

MARG sensor: A combination of 3-axis magnetometer, gyroscope and accelerometer is required to realize a MARG sensor which implements a suitable orientation filter. The MARG sensor is composed by MEMS and it measures the local magnetic field, acceleration and angular rate in three dimensions. It includes the HMC5883L magnetometer (Honeywell, USA), ADXL345 accelerometer (Analog Devices, USA) and ITG-3200 gyroscope (InvenSense Inc., USA). Resolutions of sensors are 4 mG in ± 8 G fields, 4 mg/LSB (Least Significant Bit) in ± 16 g range and 14.375 LSBs per °/s in ± 2000 °/s range, respectively. The overall dimensions of MARG sensor are suitable for realizing a wearable device.

MCU module: We adopted ATmega328 (ATMEL, USA), a low-power 8-bit microcontroller with 32kB flash memory. MCU reads the output from external MARG sensor through I^2C (Inter Integrated Circuit) bus and processes data in order to implement orientation filter, fall detection algorithm and alarm management.

RF module: We used RN-41 Bluetooth® module (Roving Networks, USA). The module is a small, low-power transceiver ideal for embedded applications. The RN-41 provides serial communications speeds up to 115200 bps via UART (Universal Asynchronous Receiver/Transmitter) interface with a maximum radio range of about 100 m over open air. Through UART interface, data processed by the MCU are transmitted wirelessly via the RF module.

Mass-storage unit: MCU memory capabilities are not sufficient to store data from sensors and orientation filter in case wireless connectivity is not available. We used a microSD card in order to provide the device with mass-storage capability. Communication with microSD card is achieved over SPI (Serial Peripheral Interface).

Battery: A very slim, extremely light weight 3.7V battery based on the new Polymer Lithium Ion chemistry has been used to power the device. This battery includes built-in protection against over voltage, over current, and minimum voltage.

Wireless receiver: A mobile phone, a personal computer or any device provided with a Bluetooth module is suitable to act as a wireless receiver.

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TABLE I
EXPERIMENTAL PROTOCOL

Category	Activities	Outcome
Backward fall	Ending up sitting	Positive
	Ending in lateral position	Positive
	Ending up lying	Positive
	Ending up lying with recovery	Negative
Forward fall	Falling on the knees ending up lying	Positive
	Ending in lateral position	Positive
	Ending up lying	Positive
	Ending up lying with recovery	Negative
Lateral left fall	Ending up lying	Positive
	Ending up lying with recovery	Negative
Lateral right fall	Ending up lying	Positive
	Ending up lying with recovery	Negative
Syncope	Slipping against a wall ending up sitting	Positive
ADL	Lying on a bed then standing	Negative
	Walking a few meters	Negative
	Sitting on a chair then standing	Negative
	Climbing two steps	Negative
	Standing after picking something	Negative

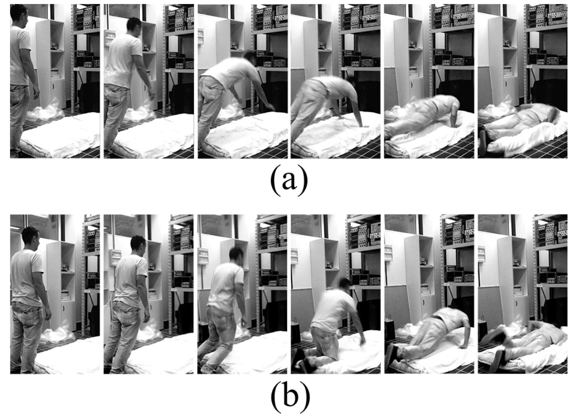

Fig. 5. Examples of demo video frames shown to the study participants: (a) Falling up lying and (b) Falling on the knees ending up lying.

IV. EXPERIMENTAL PROTOCOLS

The goal of the presented work is to develop a high reliability wearable monitoring system for fall detection. Thereby, implemented monitoring system was tested in an experimental protocol in order to evaluate its performance. Criteria for the evaluation of performance and procedures to carry out the tests were proposed by Noury *et al.* [25].

The experimental protocol constructed for this study is suitably defined to mimic realistic scenarios that most often occur among older people. In fact, the subjects involved in this study simulate falls and ADL similar to those observed in most previous studies on fall detection. [17], [22], [23], [24]. Since there is a correlation between the direction and type of falls and health consequences of the same [6], [7], [8], the adopted acquisition protocol takes into account such characteristics as well as the occurrence of individual types of fall. Therefore, the number and type of falls included in the proposed protocol refer approximately to the probabilities reported in literature.

