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# FALL DETECTION AND PREVENTION FOR THE ELDERLY: A REVIEW OF TRENDS AND CHALLENGES

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***Abstract- It is of little surprise that falling is often accepted as a natural part of the aging process. In fact, it is the impact rather than the occurrence of falls in the elderly, which is of most concern. Aging people are typically frailer, more unsteady, and have slower reactions, thus are more likely to fall and be injured than younger individuals. Typically, research and industry presented various practical solutions for assisting the elderly and their caregivers against falls via detecting falls and triggering notification alarms calling for help as soon as falls occur in order to diminish fall consequences. Furthermore, fall likelihood prediction systems have been emerged lately based on the manipulation of the medical and behavioral history of elderly patients in order to predict the possibility of falls occurrence. Accordingly, response from caregivers may be triggered prior to most fall occurrences and accordingly prevent falls from taking place. This paper presents an extensive review for the state-of-the-art trends and technologies of fall detection and prevention systems assisting the elderly people and***

***their caregivers. Furthermore, this paper discusses the main challenges, facing elderly fall prevention, along with suggestions for future research directions.***

**Index terms*: Fall detection, fall prevention, elderly monitoring, motion sensing***

# I. INTRODUCTION

In around 35 years and by 2050, it's estimated that more than one in each group of five people will be aged 65 or over. In this age group, falling is one of the most serious life-threatening events that can occur, as approximately one-third to one-half of the population aged 65 and over (mostly aging care centers residents) experience falls on a yearly basis and half of these elderly do fall repeatedly [1]. So, the automatic detection of falls would help reducing the time of arrival of medical caregiver, and accordingly reducing the mortality rate [2]. Falls are the leading cause of injury in elderly people and the leading cause of accidental death in those 75 years of age and older [3]. Also, more than 90% of hip fractures occur as a result of falls in persons aged 70 years and over [4]. Falls not only cause physical injury such as many disabling fractures [5]; they also have dramatic psychological, medical and social consequences. The emerging picture is that falls are not a rare occurrence among older persons.

Accordingly, in order to achieve a good degree of fall prevention for elderly people, there is a serious need for developing automatic monitoring and fall detection systems that call for help from caregivers even if the patient is unconscious or unable to get up after the fall. Most often the available sensors for movement detection and monitoring are wearable; however this might impact the acceptance of usage from the users. So, that is why efforts are focused on developing other contact-free means of movement monitoring and fall detection [6]. Both developing commercial products and conducting academic research on fall detection have been motivated by the considerable risks of falls and the substantial increase of the elderly population. A typical fall detection system has two major functional components: the detection component, which detects falls and the communication component that communicates with emergency contact after fall detection [7]. So, in the light of that typical architecture for fall detection systems, another category of fall likelihood prediction systems has been emerged based on the manipulation of the medical and behavioral history of elderly patients in order to obtain specific model for each patient describing his/her behavior and predicts the possibility of falls occurrences. Based on such fall prediction systems, response from caregivers may be triggered prior to most fall occurrences and accordingly prevent falls from taking place.

This paper brings the concept of elderly fall detection and prevention to the light via presenting the recent research directions and trends in monitoring and responding on detecting movements of elderly people. It also reviews the state-of-the-art research work done in the field of early detection and prevention of elderly falls. In addition, the paper surveys the already available in market solutions and products for monitoring, detecting, controlling, and preventing falls for elderly people. Moreover, this paper provides facts about the main challenges facing research and development in that field.

The rest of this paper is organized as follows. Section II discusses causes and consequences of elderly falls. Section III reviews the major research work done recently in the area of elderly monitoring as well as fall detection and prevention. Several categories of modern commercial sensor devices assisting the elderly and their caregivers for detecting and preventing falls and consequent injuries are presented in section IV. Finally, section V concludes the paper and discusses the main challenges facing research and development in the field of elderly fall prevention along with recommendations and suggestions for future research directions.

## II. CAUSES AND CONSEQUENCES OF ELDERLY FALLS

Falling among the elderly happens due to different causes as well as it leads to different consequences. Being aware of those reasons and consequences serves researchers, designers, and developers of fall detection and prevention systems to develop various creative solutions for the problem of elderly falls.

