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A Review of Accelerometry-based Fall Detection Methodologies

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Abstract— According to the World Health Organization [1] approximately 28-35% of people aged 65 and over fall each year increasing to 32-42% for those over 70 years of age. It is the sixth cause of death for people over the age of 65, the second for people between 65 and 75, and the first for people over 75. Researchers have attempted to detect falls using cameras, accelerometers, gyroscopes, microphones or a combination of these techniques. Accelerometers have been widely accepted as useful and practical sensors for wearable devices to detect falls. This paper presents an extensive review of fall detection systems based on the use of accelerometry. This paper analyses and compares the various proposed methodologies to provide an outlook of current development status. Trends and challenges in fall detection have been identified after the reviewing work. Furthermore, this paper discusses suggestions for future research directions.

Keywords*-Fall detection, Activities of daily life, sensors, smart phones, healthcare, elderly, tri-axial accelerometer, gyroscope*

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Introduction (Heading 1)

Falls in elderly people are the main cause of admission and extended period of stay in a hospital. The continuous risk of falls and increase in the elderly population makes the fall detection system become very crucial. Typically, research presented various solutions for assisting the elderly and their caregivers against falls by detecting falls and triggering alarms calling for help as soon as falls occur in order to diminish fall consequences.
A fall detection system can be defined as an assistive device whose main objective is to alert when a fall event has occurred. In a real-life scenario, they have the potential to mitigate some of the adverse consequences of a fall. Fall detectors can have a direct impact on the reduction in the fear of falling and the rapid provision of assistance after a fall. Falls and fear of falling depend on each other; an individual who falls may subsequently develop fear of falling, and vice versa, the fear of falling may increase the risk of suffering from a fall [2].

The other important aspect that fall detectors may help to reduce is the time for elderly lying on the floor after falling. This time is one of the key factors that determine the severity of a fall. Many older fallers are unable to get up again without assistance and any subsequent long lie can lead to serious problems [3, 4]

This paper analyses and compares the various proposed methodologies for fall detection based on the use of accelerometry. The rest of this paper is organized as follows: first, some terms related to falls are defined followed by the classification of fall detection systems. Then the general architecture of fall detection systems is presented followed by the parameters that are used to evaluate a fall detection system. Then the various approaches based on wearable sensors and smart phones are analyzed. Emerging trends and challenges in fall detection have been highlighted providing directions for future research.

I. Terminology Related to Falls

A fall can be defined as ‘Unintentionally coming to the ground or some lower level and other than as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke’.

A. Sagittal and Frontal planes

A fall usually occurs along one of two planes, called sagittal and frontal planes. A fall along the sagittal plane can occur forward or backward and a fall along the frontal plane can occur right or left lateral.

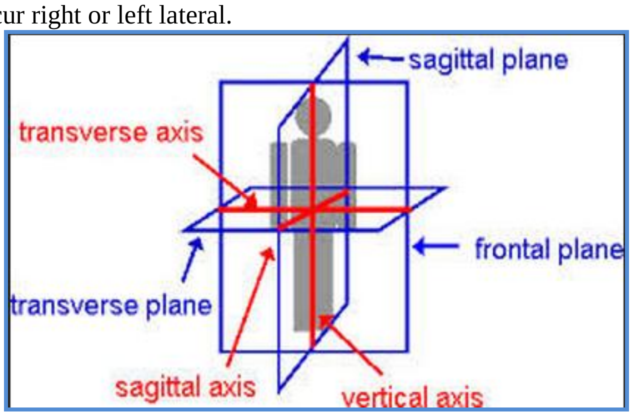

Figure 1: Sagittal and Frontal planes

B. Toppling

Toppling simply refers to a loss in balance. When the vertical line through the center of gravity lies outside the base of support the body starts toppling. If there is no reaction to his loss of balance, the body falls on the ground.

C. Posture

Posture is a configuration of the human body that is assumed intentionally or habitually. For example: sitting, standing, bending and lying. A posture can be determined by monitoring the tilt transaction of the trunk and legs.

II. CLASSIFICATION OF FALL DETECTION SYSTEMS

Noury et al. [5] classified the different studies on fall detection according to whether they only focus on the detection of the impact shock, or they also include the detection of the postfall phase. The fall is broken into 4 phases, that is, the prefall phase, the critical phase, the postfall phase and the recovery phase.

During the prefall phase, the person performs usual activities of daily living with occasional sudden movements, like sitting or lying down rapidly, which must be distinguished from a fall. The critical phase consists in the sudden movement of the body towards the ground, ending with a vertical shock on the ground. During the postfall phase, the person remains inactive, frequently lying on the ground. Eventually, the recovery phase is either intentional- the person stands up on his own- or with the help from another person.

