Fall-MobileGuard: a Smart Real-Time Fall Detection System

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***Abstract*—This paper proposes Fall-MobileGuard, a novel real-time non-invasive fall detection and alarm notification system. The proposed system, in particular, is able to recognize different types of falls and is based on a wearable inertial sensor node, equipped with a tri-axial accelerometer, worn at the waist and a personal mobile device. The detection method consists of two main processing blocks; the first is threshold-based trigger and is executed on the wearable sensor while the second includes posture classification and operates on the mobile device. Conversely to previous literature, we introduced multiple severity levels of detected fall events. The system is primarily intended for elderly people living alone or in retirements homes and supports alarm notifications of fall events over diversified channels, including social networks and automatic voice calls, according to the severity of the event. A comprehensive and well defined experimentation has been conducted, collecting in semi-controlled environment acceleration data from twenty subjects emulating falls and performing everyday life activities. Performance evaluation of our system has been carried out, resulting in 97% specificity, 83% sensitivity and 90% precision.**

Keywords—Fall detection, wearable devices, cloud computing, BodyCloud.

I. Introduction

Automatic human activity detection in uncontrolled environments is an important component of many research studies. Non-invasive activity recognition systems may help to ensure the continuous monitoring of elderly and patients to increase their safety and provide better insights on their health status. Fall detection is a specific problem of this research domain attracting wide scientific interest; it is addressed with very diversified methodological and technological approaches.

More specifically, in this paper we introduce Fall-MobileGuard, a fall detection and alerting system based on a wearable motion sensor and a personal mobile device.

The main issues of a fall detection system based on wearable devices are related to the number of sensors, their position on the body and the accuracy of the system itself.

On the one hand, more sensors will result in more information available for the system, with more chances of better accuracy. On the other hand, however, a more complex system results in higher economic costs and comfort issues; users expects to use such systems seamlessly and in fact to conduct their daily life activities without any interferences.

This work hence proposes a method and a practical solution for real-time recognition of different types of falls which involves the use of:

- a single sensor node placed in comfortable, convenient location on the body (for example with a belt clip or in the trousers pocket);
- the SPINE open-source framework [1], [2] for flexible dynamic sensor node configuration;
- pattern recognition techniques to support fall detection algorithm;
- an Android smartphone that serves as end-user device.

The rest of the paper is structured as follows. Section II gives a classification of several type of falls and analyzes a wide plethora of related works, providing useful comparison tables. Section III describes in detail our fall detection method. In Section IV we present the Fall-MobileGuard, discussing the prototype and reporting performance evaluation results; the section also describes the experimentation activities we conducted. Finally, in Section V conclusive remarks are drawn and directions of future work are briefly outlined.

II. Background

Every year there are more than 30 million domestic accidents in the US only, predominantly affecting the elderly, with major consequences in terms of temporary and permanent disability, hospitalization and mortality. Among domestic accidents, falls represent the most common cause and it is estimated that one third of the population over the sixties has suffered at least one significant fall and among the elderly residing in retirement houses and medical centers, this percentage is even greater [3].

The fall event is usually caused by a complex interaction of personal and environmental factors and circumstances related to the simple daily activities. Falls can be caused by intrinsic factors (e.g. age-related changes, muscular and skeletal problems, and disorders that affect the normal operation vestibular, proprioceptive and visual cognitive mechanisms) and extrinsic factors (e.g. obstacles in the environment). Independent elderly

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are typically less debilitated at physical level, but at the same time tend to be exposed to greater environmental factors that contribute to the risk of falling. Falls, especially for the elderly, have varied and complex implications [4]: about 20% of falls require medical intervention, 5-10% result to hip fracture (and 7% of elderly who suffered hip fracture eventually dies). Falls are also the second leading cause of head and spinal traumas. Finally, a very severe consequence of the fall is the fracture of the thigh bone that occurs in 0.6% of fall victims under 64 years, rising to 10.8% for people over 64, to 12.9% for people over 74 years and 14.2% for those above 79 years.

A. Fall taxonomy

Fall can be defined as a sudden and unexpected change of the body position in which static and dynamic balance mechanisms fail and the voluntary responses are inadequate to correct the lack of balance. Falls can be classified correctly only if all the different related factors are identified.

In Table I we report a wide, yet not exhaustive, classification of falls.

