Human fall detection and alert system using accelerometer and gyro sensors

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***Abstract*—we propose in this paper a novel algorithm as well as architecture for the fall accident detection and corresponding wide area rescue system based on a smart phone. In the proposed architecture, a specific application in each component permanently tracks and analyses the motorist's movements. Diverse fall detection algorithms were implemented in the developed Android apps to discriminate falls from the conventional activities of daily living. As a novelty, a fall is only assumed to have occurred if it is simultaneously and independently detected by both gyro sensors and accelerometer. With this system it is possible to notify an emergency center after an accident with your motorcycle. The emergency center cancall a rescue team after processing a rescue plan. Provided medical data and the current position will be sent from the phone to the emergency center to ensure quick help for the injured rider.**

Key words: Electronic compass, fall detection, global positioning system (GPS) system, smart phone, support vector machine (SVM), triaxial accelerometer, gyro sensors.

I. INTRODUCTION

In case of an accident it is very important, that the rescue chain is started very quick. This assumes that the injured motorcyclist or other people set off an emergency call and notify a rescue team. If this step is done, it can be the case that important medical data from the motorcyclist cannot be provided or even the current position is unknown. Lots of motorcyclists ride alone. This circumstance can be fatal in case of an accident, if the rescue chain cannot be initiated. With this system it is possible to notify an emergency center after an accident with your motorcycle. The emergency center can call a rescue team after processing a rescue plan[2]. Provided medical data and the current position will be sent from the phone to the emergency center to ensure quick help for the injured rider.

Many automatic fall detection systems suffer from the problem of false alarms, caused by some fall-like activities of daily living (ADLs), such as sitting on a sofa or lying on a bed. For this reason, in our approach to fall detection we devoted a special attention to the study of the acceleration signal produced by fall-like ADLs and to the design of novel filtering techniques [14]. In this paper, we describe the design rationale and the implementation of a fall detection system based on wearable sensors. The system relies on commercially available smartphones and is capable of automatically sending an alarm message to the caregivers in case of fall [4]. The acquisition of kinematic data can be carried out either using the accelerometer available on many smartphones or using an external sensing unit. The usability of the system has been confirmed by a set of interviews with some aged people, while its performance, in terms of precision and recall, has been evaluated both in lab sessions and through continuous monitoring of three subjects (including indoor and outdoor activities). A comparison with similar existing fall detection techniques is also reported.

A fall detection system can be useful for people working or doing recreational activities in isolated places with high risk of falls, such as country workers, mushroom hunters, or skiers. However, the category of people that can benefit more significantly from a fall detection system are the motorists[8].

In fact, in the last years life expectancy has increased making a larger fraction of the population more prone to falls. Unfortunately, the injuries due to falls are a major cause of hospitalization, disabilities and lack of first aid at the earliest.

Thus, the caregiving process and the quality of life of people can be improved by adopting systems for the automatic detection of falls. This system presents a smartphone-based accident

detection system that monitors the movements of people, recognizes an accident, and automatically sends a request for help to the caregivers.
Thus, the caregiving process and the quality of life of people can be improved by adopting systems for the automatic detection of falls.
Unlike the environmental monitoring-based systems that can function only in a predefined space, the wearable sensor-based fall detection systems can function in a larger area. However, most of the wearable sensor-based fall detection systems are made of a self-designed circuit module that should be placed and fastened around certain position, e.g., the chest or the waist, of the user. Therefore, the necessity of wearing an additional sensor module can cause the people feel uncomfortable and lead to certain degree of inconvenience. In addition, how to address the current position of the people when a fall accident event occurs is a problem to be solved in wearable sensor-based fall detection systems. Moreover, the power consumption burden is another issue that should be treated carefully in mobile devices as well as in wearable sensor-based fall detectors[2].