The 18 activities of the experimental protocol are shown in Table I and are grouped in 6 categories: backward fall, forward fall, lateral left fall, lateral right fall, syncope and ADL.

Most falls occur in the anteroposterior plane, forward or backward, stumbling on an obstacle during walking or backwards slipping on a wet floor [6], [7], [8]. A fall also occurs sideways [6], [7], if the person becomes unbalanced or during a badly controlled standing up from sitting position. To simulate these events in the experimental protocol backward, forward, lateral left and lateral right fall categories have been introduced. In these categories falls with recovery were also added in order to verify the system ability to avoid sending useless alarms when the subject has raised up after a fall.

When a person slowly loses consciousness could lean against a wall and then sliding on it ending up sitting. This event is commonly called syncope and must be considered as a fall since injurious consequences such as fractures, laceration and bruises have been reported [26], [7]. In order to simulate this type of fall, the syncope category was introduced in the adopted experimental protocol.

In the experimental protocol ADL category was also inserted in order to verify if the fall detection system generates false alarms [25]. In this case, a subject performing an ADL must be classified by the system as not a fall.

The activities of the experimental protocol are classified by a positive or a negative outcome as shown in Table I. An ideal fall detector should identify as a fall all the activities with positive outcome. The system should recognize as not a fall activities with negative outcome. As proposed by Noury, types of activities have been specifically chosen so as to have 50% positive and 50% negative results. In particular, the adopted experimental protocol consisted of 9 simulated falls with positive outcome and 9 activities with negative outcome (4 simulated fall with recovery tasks and 5 ADL tasks).

Young subjects were involved into the activities of the experimental protocol. The engagement of elderly subjects to simulate falls that anyway could cause injuries was not appropriate. In fact all the experimental protocols used in the literature for the validation of fall detection systems exclusively employ young persons who simulate falls. According to a study recently released by Kangas *et al.* [32] comparing real-life accidental falls in older people with experimental falls in younger test subjects, participants received oral information about the study and were introduced to the circumstances of falling by a video tape showing the activities of the experimental protocol (Fig. 5).

The device is placed inside a hard plastic box and has been fixed on an elastic belt through adhesive Velcro. The elastic belt was worn by the subjects on the waist thus ensuring that the sensor was integral to the body. Subsequently, subjects were asked to simulate falls onto a small mattress (thickness 15 cm) according to the instruction of the support staff. All falls and activities of daily living (ADL) were performed under the direct supervision of the support staff. The tests were repeated for those rare cases in which the sensor is moved or dropped by the person. A special mattress is used to reduce the impact on the ground of a fall event and to protect the person during

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the simulated falls. Therefore, simulated falls onto a mattress are characterized by a lower peak of acceleration with respect to a real fall. Nonetheless, Kangas *et al.* [32] demonstrated similarities between acceleration data obtained from real-life falls of older people and simulated falls performed by younger subjects in an experimental context.

The study involved 10 volunteer subjects performing given scenarios. The subjects (8 male and 2 female) ranged in age from 22 to 29 years. Every subject repeated the 18 scenarios by 3 times. A total of 540 tests with simulated falls, simulated falls with recovery and ADL were carried out for the experimental protocol of Noury.

Fall detection performance for the proposed device were also assessed according to the Kangas' experimental protocol. It is important to point out that this experimental protocol only contemplates falls ending in lying position. In order to compute fall detection performance for the proposed algorithm according to the experimental protocol adopted by Kangas, only falls and ADL ending in lying position must be taken into account. Thus, syncope falls and backward falls ending in sitting position were not considered for performance evaluation. Furthermore, in order to have 50% positive and 50% negative results, even lateral left and right falls with recovery were not considered for performance evaluation. A total of 420 tests were then considered for the experimental protocol of Kangas. The activities of this experimental protocol were comparable to those used in previous studies on fall detection [18], [22], [23], [24].