TABLE I. FALLS CLASSIFICATION

Fall	Description
Front-lying	From a standing position one falls toward the ground and keeps the lying position after the impact. This fall commonly happens when people lose balance or stumble.
Front-protecting-lying	From a standing position one falls to the ground by attenuating the fall with the arms, yet keeping the lying position after the impact.
Front-knees-lying	From a standing position one falls, landing initially on the knees and then lying on the ground.
Front-right/left	From a standing position one falls toward the ground assuming a side position.
Front-quick-recovery	From a standing position one falls toward the ground but quickly recovers the standing position after the impact. This type of fall often does not result in immediate significant consequences, although the risk of delayed implications should not be excluded.
Front-slow-recovery	From a standing position one falls toward the ground and slowly recover the standing position after the impact. In this type of fall, the person is able to stand up but presents some difficulties, possibly reporting traumas due to the impact with the ground.
Back-sitting	From a standing position one falls backward the ground ending in a sitting position.
Back-lying	From a standing position one falls backward to the ground ending in a lying position. This fall commonly occurs on slipper, wet floors. This type of fall more easily leads to significant consequences as the head is more exposed to impacts.
Back-right/left	From a standing position one falls backward to the ground ending up in a sideway lying position. This type of fall also can easily lead to serious injuries.
Right/left-sideway	From a standing position one falls sideways to the ground ending in a lying position without any ability to recover the standing posture.
Right/left-recovery	From a standing position one falls sideways towards the ground but quickly recovers the standing position after the impact.
Syncope	It is also known as fainting and consists of a short loss of consciousness and muscle strength followed by spontaneous recovery.
Rolling-out-bed	From a lying position one rolls out of bed falling to the floor. Falling out of bed is unfortunately a frequent event for the elderly.
Falling-from-stairs	Descending the stairs one stumbles and rolls down. This type of fall is extremely dangerous especially for the elderly due to bone fragility.

B. Related work

There are three major fall detection approaches based respectively on (i) image and video analysis, (ii) acoustic devices, and (iii) wearable devices. Systems based on video analysis capture images of human movement through one or more video devices (e.g. webcams or infrared cameras) and determine the occurrence of a fall by examining the variations of specific features of the image. Systems based on acoustic devices detect a fall through specific patterns in audio signals. Usually these systems are heavily influenced by environmental noise, particularly in open spaces, and therefore are typically supported with additional systems. Finally, systems based on wearable sensing devices allow to continuously and unobstructively acquire body motion data which are analyzed to detect (and report in real-time) fall events.

In this section we briefly outline the results of our study of the works related to the latter approach. We support in fact the idea of developing a fall detection systems that should be able to continuously monitor elderly so to favor them to carry out normal daily life activities (such as living independently, walking in their neighborhood, doing groceries). In addition, timely alerts to relative and caregivers should be issued upon the detection of any relevant fall, with the aim of avoiding worse situations.

It is worth noting that current mobile devices (such as commercial smartphones) integrate various sensors and are gaining always greater capabilities in terms of computing power, communication, and storage; as a consequence, we also analyzed works that use directly smartphones for sensing body movements. Being able to use uniquely the mobile device to realize a robust fall detection system has the significant advantage of not having to wear additional items (that are not easily accepted by the elderly); however, there are disadvantages too, mainly related to increased battery discharge of the device.

The following tables summarize the main aspects on the related work we analyzed; in particular, Table II contains information on the adopted sensors and their location on the body, Table III presents detection methods and algorithms, while Table IV synthesizes the obtained performance results.

Interested readers could also refer to recent and interesting surveys [5], [6] that discuss several works on fall detection and analyze the problem under various point of views.

TABLE II. SENSOR TYPES AND LOCATION ON THE BODY

Ref.	Wearable sensors	Smartphone sensors	Sensor location	Sensor type
[7]	X	-	waist	accelerometer
[8]	X	-	waist, head	accelerometer
[9]	X	-	head	accelerometer
[10]	X	-	chest, thigh	accel., gyroscope
[11]	X	-	chest, thigh	accel., gyroscope
[12]	X	-	chest	accelerometer
[13]	X	-	chest, thigh	accelerometer
[14]	-	X	waist	accelerometer
[15]	-	X	N/A	accelerometer
[16]	-	X	N/A	accelerometer
[17]	-	X	N/A	accelerometer
[18]	-	X	waist	accelerometer
[19]	-	X	waist	accelerometer
[20]	X	-	N/A	accel., barometer
[21]	X	-	waist	accelerometer
[22]	X	-	waist, back	accel., gyroscope