### a. Causes

There are several reasons why elderly fall. Some reasons; such as age, gender, being unconscious, or suffering from chronic neurological or mental problems, cannot be controlled. Whereas other causes; such as medications side effects, insufficient vision, poor hearing, or muscle weakness can be controlled or modified. Figure 1 classifies the most common reasons causing falls in the elderly according to their origin and controllability. The presence of more than one cause of falling is common, and several studies have shown that the risk of falling increases dramatically as the number of causes increases. Several studies [8–10] classify the factors associated with falls/causes of falls as extrinsic/environmental and intrinsic/personal. Environmental factors, which refer to factors originating from the patient's surrounding/external environment such as, loose carpets, wet or slippery floors, poorly constructed steps, etc. These factors cause falls in the local setting. On the other hand, considering the fact that the leading causes of injury and mortality for elderly people are no longer infectious in nature, personal factors appear to also contribute to increase risk of falling. Intrinsic or personal factors, which relate to age-associated physiological and neurological functions changes, medications (such as: antidepressants or sedatives), as well as diseases (such as: hypertension, osteoarthritis, diabetes and sensory impairment, Alzheimer's disease or other forms of dementia, etc.), represent factors related to co-morbid conditions and reflect the rise and predominance of chronic diseases and accordingly the rise of elderly falls rate due to these diseases [11].

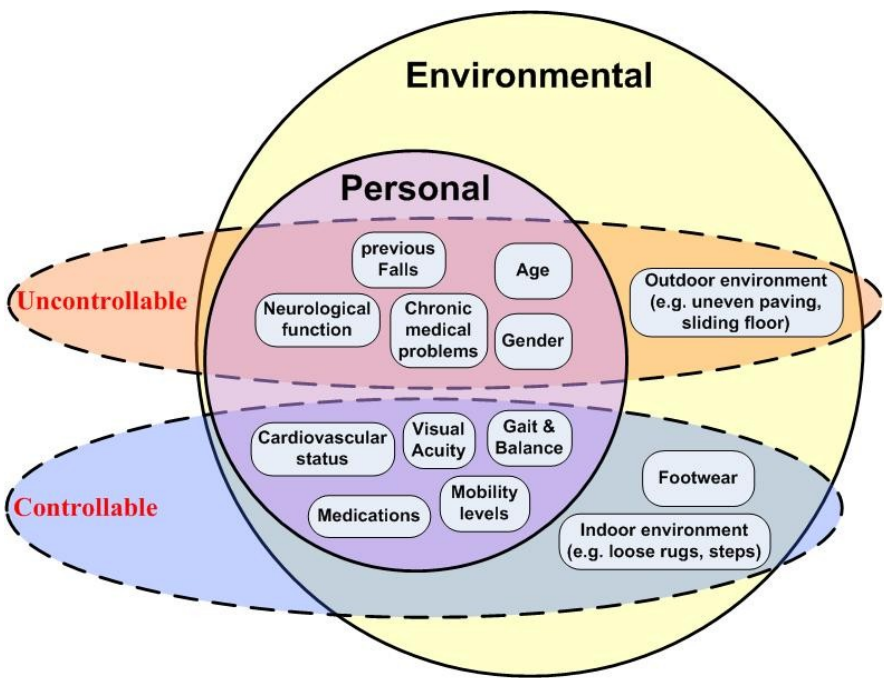



Figure 1.  Categories of common reasons causing falls

b. Consequences

The average length of hospital stay is more than twice, as long in each age group for falls, for different causes of hospitalization for people over the age of 65. Falls among the elderly is increasingly being recognized as an issue of concern in all types of countries whether developed or developing countries [11]. Any individual, especially if an aging person, can be negatively affected in various ways as a result of falling. Even a small fall can profoundly affect the health of elderly people. Yet, in this population, falls continue to be a predominant cause of loss of functioning and death. Falls in the elderly may precipitate adverse physical, psychological, social, financial and medical, as well as governmental and community consequences. Figure 2 shows the main consequences related to elderly falling.