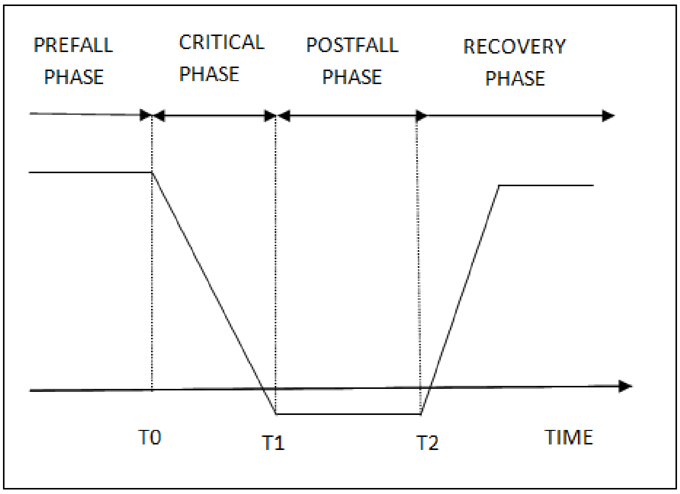

Figure 2: Different phases of a fall

By contrast, Mubashir et al. [6] divided fall detectors into three categories: wearable device based, ambience sensor based and vision based.

A vision-based approach uses fixed cameras that continuously record the movement of the persons. The acquired data is submitted to specific image algorithms that are able to recognize the pattern of a fall to trigger an alarm. The main limits of this approach are the time and cost of installation, the limited space of application and privacy violation.
Ambience sensor based systems use sensors deployed in the environment to detect falls. Their main advantage is that the person does not need to wear any special device. However, their operation is limited to those places where the sensors have been previously deployed [7]. Among all the possible types of sensors, the most common are floor sensors, infrared sensors and pressure sensors. The use of environmental devices is an approach based on the installation of sensors in the places to be monitored. When people interact with the environment, infrared or pressure sensors on the floor are able to detect a fall.

In the wearable approach, one or more wearable devices are worn by the person. They are usually equipped with movement sensors such as accelerometers and gyroscopes, whose values are transmitted via radio and analyzed.

A. Early detection of the critical phase of fall

During the critical phase of a fall, there is a temporary period of free fall during which the vertical speed increases linearly with time. Researchers have shown that vertical and horizontal speeds are higher during a fall than for any other controlled movement. Thus, if the vertical and horizontal speed of controlled movements of the person is measured, it is possible to discriminate these speeds from those occurring during a fall, which would exceed a predetermined threshold.

B. Direct detection of the end of the critical phase of fall

At the end of the critical phase, the body frequently hits the ground or an obstacle. This is known as impact shock. The event can be detected with an accelerometer or a shock detector, which is actually an accelerometer with a predetermined threshold. Difficulty is deciding the location of the sensor on the body. Depending on whether or not the sensor is near the point of impact, the signal recorded at the time of shock can be significantly different and it thus becomes more difficult to recognize a fall when it occurs and leading to a number of false positives.

C. Detection during postfall

As many falls end with the person lying on the ground, the simplest approach is to detect the horizontal position. The problem is that the elder may be lying naturally even outside normal sleeping hours. So, this method is prone to many false positives. Another approach is based on the absence of motion during the postfall. After a serious fall, the person frequently remains immobile in a posture. The lack of movement can thus be a consequence of a fall event. This can be detected with a basic movement or vibration sensor, laced on one of the extremities of the body, which are more mobile.

III. GENERAL ARCHITECTURE OF FALL DETECTION SYSTEM BASED ON WIRELESS SENSOR NETWORK

A. Architecture

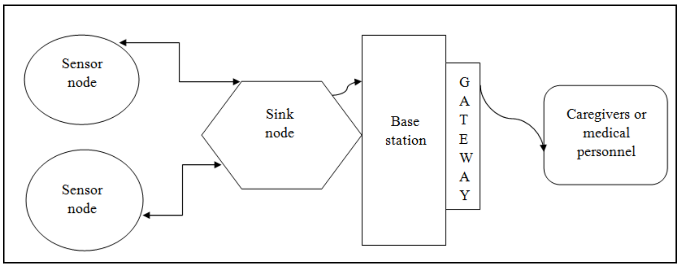

Figure 3: Architecture of a Fall Detection System

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The above figure shows the general architecture of fall detection system based on wireless sensor network. One or more sensing nodes are used to collect raw data. Analysis of the data can be performed on the node or on the base station by computer/laptop/smartphone. The wireless connectivity standard between the nodes can be different from the one that connects the sink node with the base station. The base station in turn acts as a gateway to communicate with the caregivers through wireless and/or wired connection.