Regardless of the sensing device, most of the works found the waist to be the most suitable location to place the sensor [7], [8], [14], [18], [19], [21], [22], although a few others place the sensor on the chest [10], [11], [12], [13], or at the head [8], [9]. The use of a threshold-based approach to detect abrupt acceleration peaks is extremely common, while

TABLE III. METHODS

Ref.	Pre-filtering	Pattern recognition	Use of thresholds	Posture recognition
[7]	-	-	X	X
[8]	X	-	X	X
[9]	X	-	X	-
[10]	-	-	X	X
[11]	-	X	-	-
[12]	X	X	-	X
[13]	-	-	X	-
[14]	-	-	X	-
[15]	X	-	X	-
[16]	-	-	X	X
[17]	X	-	X	-
[18]	X	X	-	X
[19]	-	-	X	-
[20]	X	X	X	-
[21]	X	-	X	-
[22]	-	X	-	-

TABLE IV. PERFORMANCE EVALUATION COMPARISON

Ref.	Specificity	Sensitivity	Precision	No. of subjects
[7]	N/A	N/A	N/A	2
[8]	100%	95%	N/A	2
[9]	N/A	N/A	N/A	2
[10]	92%	91%	N/A	3
[11]	N/A	N/A	81%	8
[12]	N/A	N/A	84%	6
[13]	100%	95,5%	100%	20
[14]	N/A	N/A	N/A	15
[15]	N/A	N/A	95%	5
[16]	N/A	N/A	N/A	N/A
[17]	N/A	N/A	N/A	N/A
[18]	N/A	N/A	N/A	N/A
[19]	81%	77%	N/A	18
[20]	96%	96%	97%	-
[21]	100%	81%	90%	-
[22]	99%	97%	N/A	-

only few works also include posture recognition [7], [8], [10], [12], [16], [18]. Most of the related works are based on the use of accelerometer sensors (to detect body accelerations exceeding preset thresholds) and the detection of body postures (to contextualize acceleration peaks). However, carrying out a quantitative comparative analysis is not easy [23]. One of the main reason is that the set of analyzed actions referring to both the normal activities and the type of falls are not always indicated; secondly, the test sample (number and heterogeneity of participants to the experiments) is very variable and for some works very limited. Last, but not least, a problem that makes it difficult to perform a comparison among the various proposed solutions is the absence (in most cases as depicted in Table IV) of performance indexes, for instance in terms of sensitivity, specificity, and precision that would quantitatively characterize the achieved accuracy.

III. METHOD

The first phase of the development focused on the acquisition of accelerometer data during a series of (emulated) falls. To this purpose, we setup an experimentation in which twenty subjects were asked to wear a Shimmer2R sensor node [24] (which features an embedded tri-axial accelerometer) in their front pocket and to emulate a series of predefined falls (as described in section II.A).

Using the SPINE programming framework [1], [2], [25], [26], the wearable sensor was configured to continuously transmit over Bluetooth raw x, y, z acceleration data, setting the sampling rate to 40Hz. Data are received by the mobile coordinator device.

The first step of our detection method consists of a threshold-based trigger. Specifically, the raw acceleration signals are preliminarily scaled down around zero, then instantaneous (sample-by-sample) cross-axial energy, is computed as follows:

$$E_{tot} = x^2 + y^2 + z^2 \tag{1}$$

The choice of this function depends on its definition: the value of cross-axial energy depends on all three axes, therefore, regardless the nature of the fall and the orientation of the sensor, this value is expected to present a significant change. The plot in Fig. 1 shows the acceleration signals related a front-lying emulated fall. The plot in Fig. 2 shows the scaled acceleration signals corresponding to the fall event shown in Fig. 1. Finally, the plot in Fig. 3 shows the corresponding cross-axial energy signal.