- **Physical consequences**: are represented in possible injury i.e. broken bone or soft tissue injury, pain and discomfort, reduced mobility and possible long-term disability, and most of the time lead to increase the loss of independence and the ability to look after himself/herself.
- **Psychological consequences**: lead to loss of confidence when walking and moving due to the increased fear of repeated falling, fear and anxiety, in addition to distress, and embarrassment.
- Social consequences: are represented in curtailment of possible routine social activities, loss of independence and a reliance on family, friends or possible move into aging residential or nursing care center.
- **Financial and medical consequences**: signify the direct costs of medical care associated with injuries represented in increased costs to the statutory services such as physiotherapy rehabilitation, hospital care, and social care. Also, the immediate impact and consequences from the falls seen in health center were laceration (sometimes resulted in tissue damage) needing cleaning and dressing. For some patients, the wounds resulted in difficult to heal, chronic leg ulcers requiring frequent cleaning and dressing at the health center [11].
- **Governmental and community consequences**: indicate the fact that falls can have devastating effects on people's health and that falls greatly contribute to the level of hospital admissions and health insurance costs. So, from that point, governments may work hard to improve both the prevention and treatment of falls and these are most effective when social care and the government work together putting in place the legal conditions and financial incentives to drive such integration. Also, another fact is that as the population gets older, it has to be recognized that community health and social care organizations need to work more closely to set up effective falls prevention programs and to consider this as even more of a

priority. That is, for little initial investment patients are getting better care, more falls are being prevented, and money is being saved. Generally, a concerted drive from the national to the local level in order to work for tackling elderly falls has to be adopted and activated in order to get organizations across health, social care, and local community authorities working together.

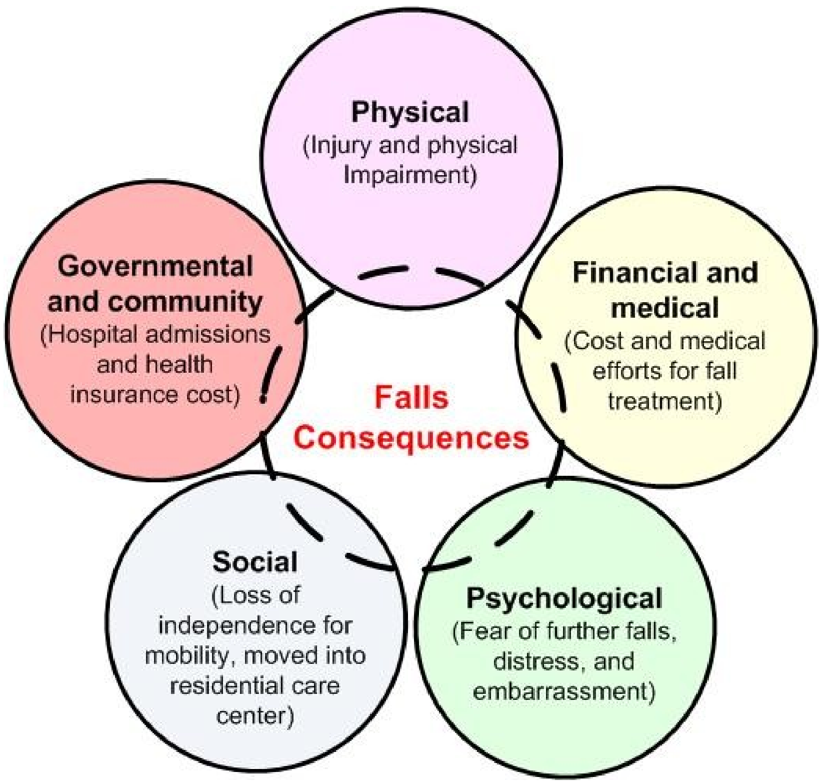



Figure 2. The main consequences related to elderly falling

## III. REVIEW OF LITERATURE

There has been significant interest in falls both from a research and commercial perspective for many years. A variety of approaches have been taken technologically towards falls detection with varying degrees of accuracy. A number of attempts have been made to monitor not only falls, but also to generally monitor daily activities without attaching devices to the body, then to prevent falls accordingly.