V. Fall detection algorithm

In this section the implemented fall detection monitoring system is presented. A new set of acceleration and orientation thresholds has been defined for discriminating between real fall events and ADL, as well as to assess the ability of a subject to get up after a fall without help. The human body has its center of mass at the waist, and all movements center on the waist. The device described in this paper was then worn at the belt of the subjects involved in the study. In this way the subject is able to move unrestricted and the system can be used in everyday life without disturbing its owner. The device applied to the waist of the subject monitors acceleration and orientation data processed by the orientation filter implemented in the system. In particular, the monitoring system analyzes the RMS of acceleration and Pitch and Roll angles. The RMS is calculated from the data of the embedded accelerometer and Pitch and Roll angles are obtained by the orientation filter implemented in the device. Data measured by the monitoring system during a fall event are shown in Fig. 6 where a forward fall ending up lying with recovery has been simulated. Analyzing data collected by the proposed monitoring system, the *Impact*, *Aftermath* and *Posture* phases previously described and illustrated in Fig. 1 are easy to recognize even in this fall event (Fig. 6) as well as in many other experimental simulations.

On the basis of acceleration and orientation data, the monitoring system detects a fall by means of the algorithm proposed in this paper and shown in Fig. 7. Such algorithm is based

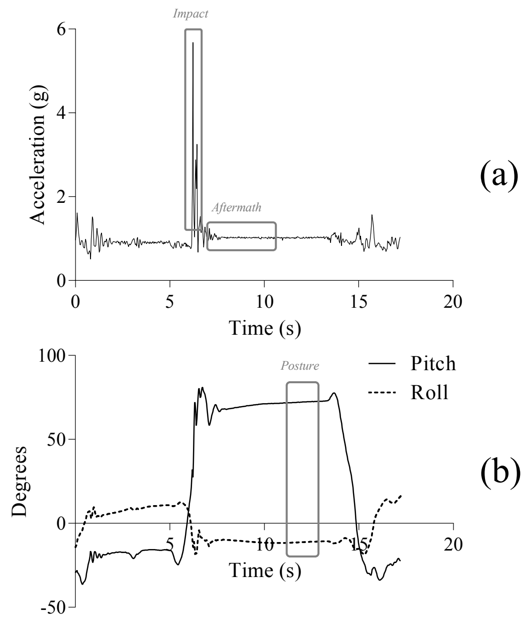

Fig. 6. RMS of acceleration (a) and Pitch and Roll angles (b) during a forward fall ending up lying with recovery.

on the detection of *Impact*, *Aftermath* and *Posture* phases of a fall event by means of a series of threshold comparisons. *Impact* and *Aftermath* phases are detected via the RMS of acceleration provided by 3-axis accelerometer. *Posture* phase is detected by observing Pitch and Roll angles provided by the orientation filter. Acceleration and orientation thresholds were selected by observing experimental data for some tests. In particular, acceleration thresholds have been selected after an accurate training process using the Support Vector Machine (SVM) method. In our case of study we implemented a one-dimension SVM base form with linear threshold functions. The training process consisted of 50 simulated falls and 50 ADL. Then, data extracted by our fusion algorithm have been processed offline with SVM method for threshold calculation. Orientation thresholds have been derived from Karantonis' [18] studies and experimentally verified by us through 100 simulated falls and ADL. Time thresholds for Aftermath and Posture were chosen on the basis of Kangas' studies [17].

An *Impact* phase occurs when a peak of the RMS of acceleration is detected. As proposed by Kangas, a fall impact is detected when the RMS of acceleration exceeds 2 g. Collected data for the present work show that RMS peak is much greater than 2 g for some tests so, according to SVM threshold calculation, the impact acceleration threshold At_I (Acceleration threshold for Impact) has been set to 2.5 g.

Furthermore a *Aftermath* phase is detected when the RMS of acceleration presents an almost flat trend and close to 1 g. In order to verify this condition the algorithm checks if the RMS of acceleration is between 0.72 g (Alt_A: Acceleration lower threshold for Aftermath) and 1.28 g (Aut_A: Acceleration upper threshold for Aftermath) within Tt_A = 1 s (Time threshold for Aftermath) after exceeding At_I.