B. *Sensor placement*

A sensor is typically instrumented with the following sensors:

- Accelerometer, to measure the linear acceleration
- Gyroscope, to measure the angular velocity

The placement of sensors on the body is the key to differentiate the influences of various fall detection algorithms. Popular positions selected by researchers for wearing sensors are waist, wrist, chest, trunk, thigh etc. Each position has its own advantages and disadvantages. Sometimes, the sensors are inserted in clothes.

IV. PERFORMANCE EVALUATION OF FALL DETECTION SYSTEM

The performance of a fall detection system can be described in terms of parameters like sensitivity, specificity and accuracy.

In order to test a fall detector, it is necessary to collect data from falls and ADL, which can be real or simulated by volunteers. These data are recorded by sensors and can be in the form of acceleration signals, images, pressure signals etc. Then, they are processed and classified using a fall detection technique capable of distinguishing between falls and ADL.

A. *Activities to be detected as falls*

Table 1: Activities to be detected as falls

S.No.	Name	Direction	Description
1	Front-lying	Forward	From vertical going forward to the floor.
2	Front-protecting-lying	Forward	From vertical going forward to the floor with arm protection
3	Front-knees	Forward	From vertical going down on the knees
4	Front-knees-lying	Forward	From vertical going down on the knees and then lying
5	Front-right	Forward	From vertical going down on the floor, ending in right lateral position
6	Front-left	Forward	From vertical going down on the floor, ending in left lateral position
7	Back-sitting	Backward	From vertical going on the floor, ending sitting
8	Back-lying	Backward	From vertical going on the floor ending lying
9	Back-right	Backward	From vertical going on the floor ending lying in right lateral position
10	Back-left	Backward	From vertical going on the floor ending lying in left lateral position
11	Right-sideway	Right	From vertical going on the floor, ending lying
12	Left-sideway	Left	From vertical going on the floor, ending lying
13	Rolling-out-bed	Lateral	From lying, rolling out of bed and going on the floor.

B. *Activities not to be detected as falls*

These are some activities that must not be detected as falls as described below:

Table 2: Activities that must not be detected as falls

S.No.	Name	Direction	Description
1	Lying-bed	Lateral	From vertical lying on the bed
2	Rising-bed	Lateral	From lying to sitting
3	Sit-bed	Backward	From vertical sitting with a certain acceleration on a bed
4	Sit-chair	Backward	From vertical sitting with a certain acceleration on a chair
5	Walking	Forward	Walking
6	Jogging	Forward	Jogging or running
7	Bending	Forward	Bending down
8	Bending-pick-up	Forward	Bending down to pick up an object

C. *Performance parameters*

A real working fall detection system requires being sufficiently accurate in order to be effective and alleviate the work of the caregivers. The quality of the system is given by three indexes that have been proposed based on the following possible situations:

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Table 3: Possible scenarios in Fall Detection System

	A fall occurs	A fall does not occur
A fall is detected	True Positive (TP)	False Positive (FP)
A fall is not detected	False Negative (FN)	True Negative (TN)

Sensitivity: is the capacity to detect a fall. It is given by the ratio between the number of detected falls and the total falls that occurred.

Sensitivity = TP/TP+FN

Specificity: is the capacity to avoid false positives. Intuitively, it is the capacity to detect a fall only
. if it really occurs.

Specificity = TN/TN+FP

Accuracy: is the ability to distinguish and detect both fall and non fall movement.

Accuracy = TP + TN/ P + N

Where P and N are respectively, the number of falls performed and the number of non-falls performed.

V. Body Attached Accelerometers

Accelerometers can be defined as miniature electronic sensor-based devices that are worn by the bearer under, with or on top of clothing [8]. Accelerometers are basically sensors to sense linear acceleration along one or more directions. Acceleration data are collected during falls using independent tri-axial accelerometers attached to different parts of the body. The vast majority of wearable fall detectors are in the form of accelerometer devices. Some of them also incorporate other sensors such as gyroscopes to obtain information about the person's position.

The possible techniques for fall detection are threshold based methods, in which a fall is reported when the acceleration reaches predefined thresholds and machine learning methods. Most of the existing works use thresholding techniques for automatic fall detection, although the machine learning approach has increased its influence since 2010. The methods applied include Support Vector Machine [14], Particle Swarm Organization, Gaussian distribution of clustered knowledge [22], Naïve Bayes.