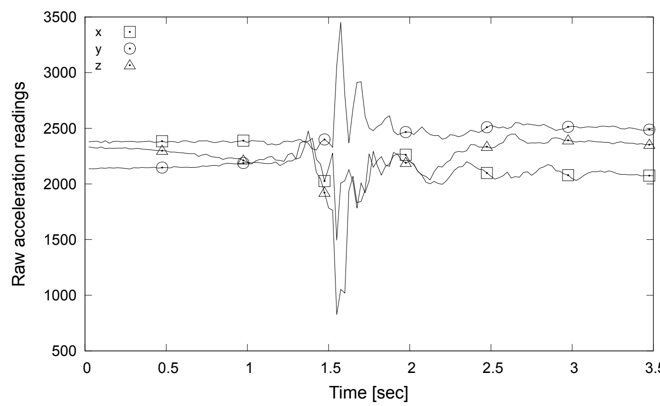

Fig. 1. Acceleration signals during a *front-lying* fall

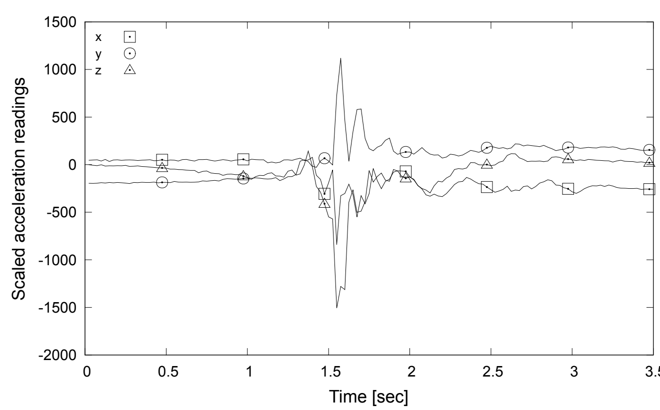

Fig. 2. Scaled acceleration signals

All these signal processing steps are executed online by the wearable sensor that checks if cross-axial energy exceeds the predefined threshold.

However, as previously examined [7], [8], [10], [12], [16], [18], solely relying on acceleration thresholds may induce the system to mis-detection errors, exchanging actual falls for normal physical activities and viceversa.

To avoid this problem, our recognition method is actually based on two main processing blocks. The first is performed directly on the sensor node, it has the purpose of detecting potential falls and is based on the threshold mechanism described so far; the second runs on the mobile device, includes a KNN algorithm for posture classification and determines whether the potential event actually corresponds to a fall.

Specifically, as the energy signal exceeds the predefined threshold, the wearable sensor node triggers an alarm to the smartphone which in turns starts the classification posture process to complete the detection procedure. Posture recognition is based on a binary classification of the current subject's posture, designed to simply detect *lying* and *not lying* status. The wearable node, in addition to the total energy, also computes and periodically transmits over Bluetooth the features useful for the classification (see Table V).

TABLE V. DATA COMPUTED AND TRANSMITTED BY THE SENSOR

Data type	Feature	Axis
Periodic	max	y
	min	y
Sporadic	cross-axial energy	x, y, z

To determine the actual subject's posture after the potential fall detection, we actually use a *m-out-of-n* classification decision. Determining the posture using a single classification immediately after the reception of the potential fall alarm may in fact introduce issues. For example, the person might stumble being able to recover the standing position right after: in this case, analyzing a single posture classification would generate a false positive. To address this issue, we analyze n posture classifications within 30 seconds after the potential fall event, and if at least m of them result equal to *lying*, then we can infer the subject has actually fallen. In addition, with the sake of allowing for more flexibility in reporting fall events, we introduce three different levels of alarm severity:

1) *Green* alarm: to indicate minor falls. The subject has fallen and recovers the standing position quickly.
2) *Yellow* alarm: to indicate major falls. The subject has fallen but slowly recovers the standing position.
3) *Red* alarm: to indicate critical falls. The subject has fallen and is unable to recover the standing position (the subject is unconscious and/or has reported major traumas).