Changes in Pitch and Roll angles are to be observed in order

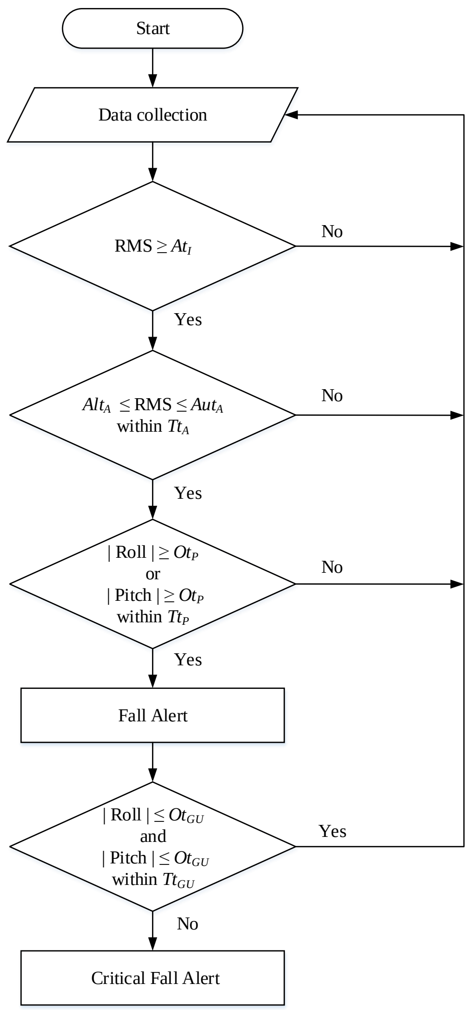

Fig. 7. Flow chart of the proposed fall detection algorithm.

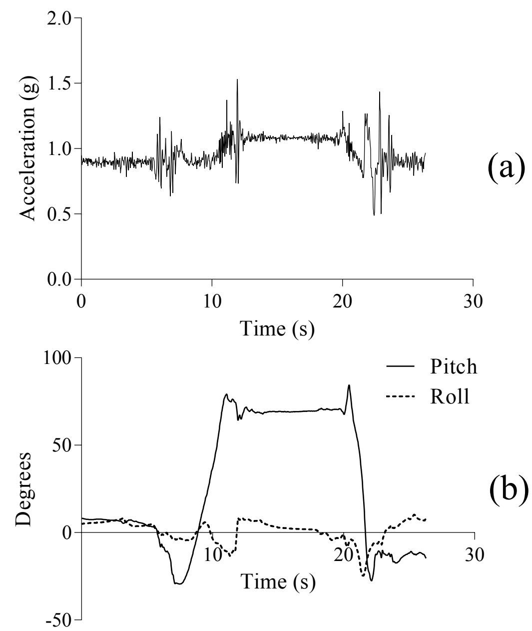

Fig. 8. RMS of acceleration (a) and Pitch and Roll angles (b) during an ADL like lying on a bed then standing.

to identify a *Posture* phase. In particular, defining Ot_P as the Orientation threshold for Posture, the algorithm verifies if the absolute value of Pitch or Roll angle has exceeded Ot_P = 50° within Tt_P = 1 *s* (Time threshold for Posture) after the detection of *Aftermath* phase (thus within 2 *s* after exceeding At_I). At this point the algorithm generates a Fall Alert to indicate that a fall has occurred.

The inability to get up without help after a fall is a crucial event [10] that should be monitored by the fall detection system. In addition a fall detection algorithm must also assess if one who has fallen has raised up in order to indicate that assistance is not required. Therefore the proposed algorithm generates a Critical Fall Alert signal if a subject has not raised up after a time of Tt_{GU} (Time threshold for Get Up) following a fall. This is achieved by checking if the absolute value of both Pitch and Roll angles is back below Ot_{GU} = 40° (Orientation threshold for Get Up) within Tt_{GU} = 30 *s* after a Fall Alert.

The developed fall detection algorithm is based on a simple approach compared with other studies that have used neural networks or Hidden Markov Models. However, such methods are infeasible in a real time application if it is implemented on a low cost MCU with limited processing resources as the one we proposed. Therefore, we chose to use this simpler and efficient technique based on a series of acceleration and orientation thresholds.

An event that does not fit the conditions of the proposed algorithm in the established sequence and within the time thresholds is classified as not a fall. For example, in an ADL like lying on a bed then standing could be possible to identify the *Aftermath* and *Posture* phases but not the *Impact* phase. In fact, as shown in Fig. 8, in this ADL the proposed algorithm does not detect a fall because it does not identify an acceleration peak greater than 2.5 *g* characterizing the *Impact* phase.