Chen et al. [13] proposed a method that detects a fall and also find the location of the victim. They used a threshold based algorithm and considered the change in orientation. The threshold was set based on empirical data. The smallest acceleration measured from a fall was about 3G, but usually ranged up to several G's higher. Normal activity usually doesn't exceed 3G. From the orientation information, the angle of change is estimated using the dot product of the acceleration vectors before and after a fall. Once a fall is detected, an appropriate action can be taken , such as calling for medical assistance and determining the location of the individual. Since only the change in orientation is considered, the algorithm is much less prone to user errors. With an absolute orientation detection method, it is imperative that the device be worn properly so the correct orientation can be detected. However, by using the change in orientation, this requirement is mitigated, thus avoiding many of the problems caused by improper use of the device.

Zhang et al. [14] used a wearable tri-axial accelerometer to capture the movement data of human body and proposed a fall detection method based on one-class support vector machine. The one-class SVM model is trained by the positive samples from the falls of younger volunteers and the outliers from the non-fall daily activities of younger and the elderly volunteers. It classifies the data of fall and daily movements. One-class SVM is an extended algorithm of SVM, it divides all samples into objective field and non-objective field, mapping all the samples into high dimensional feature space. Then, in the feature space, one-class SVM computes the surface of a minimal hypersphere which involves all the objective data inside, and this minimal hypersphere will be the classifier. A group of variables are introduced to realize the trade off between the radius of the hypersphere and the number of the samples outside the hypersphere. All the samples inside the hypersphere are known as positive samples, the outside samples as outliers. Unlike other approaches, this approach does not need a precondition that in case of a fall, the posture changes rapidly to horizontal.

Bourke et al. [15] applied a threshold based algorithm to detect falls. In this approach the accelerometers were placed on trunk and thigh. Activities of daily living were performed by elder subjects and simulated falls were performed by young people. Falls that were performed are forward falls, backward falls, lateral falls to right, lateral falls to left, falls with both legs straight and falls with knee flexion. The upper and lower fall thresholds for trunk and thigh were derived. A fall is said to have occurred if the value is greater than any of the thresholds. The study showed that trunk is a better place than thigh to place sensors. The problem is that using only accelerometer for fall detection causes many false positives such as in case of sitting down quickly and jumping, when vertical acceleration is high.

Doukas et al. [16] provided an implementation of a fall detection system that may be used for patient activity recognition and emergency treatment. Sensors equipped with accelerometers are attached on the body of the patients and transmit patient movement data wirelessly to the monitoring unit. The methodology of support vector machines is used for precise classification of the acquired data and determination of a fall emergency event. The recorded movements are classified into 3 categories: fall, walk and run. Then a context-aware server transmits video from patient site properly coded according to both patient and network status

Kangas et al. [17] investigated the acceleration signal measured with body attached accelerometers from intentional falls and activities of daily living. The aim of this study was to determine acceleration thresholds for fall detection, using tri-axial accelerometric measurements at the waist, wrist and head. They also demonstrated that using simple thresholds alone is not optimal for fall detection. There were some overlapping values between ADL and fall when only threshold is used. They assumed that the person is in lying posture after the fall and combined the threshold based algorithm with posture detection. The results showed that they were able to achieve sensitivity and specificity upto 100%. Also, results showed that the measurements from the waist and head have the potential to distinguish between falls and ADL and hence they are relevant sites for accelerometric detection of falls. On the contrary, the wrist did not appear to be an optimal site for fall detection

.Kangas et al. [18] performed a study whose aim was to evaluate different low-complexity fall detection algorithms, using tri-axial accelerometers attached at the waist, wrist and head. The fall data were obtained from standardized types of intentional falls: forward, backward and lateral in three middle-aged subjects. Data from activities of daily living were used a reference. Three different detection algorithms with increasing complexity were investigated using two or more of the following phases of a fall event: beginning of the fall, falling velocity, fall impact and posture after the fall. The results indicated that fall detection using a tri-axial accelerometer worn at the waist or head is efficient, even with simple threshold-based algorithms, with a sensitivity of 97-98% and specificity of 100%. The most sensitive acceleration parameters in these algorithms appeared to be the resultant signal and the calculated vertical acceleration. In this study, the wrist did not appear to be an applicable site for fall detection. Since a head worn device includes limitations concerning usability and acceptance, a waist worn accelerometer , using an algorithm that recognizes the impact and the posture after the fall, might be optimal for fall detection.