II. SYSTEM OVERVIEW

The architecture of the proposed fall accident detection and rescue system is shown in Fig. 1. As can be seen in Fig. 1, the proposed system is mainly composed of three blocks: the smart phone-based pocket fall accident detector, the coordination center, and the rescue center which is composed of the hospitals nearby or the first-aid stations

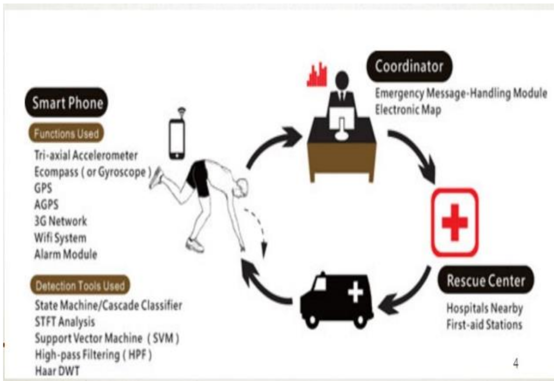


Fig. 1 Architecture of the proposed fall accident detection and rescue system.

An effective accident detection system must address the following requirements: automation, to be able to send a sos message without the need for the user to press a button; promptness, to provide quick help and avoid worsening of health condition; reliability, concerning the capability of detecting fall events while filtering fall like ADLs; communication, in order to be always connected and able to alert the care givers, relatives or friends; usability, for facilitating users' acceptance [11].

A fall detection system should be designed based on the following guidelines:

- Detection of falls should be carried out using only acceleration-based information. Previous work demonstrated that acceleration is the most reliable information that can be used in detecting a fall, while other kinematic data, such as angular velocity, is less relevant.
- Usability is strongly influenced by the number of wearable sensors and by their placement on the user's body. For this reason, detection should be performed using a single sensor.
- Some fall detection systems use posture information to improve their precision. Posture can be calculated either assuming a known orientation of the axes of the accelerometer with respect to the user's body, or using two or more sensors. As both approaches reduce the usability of the system, solutions that do not need posture information should be preferred.
- The fall detection algorithm has to be self-learning; in this way, it can automatically adjust the parameters of operation according to the specific characteristics of the user (height, weight, movement speed, etc.).
- A human-machine interface, even if rudimentary, is mandatory for two reasons: i) a stop button is necessary to avoid sending a request for help in case of false alarms; ii) to provide a feedback to the self-learning detection algorithm.

Sensing process

The sensing process can be described as a finite state machine . Initially, the machine stays in the Sampling state until a threshold peak is detected. After that, the machine moves to the Post-peak state and starts waiting for a bouncing timer. When the bouncing interval is elapsed, the machine moves to the the Post-fall state and starts a post-fall timer. When the post-fall timer fires, the Activity test introduced in Section 2.3 is performed. If the event does not pass the test, i.e. there is a high level of body activity immediately after the supposed fall, the event is considered a false alarm and the system returns to the Sampling state. Otherwise, the detection of a fall-like event is signaled to the application[11].

Notification system

The Notification System is responsible for alerting the caregivers whenever a fall is detected. Each time a fall-like event is classified as a real fall by the Classification Engine, an acoustic alarm is emitted continuously for 30 seconds. At the same time, a notification appears on the Android's notification bar and a foreground screen is shown. The screen simply contains some informative text and a flashing "stop" button, that can be used to deactivate the alarm. If the user does not deactivate the alarm by a given time, the stop screen is dismissed and a text message is sent to one or more specified contacts. The message contains basic details about the event and information about the last known location. If the "stop" button is pressed, the user can provide some feedback to the Classification Engine. Through another screen, the user specifies the type of activity that raised the false alarm. When any of these buttons is selected, the acceleration pattern is archived together with information related to that event[11].

III. SIGNAL ACQUISTION AND FEATURES SELECTION

It is noted that most of the smart devices are equipped with certain kinds of inertia detectors, e.g., the triaxial accelerometer (also known as G-Sensor), the electronic compass, or the gyroscope, so that the orientation of the device can be recognized by its operating system. Considering the availability, we use the triaxial accelerometer (G-Sensor) and the electronic compass as the major sensors for input signal acquisition and generation in the proposed system.