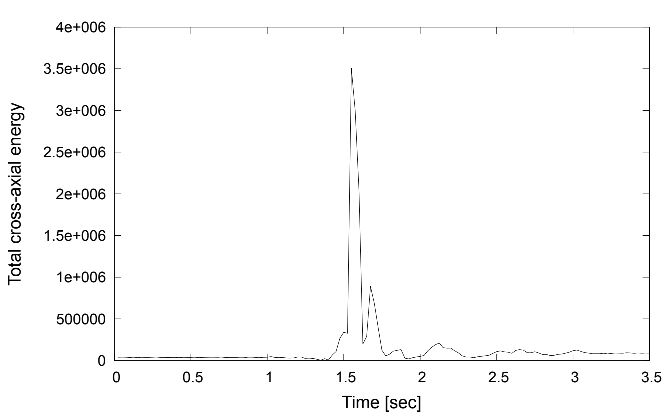

Fig. 3. Cross-axial energy signal

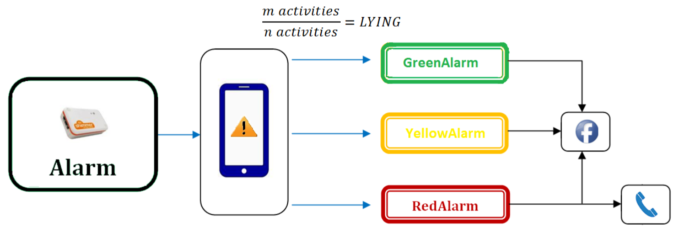

Fig. 4. Schematic diagram of our multi-level fall detection method

In Fig. 4 a simplified diagram of our multi-level fall detection method has been depicted. This fall detection modeling significantly improves the approach previously proposed in [27].

IV. FALL-MOBILEGUARD

Fall-MobileGuard is a smart fall detection system, implementing the method proposed in Section III. It is primarily intended for elderly who live alone or without continuous assistance and for patients with underlying medical conditions that raise the risk of falls. The system consists of an Android-based personal mobile device (e.g. a smartphone) that communicates via Bluetooth with a single Shimmer2R sensor node running the SPINE framework [1], [2], [25], [26]. The sensor can be worn with belt clips or placed in a pocket.

The end-user application runs on the smartphone and integrates a functionality to connect to Facebook. On the detection of any levels of fall, this feature allows to automatically write, on the user's personal wall as well as to predefined Facebook friends (e.g. relatives or caregivers), simple messages containing information about the detected event. Furthermore, it is possible to specify a list of preset phone numbers that are reached with an automatic emergency recorded voice message in case of red fall alarms (see Section III).

In addition, through the integration with BodyCloud [28], [29] platform, Fall-MobileGuard allows to keep an historic track of the fall events for diagnostic and prevention purposes. The underlying reasoning is that elderly people are often afraid (and ashamed) to report the happening of frequent fall episodes (unless they suffer immediate health consequences). In addition, with a system like Fall-MobileGuard, that does not rely on fixed infrastructures, the assisted user can be monitored in mobility and fall events can be detected and reported even when the user is outdoor, away from home.

It is worth noting that our system requires a 'one time' setup procedure (to connect to Facebook and to set the list of friends and emergency phone numbers), it features a very simple, intuitive user interface to launch the application, and does not involve any user interaction while running; the application indeed keeps operating in background as it is programmed as an Android *service*. This design choice gives more chances for the elderly, who are typically not familiar with electronic devices, to use the system in a seamlessly manner. Also, the use of a single sensor node requires quick wearing time and minimum maintenance (in practice, to only recharge the battery periodically).

Fig. 5. Participant to the experiment emulating a fall on the mattress

A. Experiments

Before evaluating the performance of the proposed system, it is necessary to define the scenarios in which it will eventually work. We therefore set the main body movements that are executed during our experiments:

1) emulated falls;
2) everyday life activities.

The experiments involved a sample of 20 participants with the following characteristics:

- *Gender*: M, F
- *Age*: 18÷58
- *Weight*: 50÷91 kg
- *Height*: 1.49÷1.92 m

During the test experiments, we collected accelerometer data from 340 emulated falls and 320 classification samples of everyday life activities.

Emulations have been performed for all types of falls described in Section II.A (except the fall from the stairs, to avoid obvious safety implications of the participants). In addition, since accidental falls can occur while performing daily life activities but at the same time certain activities could be misclassified as falls (if the recognition process is not robust enough), we decided to define the set of such most common activities and included them in our experimentation protocol. We reported the list of performed activities in Table VI.

In addition, we would stress that our system has been designed to detect falls as per the definition and the classification provided in Section II.A. Hence for instance, if the assisted subject collapses gradually on the ground or reaches a sitting position, the system will not issue an alarm as this situation goes beyond its specified capacity.

For guaranteeing the safety of the participants all the emulated falls have been performed on a mattress of size $190cm \times 80cm \times 18cm$, shown in Fig. 5. The thickness of the mattress plays a key role because if it is too thick, the measured acceleration patterns could not due to the fall itself but to bouncing effects after the impact with the mattress. Conversely, if the mattress is very thin, there are more chances to cause harm to the participants.

The mattress protects the participants and prevents direct impact with the ground. This allowed participants to the tests to emulate all the falls without any issues.