Li et al. [19] present a fall detection algorithm that can reduce both false positives and false negatives by using gyroscopes and accelerometer-derived posture information. It also features low computational cost and fast response. In this approach, the human activities are divided into 2 categories: static postures and dynamic transitions between these postures. Using 2 tri-axial accelerometers at different body locations, this system can recognise 4 kinds of postures: standing, sitting, bending and lying. This is more accurate than only using orientation information. For static segments, the accelerometer readings are used to determine the posture including standing, bending , sitting and lying. If the posture is lying, it must be examined whether the transition to the lying posture was an intentional movement by examining the previous 5 seconds of data. To determine whether a transition is intentional, the system measures not only linear acceleration, but also angular velocity with gyroscopes. If the transition was unintentional, it is flagged as fall. This method has difficulties in differentiating jumping into bed and falling against wall with a seated posture. To distinguish these activities, context information needs to be exploited.

Bourke el al. [20] evaluated different combinations of existing fall detection algorithms for a waist-mounted accelerometer based system. In total, 21 algorithms of varying degrees of complexity were tested against a data-set recorded from 10 young healthy volunteers performing 240 falls and 120 activities of daily living and 10 elderly healthy volunteers performing 240 scripted ADL and 52.4 walking hours of continuous unscripted normal ADL. This study uses simulated falls performed by young volunteers onto crash mats, as opposed to real-life hard surfaces. Thus the impact values recorded here are expected to be lower than would occur in real conditions. Results show that using an algorithm that employs thresholds in velocity, impact and posture achieves 100% specificity and sensitivity with a false positive rate of less than 1 per day of waking hours. This algorithm is suitable method of fall detection when tested using continuous unscripted activities performed by elderly healthy volunteers. Lai et al. [21] aimed to use several triaxial acceleration sensor devices for joint sensing of injured body parts, when an accidental fall occurs. The model transmitted the information fed by the sensors distributed over various body parts to the computer through wireless transmission devices for further analysis and judgment, and employed cognitive adjustment method to adjust the acceleration range of various body parts in different movements. The model can determine the possible occurrence of fall accidents, when the acceleration significantly exceeds the usual acceleration range. In addition, after a fall accident occurs, the impact acceleration and normal (habitual) acceleration can be compared to determine the level of injury.

Yuvano et al. [22] used a waist-worn wireless tri-axial accelerometer combined with digital signal processing, clustering and neural network classifiers. The feature extraction stage makes use a custom method we refer to as Gaussian distribution of Clustered Knowledge (GCK) signal generation. Clustering is done with Regrouping Particle Swarm Optimization (RegPSO). Classification is undertaken by a newly developed “Augmented Radial Basis Function” (ARBF) neural network alongside a multilayer perceptron (MLP). Preliminary testing with 8 healthy individuals in a home environment yields 98.6% sensitivity to falls and 99.6% specificity for routine Activities of Daily Living (ADL) data. Single ARB and MLP classifiers were compared with a combined classifier. The combined classifier offers the greatest sensitivity, with a slight reduction in specificity for routine ADL and an increased specificity for exercise activities. In preliminary tests, the approach achieves 99.33% specificity on routine ADL, and 96.59% specificity on exercise ADL.

Yasar et al. [23] proposed a tracking system, GeTraSys (Geriatric Tracking System), which is composed of a watch to detect falls and, a computer connected to the Internet. The watch is strapped to the chest of the patient, and the 3-axis accelerometer data is used for real time fall detection. The system also allows for personal calibration to adapt to personal movement styles, such as walking and sleeping, therefore allowing a decrease in the amount of false fall alarms. In addition, the proposed system enables the monitoring of up to 1024 people; hence, it avoids privacy problems in institutions, such as rest homes where cameras would be intrusive. Wen-chang et al. [24] proposed a cascade-Ada-Boost-support vector machine classifier to complete the tri-axial accelerometer-based fall detection method. The method uses the acceleration signals of daily activities of volunteers from a database and calculates feature values. The cascade-Ada-Boost-support vector machine algorithm can self-construct based on training vectors, and the algorithm of each layer can automatically select several optimal week classifiers to form a strong classifier, which accelerates effectively the processing speed in the testing phase, requiring only selected features rather than all features.. The accelerometers are worn around the left and right ankles, and on the chest as well as the waist. The results are compared to those of the neural network, support vector machine, and the cascade Ada-boost classifier. Results show hat the triaxial accelerometers around the chest and waist produce optimal results.