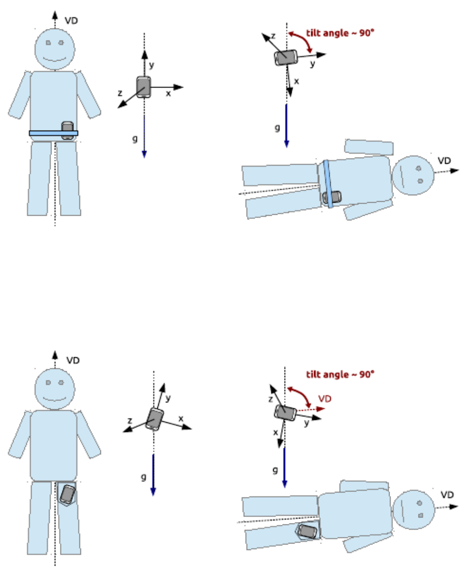


Fig .2 Basic Representation

A. Triaxial Accelerometer

In this paper, the outputs of the triaxial accelerometer will be sampled periodically as the input signals of the proposed system with a frequency of 150 Hz. The sampled signal is a three-dimensional data sequence, i.e., [ax [n], ay [n], az [n]]. To simplify the dimension of the sampled signal, we apply in this paper the use of the one-dimensional signal magnitude vector (SMV) S[n] as shown below

$$S[n] = \sqrt{a2\,x\,[n] + a2\,y\,[n] + a2\,z\,[n]}$$

where n is the sample index, ax [n], ay [n], and az [n] are the gravitation values along the x-axis, y-axis, and z-axis, respectively the moment at which the value of S[n] is equal to 0.6G [i.e., the 50th data sample will be used as the reference point for the sampling of the S[n] sequence [18]. That is, the 50 and 250 data samples just before and after the reference point will be recorded by the proposed system to form a sequence of 300 samples. The 300 samples will be sent to the proposed state machine and examined by the proposed algorithm to check if the features of a fall accident event can be satisfied in a sequential manner. Moreover, the appearance of an S[n] value smaller than 0.6 G and greater than 1.8 G, as well as the slowly varying waveform of S[n] value will be used as the first three characteristics or features, i.e., the first three state, of the proposed system.

B. Electronic Compass and Device Orientation

The pitch angle acquired by the electronic compass is used to assist in discriminating real fall events from normal activities. The coordinate convention of the triaxial accelerometer and the orientation definition of the electronic compass are shown in Fig 3

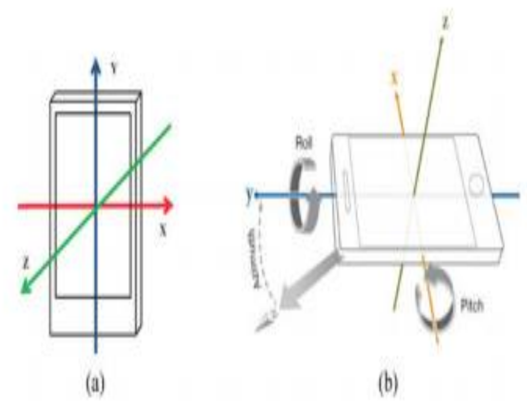


Fig. 3 (a) Coordinate convention of the triaxial accelerometer. (b) Orientation definition of the electronic compass.

Acceleration magnitude threshold and median filtering

The simplest approach to detect falls using an accelerometer consists in using a single threshold on the acceleration magnitude [8]. However, it has been shown that many ADLs present acceleration magnitude peaks similar to those of falls, thus making ADLs really difficult to be distinguished from dangerous impacts on the ground [10, 14]. In particular, all the fall-like events of our training set present a peak equal or greater than 3g and, thus, such a simple method fails in isolating ADLs from real falls. Median filtering of the acceleration magnitude - using a three samples window - has been suggested as a way to reduce noise and improve the specificity of the detection

C.Gyroscope Signal for a Falling Motorbike

Figure 13, shows spikes on the signals of each of the 3 axis of the accelerometers. Correspondingly, the gyro output signal also appears to have the same shape. The graphs are relatively stable and then a sudden change happens in a short period of time and then stabilizes again for the time period between 0 seconds and the start of the spike. Gyro and Accelerometer signals: The spikes represents the falling moment of the motor cycle. Figure 4 shows a bouncing motorcycle after falling. Each peak represents vibration. The sideway right fall has a positive going signal spikes, whileas the left fall has negative going signal.