VI. Results

We present a large set of results showing the performances of our approach and those of other algorithms proposed in the literature. The considered algorithms are:

- Algorithm A: this is our full algorithm described in Section V;
- Algorithm B: this is a reduced version of Algorithm A, in which the detection of the *Aftermath* phase is not expected;
- Algorithm 1: this was proposed by Kangas in [17] and generates a fall alert if *Impact* and *Posture* phases are detected;
- Algorithm 2: this is an extended version of Algorithm 1, in which the *Start* phase is also detected;

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TABLE II
EXPERIMENTAL RESULTS

Activity	Algorithm A		Algorithm B		Algorithm 1		Algorithm 2		Algorithm 3	
	Overall correct	Acc. (%)	Overall correct	Acc. (%)	Overall correct	Acc. (%)	Overall correct	Acc. (%)	Overall correct	Acc. (%)
Backward fall										
Ending up sitting	5	16.67	5	16.67	3	10	3	10	3	10
Ending in lateral position	30	100	30	100	30	100	30	100	21	70
Ending up lying	30	100	30	100	30	100	30	100	16	53.33
Ending up lying with recovery	30	100	30	100	30	100	30	100	30	100
Forward fall										
Falling on the knees ending up lying	30	100	27	90	22	73.33	21	70	17	56.67
Ending in lateral position	30	100	30	100	30	100	30	100	16	53.33
Ending up lying	30	100	30	100	30	100	30	100	19	63.33
Ending up lying with recovery	30	100	30	100	30	100	30	100	30	100
Lateral left fall										
Ending up lying	30	100	30	100	30	100	30	100	26	86.67
Ending up lying with recovery	30	100	30	100	29	96.67	29	96.67	30	100
Lateral right fall										
Ending up lying	30	100	30	100	30	100	30	100	28	93.33
Ending up lying with recovery	30	100	30	100	29	96.67	29	96.67	30	100
Syncope										
Slipping against a wall ending up sitting	3	10	3	10	1	3.33	1	3.33	0	0
ADL										
Lying on a bed then standing	30	100	30	100	29	96.67	29	96.67	29	96.67
Walking a few meters	30	100	30	100	30	100	30	100	30	100
Sitting on a chair then standing	30	100	30	100	30	100	30	100	30	100
Climbing two steps	30	100	30	100	30	100	30	100	30	100
Standing after picking something	30	100	30	100	30	100	30	100	30	100

- Algorithm 3: this is an extended version of Algorithm 2, in which is also verified if subject's velocity before the impact is above 0.7 ms^{-1};

Algorithms A and B use data provided by the MARG sensor and elaborated by the implemented orientation filter whereas Kangas' Algorithms 1, 2 and 3 are based only on the measurements of the accelerometer.

Data collected during the experimental protocol were processed by each of these algorithms and in Table II the results are shown. For each performed activity the correct classifications on 30 tests (overall correct) and the percentage of it (accuracy) are reported. With these statistically significant number of tests is possible to derive algorithm average accuracy, sensitivity and specificity for evaluating the performance of fall detection monitoring system. Table III shows the performance obtained by the proposed algorithm with respect to performed experiments, together with the results from the other fall detection algorithms.

According to the experimental protocol proposed by Noury, algorithm A correctly recognized 218 of the 270 falling tasks and no false positive occurred. The algorithm has therefore an average accuracy of 90.37%, a sensitivity of 80.74% and a specificity of 100%.

Fall detection performance of Algorithm A were also evaluated according to the Kangas' experimental protocol that is similar to those adopted in many fall detection studies [18], [22], [23], [24]. In this case 210 true positives and 210 true negatives occurred (no false negative and no false positive) on a total of 420 tests. Algorithm A shows 100% average accuracy, sensitivity and specificity highlighting better performance than other fall detection algorithms tested in similar experimental protocol.

TABLE III
FALL DETECTION PERFORMANCE FOR THE PROPOSED ALGORITHM AND THREE KANGAS ALGORITHMS

Experimental protocol	Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)
Noury	Algorithm A	90.37	80.74	100
	Algorithm B	89.82	80.37	100
	Algorithm 1	87.59	76.29	98.89
	Algorithm 2	87.41	75.93	98.89
	Algorithm 3	76.85	54.07	99.63
Kangas	Algorithm A	100	100	100
	Algorithm B	99.29	98.57	100
	Algorithm 1	97.86	96.19%	99.52
	Algorithm 2	97.62	95.71%	99.52
	Algorithm 3	83.81	68.1	99.52

As shown in Table III, the proposed algorithm performs better than ones included in the performance comparison for both Noury's and Kangas' experimental protocols.