VI. SMARTPHONE BUILT IN ACCELEROMETERS

Today's smartphones come with a rich set of embedded sensors, such as an accelerometer, gyroscope, GPS, microphone and camera [25]. Several researchers are currently taking advantage of this fact to develop smartphone based fall detectors.

Sposaro et al. [26] presented an alert system for fall detection using common commercially available electronic devices to both detect the fall and alert authorities. They used a common Android-based smart phone with an integrated tri-axial accelerometer. Data from the accelerometer was evaluated with several threshold based algorithms and position data to determine a fall. The threshold is adaptive based on user provided parameters such as: height, weight, and level of activity. These variables also adapt to the unique movements that a cell phone experiences as opposed to similar system which require users to mount accelerometers to their chest or trunk. If a fall is suspected a notification is raised requiring the user's response. If the user doesn't respond, the system alerts the specified social contacts with an informational message via SMS. When a contact responds with an incoming call the system commits an audible notification, automatically answers the call, and enables speakerphone. If a social contact confirms a fall, an appropriate emergency service is alerted.

This system provides a realizable, cost effective solution to fall detection using a simple graphical interface while not overwhelming the user with uncomfortable sensors. This software is intended to integrate with the phone's existing applications. It shares resources with the other apps. A background service constantly listens to the accelerometer. It also takes position into consideration. The assumption is that a fall can only start from an upright position and end in a horizontal position. Thus the difference in position before and after the fall is close to 90. A fall is suspected if both thresholds are crossed within a duration and the position is changed. If a fall is suspected, a short timer is started. This timer allows a fallen user to regain an upright position or a dropped phone to be picked up. If the original position is resorted within the time limit the algorithm is reset. If the timer expires and position is not restored, we assume the phone/user is lying on the ground. It then emits a prompt that requires the user to respond within a short time window. A fall is confirmed if the user does not respond. This allows users to reduce the number of false positives. An alert only sends when a fall is confirmed.

Dai [27] proposed utilizing mobile phones as the platform for developing pervasive fall detection system, as they naturally combine the detection and communication components. As self-contained devices, mobile phones present a mature hardware and software environment for developing pervasive fall detection system. Mobile phone based fall detection system can function almost everywhere, since mobile phones are highly portable, all necessary components are already integrated therein, and their communication services have vast coverage. The minimum requirement for such a mobile phone platform is the presence of a simple sensor, e.g., an accelerometer. Currently, many phones, especially smartphones, contain multiple types of sensors, including accelerometers. Such phones are popular and thoroughly accepted in society. They designed two algorithms for fall detection systems using mobile phones. The first is an acceleration-based detection approach. The second algorithm is designed for the case when a certain accessory can be used to further capture human behavior information. They designed and implemented a pervasive fall detection system, PerFallD, on the mobile phone-based platform to conduct fall detection with or without other small accessories. PerFallD has few false negatives and false positives. It is available in both indoor and outdoor environment. Besides being user-friendly, it requires no extra hardware and service cost. It is also lightweight and power-efficient. We conduct extensive experiments, with both a mannequin and real persons, to evaluate detection accuracy. The experimental results show our detection system achieves superior performance in terms of low false negative and low false positive in fall detections with or without accessory.

Lopes [28] presented an application tool based on an accelerometer, call SensorFall to detect and report the acceleration caused by a fall, which allows sending alerts in the form of SMS, phone call, or by location using the GPS. We have implemented and verified the SensorFall in various environments, such as a hospital or a normal daily life for the elderly, also implemented the system calibration in order to adapt better the living conditions of each person. The results show that it performs well. This system, named SensorFall, is an innovative detection system and assistance of falls on a mobile and pervasive environment, using an accelerometer to measure the accelerations caused by movement of the human body in the tasks of day-to-day, the system incorporates an array of features, such as sending alerts, or shortest message service (SMS), or phone calls or the GPS positions, another feature relates to the fact that it can be apply to anyone and is not only restricted to the elderly people, and can be calibrated and used by an athlete, for example. The aim of this project is to construct an application for mobile devices that allows the detection of falls and corresponding notification. It pretends to give fast assistance and quality of response, in assisting the patient or user.

Albert [29] demonstrated techniques to not only reliably detect a fall but also to automatically classify the type. We asked 15 subjects to simulate four different types of falls–left and right lateral, forward trips, and backward slips–while wearing mobile phones and previously validated, dedicated accelerometers. Nine subjects also wore the devices for ten days, to provide data for comparison with the simulated falls. We applied five machine learning classifiers to a large time-series feature set to detect falls. Support vector machines and regularized logistic regression were able to identify a fall with 98% accuracy and classify the type of fall with 99% accuracy. This work demonstrates how current machine learning approaches can simplify data collection for prevention in fall-related research as well as improve rapid response to potential injuries due to falls.