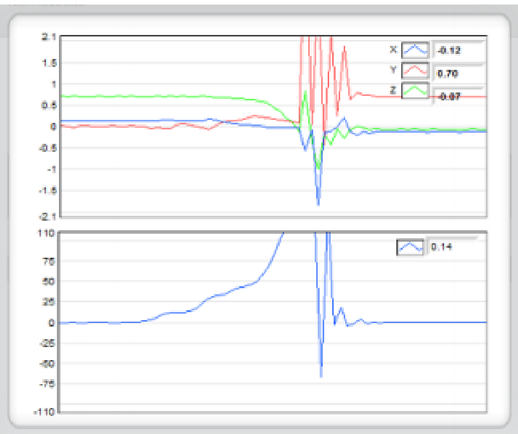


Figure 4, (Sideways- Right)

	Measured Acceleration at unidentified time	X g	Measured Acceleration/Decceleration at the spike max
X	-0.12		-1.9g
Y	0.70	9.81	2.3g
Z	-0.07	9.81	-1.2g
G	0.14		-73 (˚/sec).

Table 5. Falling Motorbike-sideways right
1g-force = 9.81 m/s2
Measured Acceleration at unidentified time X g Measured Acceleration/Decceleration at the spike max X -0.12 -1.9g Y 0.70 9.81 2.3g Z -0.07 9.81 -1.2g G 0.14 -73 (˚/sec). 1g-force = 9.81 m/s2 Table 5 shows the contents of measurements analysed from the graphs on Figure 13. The reference measurements at unidentified time were the values captured during the screen shot. The measured values at the spikes max represents corresponding accelerometer readings for the lowest point of the gyroscope measurements.

IV. Detection of Real Falls and Filtering of Fall-Like ADLs

Fall-like events that are not discarded through the Activity Test are forwarded to the Classification Engine. Then they are fed into a Feature Extractor whose task is to reduce the input. Feature extractor pattern classifies the output. This is carried out by taking advantage of domain knowledge in order to cut away unnecessary information. The Pattern Classifier takes such values and returns a membership value for each ADL class and the Falls class. The conceptual borderline between feature extraction and pattern classification is somewhat arbitrary. In fact, a perfect feature extractor would produce features that are directly membership values, or values from which the desired output can be trivially derived. This kind of extractor would require no classifier. Conversely, a perfect classifier would work without a sophisticated feature extractor.

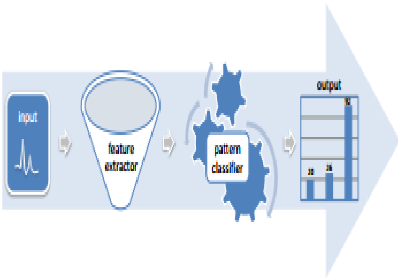
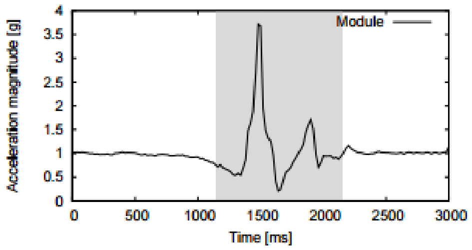


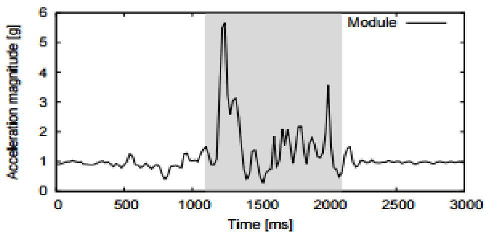
Figure 4: The Classification Engine

DIFFERENTIATING ACCIDENT FROM A NORMAL FALL

However, we find in our experiments that some of the normal activities, e.g., sit down and the behavior of wavering the smart phone up and down is also possible in generating an S[n] sequence or pitch sequence similar to that of a fall accident event. The behavior of wavering the smart phone up and down can take place when the user is in a short-term running activity and with the smart phone held in his or her hand [13]. The behavior of wavering the smart phone is a special scenario. However, this behavior does take place frequently in our daily life. Therefore, we have to find more useful features that can be used for distinguishing a fall accident event from normal activities like sit down and phone wavering. To do this, we analyze and compare the frequency components (spectrum) of the S[n]sequence under a fall accident event with that of normal activities like sit down and smart phone wavering. As the S[n] and pitch sequence of wavering the smart phone and that of a sit down activity are quite similar, the case of wavering the smart phone will be used for explanation and compared with a fall accident event for simplicity.