On the other hand, many approaches for using accelerometry to detect falls were proposed. In those approaches, a change in body orientation from upright to lying that occurs immediately after a large negative acceleration indicates a fall. However, generally despite all the research dedicated to fall detection, there still isn't a 100% reliable algorithm that catches all falls with no false alarms. Furthermore, a limited number of research works has been conducted concerning the scope of fall prediction via monitoring and modeling patients' behavior in order to take protective actions that prevent falls occurrence. This section presents a detailed review of research work achieved in order to highlight various solutions proposed for tackling the problem of fall detection and prevention from different perspectives. Table 1, summarizes the proposed fall detection approaches, the contributions, and the drawbacks/challenges for each research work surveyed in this review.

In [12], authors designed and created a fall detection system for the elderly as a wearable monitoring device, distinguishing between fall and non-fall events, which can link wirelessly with a pre-programmed laptop computer or Bluetooth-compatible mobile phone. Upon detecting a fall, the device communicates wirelessly with the laptop/cell phone to call emergency contacts. The device also detects abnormal tilt and warns the user to correct their posture to minimize the risk of falling. Moreover, in addition to the visual alert (flashing LED) fall alert, the proposed fall detection device has audio (siren) and tactile (vibrating buzzer) alert options for the seeing/hearing-impaired people and facilitates a manual cancel button in the event of a false alarm or falls that can be recovered by the user. Regarding the performance assessment of the proposed device, some actions have not been successfully distinguished, by one of the proposed algorithms, to be falls or non-falls.

In [13], a fall detection approach using both accelerometers and gyroscopes was proposed. Firstly, authors divide human activities into two categories: static postures and dynamic transitions. By using two tri-axial accelerometers at separate body locations, the proposed system was designed to recognize four kinds of static postures: standing, bending, sitting, and lying. The TEMPO (Technology-Enabled Medical Precision Observation) 3.0 sensor nodes [14] have been used. Motions between these static postures are considered as dynamic transitions. Linear acceleration and angular velocity are measured to determine whether motion transitions are intentional. If the transition before a lying posture is not intentional, a fall event is detected. The proposed algorithm, coupled with accelerometers and gyroscopes, has been found out to reduce both false positive (e.g. sitting down fast) and false negative (e.g. falling on stairs) fall detections, while improving fall detection accuracy. In addition, it featured low computational cost and real-time response. Authors reported that the proposed method has difficulties in differentiating jumping into bed and falling against wall with a seated posture as context information (environmental/physiological) is required to distinguish these activities.

Authors in [15] presented Wearable Accelerometric Motion Analysis System (WAMAS) with the purpose to create a means for real-time quantitative body motion analysis in non-laboratory settings in addition to 153 warn the wearer of pre-fall behavior. The WAMAS provided a wearable device for diagnosis and therapy of movement disorders midway between observational estimation of risk of falling and consequent injury, and expensive laboratory-based gait analysis. It can provide unattended on-site quantitative records of balance status in the homes of those undergoing outpatient treatments; it is also suitable for use in outlying clinics remote from central laboratories. The motion analysis system can monitor a patient's performance and compliance with a course of therapy. The basic WAMAS consists of two small 3-axis sensors attached to both corners of eyeglass frames to measure head motion, and two more above the hips on a belt at the waist. Also on the belt is a self-contained data acquisition package which digitally records the 12 sensor outputs. A hand-held or wearable remote control is used to command the wearable unit so the patient or test subject is unencumbered by cables. The wearable accelerometric instrument has utility to act as a diagnostic tool to quantify qualitative measures of balance and to perform as a biofeedback device during therapy and accordingly to act as a fall-prevention aid for institutionalized and community-living fall-prone elderly. Clinicians and test subjects report that the WAMAS is easy to use and the latest version constructed of the WAMAS has a design based on PCMCIA memory cards technology that improved the size, speed and power consumption of the equipment. Lighter weight unit with digital input, voice output, and real time feedback still needs to be improved.