Table 6: Comparing smart phone based techniques for fall detection

Article	Year	Objective	Technique	Sensor position	Fall types	Subjects	Result
Sposaro et al.	2009	Detect fall using smart phones and message alerts	Used the difference in position before and after the fall and whether the fallen patient is able to regain the upright position	Thigh-pocket	-	-	First smartphone based fall detector
Dai et al.	2010	Mobile phone-based platform to conduct fall detection with or without other small accessories	Used 2 algorithms-one for acceleration-based detection and second for the case when a certain accessory can be used to further capture human behavior information	Chest, waist and thigh	Forward, backward and lateral	15 graduate students (20-30 age)	Waist is the best position to attach the phone.
Lopes et al.		Detect and report the fall, through SMS and/or phone call	Accelerometer, SMS and GPS services are used	-	Forward and backward falls	-	Easy to handle, providing a very simple user interface
Albert et al.		Detect a fall and automatically classify the type	Used machine learning classifiers and support vector machines	-	Left and right lateral, forward trips, and backward slips	9 subjects	Improve rapid response to potential injuries due to falls; 98% accuracy for detecting falls and 99% accuracy for classifying type of fall

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VII. EMERGING TRENDS IN FALL DETECTION

A. Smartphone based fall detectors

The use of body-worn accelerometers has stagnated in the last years, but this trend is offset by the increase in the number of smartphone-based studies. This is still a novel technology: the first study using smartphones appeared in 2009 [26] and since then the research in this field has grown steadily. Since smart phones are self-contained devices, they present a mature hardware and software environment for developing pervasive fall detection systems [27]. They have built in communication protocols that allow simple data logging to the device and wireless transmission. Price is also significantly reduced due to production in high volume. [29]

There might be difficulties with real-time operations, the sensing architecture, the stability of the accelerometer's sampling frequency etc. The same fall detector might behave slightly differently depending on the smartphone model in which it is installed.

B. Machine learning approach

There are 2 main approaches to detect falls using acceleration signals: thresholding techniques and machine learning methods. Applications based on the first approach are simple to implement and their computational work is minimal. They are able to detect when a fall occurs. However, the rate of false positives is a significant issue [29]. The machine learning approach is more sophisticated and leads to better detection rates.

VIII. CHALLENGES IN FALL DETECTION SYSTEM

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 achieved under controlled conditions such as simulated falls and ADL are performed by the subjects. Furthermore, the fall detectors are aimed at older people, but in most of the researches, older people are not involved in the development process. Their participation is mostly limited to perform a set of simulated activities of daily living for minutes or hours [15]. Hence, the first challenge is to improve the performance of systems.

A. Usability

An ideal system should be based on only one wearable sensor with small form factor, possibly placed in a comfortable place such as a belt. This may complicate the posture detection. Smartphone-based fall detectors are attractive because of the widespread use of phones. However, most of the studies placed them in a standardized position. Future smartphone based detectors should not limit the placement of the device to a single part of the body. There should be no such restriction. The energy consumption must also be low to extend the battery lifetime.

B. Comparison of various techniques

Comparing different approaches is difficult because each researcher obtains data in a different way: types of simulated falls and ADL, the position of the detector, sampling frequency, temporal length of signal, extracted features etc. The research focus should not only be on the algorithm to be used but also on the way signals are acquired and treated before feeding a classifier.

C. Comparison of various techniques

Comparing different approaches is difficult because each researcher obtains data in a different way: types of simulated falls and ADL, the position of the detector, sampling frequency, temporal length of signal, extracted features etc. The research focus should not only be on the algorithm to be used but also on the way signals are acquired and treated before feeding a classifier.

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E. Robustness

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An ideal system should be based on only one wearable sensor with small form factor, possibly placed in a comfortable place such as a belt. This may complicate the posture detection. Smartphone-based fall detectors are attractive because of the widespread use of phones. However, most of the studies placed them in a standardized position. Future smartphone based detectors should not limit the placement of the device to a single part of the body. There should be no such restriction. The energy consumption must also be low to extend the battery lifetime.

G. Robustness

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 achieved under controlled conditions such as simulated falls and ADL are performed by the subjects. Furthermore, the fall detectors are aimed at older people, but in most of the researches, older people are not involved in the development process. Their participation is mostly limited to perform a set of simulated activities of daily living for minutes or hours [15]. Hence, the first challenge is to improve the performance of systems.