(a) AAMV window in case of sitting (0.17g)



(b) AAMV window in case of fall (0.59g)

V. ADVANCEMENTS IN THE PROPOSED SYSTEM

This section reports the results of the quantitative comparison of our fall detection approach with some relevant techniques. This includes wearable devices using sensors to detect falls and major accidents.
However there are many drawbacks in using them, some may include

Performance under real-life conditions
Fall detectors need to be as accurate and reliable as possible. A robust fall detection system should exhibit both high sensitivity and specificity. This is sometimes reached in experimental environments, but when applied to a real situation, the detection rate decreases These devices are designed and tested under controlled conditions, for example they use data from falls and ADL of young people simulated at the discretion of each author due to the lack of a standardized procedure or a public database for comparison.

Usability

Smartphone-based fall detectors are attractive because of the widespread use of phones, even among the older population. This allowed highly stereotypical measurements that aided accuracy ratings, but made the results less applicable to the way people carry their smartphones every day.

Acceptance

To overcome this challenge, the way the system operates is essential .The detector should activate and operate automatically, without user intervention. Vision systems, like other non intrusive methods, are very good in this sense. However, some wearable devices like smartphones have other advantages that can help to improve the acceptance of fall detectors. They can operate both indoors and outdoors and integrate not only fall detection but also other healthcare applications in the same device. In this way, the traditional reluctance to carry different devices, each one targeting a specific function, would be overcome.

Privacy concerns

Privacy concerns of sensor-based systems, and fall detectors are, have been a hot topic. Of course, not all types of sensors are equally vulnerable: context-aware systems in general, and vision-based systems in particular, are much more prone to privacy concerns than, for example, body-worn acceleration-based devices. In any case, the protection of sensitive context data must be guaranteed. Privacy problems should not prevent the potential benefits of assistive technologies as, at the same time, privacy cannot be sacrificed in order to bring about other benefits. In general, studies on fall detection usually lack strategies to ensure data privacy. This shows that they are still far from a real-life deployment.

VI. CONCLUSION

We propose in this paper a smart phone-based pocket fall accident detection system. The fall detection algorithm is realized with the proposed state machine that investigates the features in a sequential manner. Once the corresponding feature is verified by the current state, it can proceed to next state; otherwise, the system resets to the initial state and waiting for the appearance of another feature sequence. To speed up the efficiency of classification process, the early states are composed of simple and important features that allow a large number of negative samples to be quickly excluded from being regarded as a fall event. Those complex features are then placed in later states. With the proposed algorithm, the computational and power consumption burden of the system can be alleviated. Moreover, a distinguished performance up to 92% on the sensitivity and 99.75% on the specificity can be obtained when a set of 450 test activities in nine different kinds of activities are estimated by using the proposed cascaded classifier with SVM, which demonstrates the superiority of the proposed approach.

VII. FUTURE ENCHANCEMENT

Well-designed smart sensor system to detect falls can be both medically and economically helpful. This research introduces a portable terrain adaptable fall detection system, by placing accelerometers and gyroscopes in parts of the body and transmits data through wireless transmitter modules to mobile devices to get the related information.

The algorithm that can be used in the future might be Gravity clustering algorithm-

Research which computes the human body behavior patternsaccordingthe relationship between the center of gravity in the body and the feet portion of the body.

This algorithm is commonly used in data mining tasks. It has the advantage of producing good modeling results in many cases. However, it is sensitive to outliers and the initial cluster centers. In addition, it could not get the accurate cluster number during the algorithm. To overcome the above problems, a novel FCM algorithm based on gravity and cluster merging was presented in this paper. By using gravity in this algorithm, the influence of outliers was minimized and the initial cluster centers were selected. And by using cluster merging, an appropriate number of clustering could be specified. The experimental evaluation shows that the modified method can effectively improve the clustering performance.

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