In [16], authors proposed SPEEDY a wrist wearable watch-like fall detector for elderly people that incorporates a multi-stage fall detection algorithm. The detector is easy to wear and offers the full functionality of a small transportable wireless alarm system. Authors in this research aimed to develop a much smaller device than the system proposed in [15] in addition to propose a self-contained activity monitor (SCAM) accelerometry device [17] analyzing walking activity via measuring the variability of acceleration against walking speed relationship to test the assessment of walking distance and duration over 24-hours. The wrist-worn fall detector proposed in [16] implements a fall detection algorithm, which will alert a call center after a heavy fall. This occurs even if the wearer is unconscious or too weak or confused to press the alarm button himself. As the wrist is probably the most difficult place for detecting a fall. Authors had the aim of proving that the proposed algorithm can therefore be expected to function at other locations on the body. The major disadvantage of the proposed solution is the complexity of the fall detection algorithm. In order to comply with the small space available and the low-power requirement, three axes of acceleration sensed were only used in addition to an algorithm using only very low computing power. Also, it has been noticed that not all fall situations are detected with the same certainty such as sideways falls and the fall backwards.

In [18] authors tried to demonstrate the feasibility of using a wireless sensor network to detect fall events. The goal was to design an accelerometer mote (attached to waist-belt), based on the design of the sensor networked infrastructure of Ivy project proposed in [19] that is used to detect when a person has sustained a fall and relay this information across some medium such that immediate and appropriate action can be taken. In order to detect a fall, the sampled acceleration data is processed locally at the mobile mote instead of forwarded back to the base station (a powerful computer), which place a great burden on the network because the data would need to be continually transferred over the network when the device is on. The Ivy project proposed in [19] aimed to provide a path towards more independent living for the elderly. Using a small device worn on the waist and a network of fixed motes in the home environment, the occurrence of a fall and the location of the victim can be detected. Low-cost and low-power Microelectromechanical systems (MEMS) accelerometers are used to detect the fall while radio frequency (RF) signal strength is used to locate the person. So, generally, the main goal of the Ivy project is to provide an infrastructure of networked sensors, spread throughout the environment, which supports multiple applications simultaneously. For the Ivy network infrastructure, the motes can be divided into two types: fixed/infrastructure motes, which are attached alongside the walls and corridors, and mobile motes, whose geographical position can change over time.

The accelerometer mote presented in [18] is small and lightweight that can be worn comfortably without obstructing normal activities. Originally, the proposed accelerometer mote was intended to be worn on the arm or wrist, similar to a watch, but previous experiments in [20] have shown that the frequent and severe movements of the arm in everyday activities make it difficult to use the acceleration forces observed in arm or wrist to determine the activity performed. So, for studies on fall detectors conducted in [20], researchers have placed devices on the waist for more success. Clearly, the placement of the device on the body is of primary concern. Some of the criteria are that it should be comfortable and that the device itself should not pose a threat to the wearer in the event of a fall. Accordingly, for experiments in 18, authors attached the mote to a belt worn around the waist. The accelerometer mote applied for experiments in this research utilizes TinyOS and UC Berkeley Mica2Dot motes as a research platform for low-power wireless sensor networks [21, 22]. So, when a fall has been detected, the mobile mote can then send an alert back to the base station, and the computer can then take the necessary measures, such as notify an emergency center. Authors observed that different activities have unique acceleration profiles. Also, amplitudes and frequencies of movement vary with the size and weight of the wearer, which suggest that the design can be improved by customization, whether for individuals or groups with similar activity levels.

In [23, 24], an intelligent home monitoring unit based on ZigBee wireless sensors has been designed and developed to monitor the activities of the elderly people via continuously monitoring the basic appliances used for the day-to-day life of the elderly person. The developed system consists of two basic modules. At the low level module, Wireless sensor network of mesh structure exists for capturing the sensor data based on the usage of house hold appliances and stores the data in the computer system for further data processing. Collected sensor data is of low level information containing only status of the sensor as active or inactive and identity of the sensor. To sense the activity behavior of aging persons in real time, the next level software module analyzes the collected data by sensors attached to the house hold appliances as well as simultaneously analyzing the wellness of the elderly to foresee unusual changes both physiologically and physical activities. The investigation on the real time sensor status monitoring with the double check mechanism indicates the reduction of false alarms and optimally predicting the irregular behavior of the elder care.