H. Usability

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I. Comparison of various techniques

Comparing different approaches is difficult because each researcher obtains data in a different way: types of simulated falls and ADL, the position of the detector, sampling frequency, temporal length of signal, extracted features etc. The research focus should not only be on the algorithm to be used but also on the way signals are acquired and treated before feeding a classifier.

J. Robustness

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K. Usability

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L. Comparison of various techniques

Comparing different approaches is difficult because each researcher obtains data in a different way: types of simulated falls and ADL, the position of the detector, sampling frequency, temporal length of signal, extracted features etc. The research focus should not only be on the algorithm to be used but also on the way signals are acquired and treated before feeding a classifier.

IX. ANALYSIS AND DISCUSSION

As many falls end lying on the ground, the simplest approach of fall detection is to detect the lying position, from a horizontal inclination sensor. This method is less suitable for the detection of falls of an older person in their home environment as the sleeping hours are not regular. Therefore, this method is prone to many false positives. Another solution is to detect the person lying on the floor, using sensitive floor tiles installed in all the places. But there may be some falls which do not end on the ground, or which occur in areas which are not equipped with the specialized tiles. So, they are not detectable. When falling, the person frequently hits the ground. The impact shock can be detected with an accelerometer or a shock detector. The location of the sensor on the body relatively to the point of impact modifies the value of signal recorded at the time of shock.

Lack of movement can also be used to detect the fall, as after a serious fall, the person may remain immobilized at a place. A movement sensor placed on one of the extremities of the body can be used to detect movement. The drawback with these approaches is the choice of latency time which should be long enough to reduce false positives.

During a fall, there is a temporary period of free fall, during which the vertical speed increases linearly with time due to gravitational acceleration. If one measures the vertical speed of controlled movements of the person, one can discriminate these speeds from those occurring during a fall, which would exceed threshold. The difficulty lies in the choice of this threshold, if it is too low the device will also detect false positives but if the threshold is too high, it will not detect positive events. The threshold is also dependent on the subject-to-subject variability. To overcome this difficulty, one can call upon a learning period of either supervised or unsupervised learning. In supervised learning, wearers will be asked to carry out a specific series of acts whereas in unsupervised learning, the movements of persons are recorded during a few hours or several days, and then the collected data is analysed.

Machine learning based methods can also be used to detect falls. These start from observation (a training period) and then classification. If one proceeds through a supervised training period, one can train a neural network, which will then be used to automatically classify future situations. Only the situations met during the training can be classified. The first fall event is likely to be missed since its class is yet unknown before its first occurrence.

One of the methods used to detect falls is by utilizing accelerometer data only. The accelerometer signals are compared to determine if it is over a threshold. The next method was done with the utilization of accelerometer and gyroscope data together to detect falls. Since a gyroscope gives angular displacement, a threshold value was used to check against values related to a fall. Another method uses a combination of acceleration data, gyroscope data, and static orientation data to detect falls. The difference between the initial and final orientation is used to determine the change in position of the patient after an event.

The foremost advantage of wearable sensor based detection is that a person can go outside his home and still be monitored. There are also no such problems of noise or living environment restrictions. These systems do not have any infrastructure requirement. The issue with these systems is the battery life of the sensors.

The biggest advantage remains the cost efficiency and portability of wearable devices. Installation and setup of the design is also not very complicated. Therefore, the devices are relatively easy to operate. The disadvantages include intrusion and fixed relative relations with the object, which could cause the device to be easily disconnected. Such disadvantages make wearable devices an unfavourable choice for the elderly. They may experience discomfort to wear the gadget and the elderly people may forget to wear it all the time.

X. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Fall detection is a complex process for which currently there is not a standardized solution. Fall detectors are essential in order to provide a rapid assistance. This review examined the different fall detectors that use sensors and then define the trends in fall detection systems. There is a new trend towards the integration of fall detectors into smartphones.

The ideal fall detection system should exhibit both a sensitivity and specificity of 100%. This was sometimes reached in experimental setup, but in practicality there is a dramatic loss in performance. The existing approaches have not comprehensively satisfied the accuracy as well as robustness of a fall detection system. However, the existing approaches do provide a framework to further develop techniques as well as modify the existing algorithms to achieve better performance.

Sensor based approaches lack consistency when it comes to providing highly accurate automatic fall detection systems. Higher accuracy levels have been achieved to an extent using multi-dimensional combination of physiological and kinematic parameters.

Further research and development should continue in terms of making the design fully automatic without much intervention. The main improvements will come with the integration of the devices and reduction in the level of maintenance required.

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