An interesting finding of the experiments is that the location we selected for the sensor did not cause discomfort to the participant during normal activities nor caused inconveniences upon falling. This is a matter of fundamental importance because the involved devices should not give impediment to the user and more important must be harmless in all situations.

TABLE VI. DAILY ACTIVITIES SUBJECT TO FALSE POSITIVE FALL DETECTIONS

Activity	**Description**
Lying-bed	from standing position to lying on the bed. Elderly often do not easily control their actions and they could perform abrupt movements trying to sit or lay down. The lying posture, which in this case is voluntary, could cause a false alarm if the resulting acceleration energy exceeds the threshold.
Rising-bed	from lying posture to standing position. While getting up, it is common to sit sideways to the bed and then to reach the standing position.
Sit-bed	from standing position to sit on the bed. This is also an activity of interest for us, as soft and elastic mattresses can generate abrupt movements.
Sit-chair	from standing position to sit on the chair. This is one of the most common and frequent everyday life activities.
Sit-sofa	from position position to sit on the couch or sofa. This activity is extremely common, too; if the system does not behave properly in this situation, the number of false positive fall detections caused would make the application totally useless.
Walking	walk forward. Walking is another basic and frequent activity, therefore, the system should not generate any false positive fall detections in this case.
Walking-back	walk backward.
Jogging	Although jogging and running are not among the most common activities carried out by elderly people, it is still important to analyze the behavior of the system in this situation. Running, in particular, can easily produce accelerations that exceed the threshold, therefore, in this case the posture classification module of the system is the key to avoid false positive fall detections.
Bending	from standing position one bends the trunk forward, keeping the legs straight.
Bending-pick-up	from standing position to bend down picking up an object from the ground. This action could cause abnormal body accelerations and the position temporarily assumed by the wearable sensor could trick the detection mechanism, but the system should still be able to handle the situation and avoid false alarm.
Trip-over	pick up an object from the ground while walking. Unlike the previous case, the object is grabbed without stopping to walk.
Stumble	while walking one stumbles but recovers the balance quickly.
Limp	walking forward with the aid of a crutch.
Squatting-down	from standing position to a crouched posture to standing again. Carrying out this activity can generate strong body accelerations and the crouched posture could mislead the system.
Coughing-sneezing	both coughing and sneezing cause abrupt movements of the upper body; in this case the location of the sensor plays an important role.

B. Performance Evaluation

Before discussing the obtained results, we give a definition of necessary terms:

- *True Positive* (TP): it consists of an actual fall event that the system correctly detects.
- *False Positive* (FP): it consists of a normal physical activity or action that the system exchanges for a fall.
- *True Negative* (TN): it consists of a normal physical activity or action that the system correctly does not exchange for a fall.
- *False Negative* (FN): it consists of an actual fall event that the system fails to detect.

We analyzed the performance of the system in terms of the following metrics:

$$sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$specificity = \frac{TN}{TN + FP} \quad (3)$$

$$precision = \frac{TP + TN}{P + N} \quad (4)$$

From the experiments related to the emulated falls, we get TP and FN values, while from the ones related to the everyday activities we calculate TN ed FP values. Specifically, we obtained the following values:

- TP = 282
- FN = 58
- TN = 311
- FP = 9

Hence, we can conclude that our system shows the following results:

- *specificity*: 97%
- *sensitivity*: 83%
- *precision*: 90%

V. Conclusions

In this paper we proposed an advanced method for automatic fall detection that features novel contributions and presented *Fall-MobileGuard*, a realtime fall detection system based on a single wearable sensor and an Android smartphone. The system is able to trigger fall events using different alerting modalities to allow for prompt emergency intervention if necessary. We described in detail our methodology and the prototype system. We discussed the experimentation setup and showed the obtained results. In particular, the proposed system has been tested on 20 subjects emulating several types of falls and performing normal activities, and it reached 97% sensitivity, 83% specificity, and 90% precision. Significant attention was dedicated to the related work which allowed us to have a clear view of strength and weakness of previous proposed approaches.

Ongoing works are currently devoted to remove the need for an external wearable sensor, using the accelerometer available on the smartphone. Future developments will focus on the extension of our approach, specifically defining a crowd-sourcing method based on our BodyCloud computing middleware to perform statistical analysis based on recorded fall events from multiple users. We also plan to introduce a different activity recognition method [30] as it appears promising to improve classification accuracy.

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