VII. DISCUSSION

The results of the experimental protocols indicate that Algorithm 3 has the worst performance compared to the other fall detection algorithms. Algorithm 2 achieves better performance but misclassifies 9 forward falls on the knees ending up lying, 2 lateral falls with recovery and one ADL (lying on a bed then standing). Algorithm 1, compared to Algorithm 2, corrects one false negative when recognizing forward falls on the knees ending up lying. In this type of fall the orientation of the subject was not always detected as horizontal even though these fall events ended up in a lying posture. Such a problem has also been reported by Kangas *et al.* [17]. Anyway, results of our test as well as those proposed by Kangas confirm that Algorithm 1 detecting just Impact and Posture phases achieves the best performance among fall detection algorithms that only use accelerometer data.

The improvements obtained by our algorithms A and B with respect to Algorithms 1, 2 and 3 show the goodness of the proposed approach where, to overcome the limitation in the estimate of the subject orientation during a fall, we have used an orientation filter with low computational load. Algorithm B uses data provided by the orientation filter to identify a fall based on the detection of Impact and Posture phases. The execution of the experimental protocol has shown that Algorithm B, compared to Algorithm 1, corrects 9 false negatives and 3 false positives. In particular, the use of an appropriate estimation of orientation corrects all fall events when the subject ends with the trunk of body tilted more than 50°. This condition is not fulfilled in 3 cases in which the subject performs forward fall on the knees ending up lying. During these cases the subjects fell on knees bringing arms forward to protect themselves (frame 4 of Fig. 5b). Subsequently, they leaned on the ground with their hands (frame 5 of Fig. 5b) ending up slowly lying (frame 6 of Fig. 5b). During these gradual falls, the device detected three peaks of acceleration related to the impact on the ground of the knees, hands and trunk of the body. In these cases, however, only the first peak was above At_I and the change orientation occurred after the time threshold Tt_P.

The inclusion of the Aftermath phase detection in Algorithm A allows to assess the orientation change only after the subject ended the fall event. Therefore, Algorithm A detects a fall even in case the orientation change is not immediately following the fall. The algorithm implemented on the proposed monitoring system properly classified 5 of 30 tests when subjects performed backward falls ending up in sitting position. In addiction Algorithm A properly detected 3 of 30 syncope events. All other activities have been correctly recognized by the proposed fall detection system. Activities where subjects performed backward falls ending up in sitting position and syncope falls showed a low accuracy because absolute value of Pitch and Roll angles has not exceeded Ot_P within Tt_P of the fall detection algorithm.

VIII. CONCLUSION

A prototype of a wearable wireless device for fall detection implementing orientation filter has been realized and presented in this paper. The orientation sensors are integrated within a compact module allowing the owner to move unrestricted and data are transmitted wirelessly. The fall detection algorithm was validated through experimental tests including simulated falls, simulated falls with recovery and ADL. The experimental tests were conducted according to both the protocols proposed by Noury and Kangas. Performance of the proposed monitoring system were evaluated by computing sensitivity and specificity of algorithm and then compared with those obtained from three detection algorithms proposed by Kangas. An ideal fall detector should exhibit 100% average accuracy, sensitivity and specificity. Results show that proposed monitoring system performed better than Kangas algorithms. In particular, taking into account the protocol proposed by Kangas, we obtained 100% average accuracy, sensitivity and specificity. Average accuracy was 90.37% and sensitivity was 80.74% when the protocol proposed by Noury was adopted. A further comparison has been made between performance obtained by the proposed algorithm with and without considering the Aftermath phase. Better results with respect to the detection of falls on the knees ending up lying were obtained taking the Aftermath phase into account. The proposed device can also provide the fall typology and the end position of the subject.

Despite the excellent results achieved, in order to improve the sensitivity of the system we have embedded a barometer into the device for detecting the variation in height of the subject. This solution has immediately shown considerable improvements in the detection of a fall. Further efforts are currently underway to refine the system.

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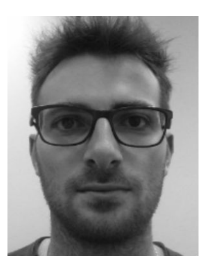

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