Authors in [23, 24] suggested incorporating elderly concurrent activities in the proposed behavior recognition model. Also, they suggested to widely apply the classification model of regular and irregular sensor activity to the generated activity pattern and to include other sensors in order to study highly structured behavioral pattern for more precise abnormal detection.

In [25], authors proposed a hierarchical-based architecture for healthcare monitoring applications. The proposed healthcare monitoring architecture is coupled with wearable sensor systems and an environmental sensor network for monitoring elderly or chronic patients in their residence. The wearable sensor system, built into a fabric belt, consists of various medical sensors that collect a timely set of physiological health indicators transmitted via low energy wireless communication to mobile computing devices. Also, the group-based data collection and data transmission using the ad hoc mode promote outpatient healthcare services for only one medical staff member assigned to a set of patients. Moreover, adaptive security factors for data transmission are performed based on different wireless capabilities. The implemented schemes were verified as performing efficiently and rapidly in the proposed network architecture.

Authors in [26] explored the collaborative detection of body behavior modes and accidental falling incidents by using collaborative sensors. Information is provided by sensors distributed over the body that transmit positions to analyze and recognize human motion. Under gravity, direction of force on each limb of the body varies. These characteristics are utilized to study the collaborative detection of sensors. As everyone has different living habits, manifestations of poses will differ as well, therefore, an adaptive adjustment model has been used to detect elderly body postures more accurately in order to detect falls. Authors in [26] reported lack of correctly determining the situation of body after collision, hence they suggested applying gyroscope to reconstruct the falling situations.

On the other hand, some research work has been done recently to detect falls using camera-based surveillance systems and image processing techniques. A simple method was used in [27, 28] based on analyzing aspect ratio of the moving object's bounding box. This method could be inaccurate, depending on the relative position of the person, camera, and perhaps occluding objects.

In [27], human motion in video is modeled using Hidden Markov Models (HMM) in addition to using the audio track of the video to distinguish a person simply sitting on a floor from a person stumbling and falling or in other words to use the impact sound of a falling person as an additional clue of a fall and to avoid false alarms. Audio channel data based decision is also reached using HMMs and fused with results of HMMs modeling the video data to reach a final decision. Video analysis algorithm starts with moving region detection in the current image. Bounding box of the moving region is determined and parameters describing the bounding box are estimated. In this way, a time-series signal describing the motion of a person in video is extracted. The wavelet transform of this signal is computed and used in HMMs, which were trained according to possible human being motions. It is observed that the wavelet transform domain signal provides better results than the time-domain signal because wavelets capture sudden changes in the signal and ignore stationary parts of the signal. The proposed approach has been proven to be computationally efficient and can be implemented in real-time. However, due to using a low cost standard camera instead of an omnidirectional camera, similar to the one used in [29], it is hard to estimate moving object trajectories in a room. So, authors concluded that the proposed fall detection method proposed in this research can achieve a better performance, if an omnidirectional camera is available. In [29], the use of ’unusual inactivity’ detection as a clue for fall detection is demonstrated. Motion trajectories extracted from an omnidirectional video are used to determine falling persons, however without considering audio information to understand video events. In [25], the person was tracked using an ellipse and inferring falling incident when target person is detected as inactive outside normal zones of inactivity like chairs or sofas. The tracker uses a coarse ellipse model and a particle filter to cope with cluttered scenes with multiple sources of illumination. Summarization in terms of semantic regions is demonstrated using acted scenes through automatic recovery of the instructions given to the subject.

Authors in [28], proposes a vision-based fall detection system for the elderly and patients at home or in health-care centers. Similar to the system proposed in [29], the system proposed in [28] uses an omnidirectional camera to avoid blind spot (where no light rays captured). The recognition features proposed for the system include angle and length variation associated with the body line and motion history images. Given these features, a simple thresholding and decision tree technique is adopted for fall detection. Experimental results show that the proposed system can solve the problems of light source glimmer and static abandoned objects. The system successfully recognized most fall events, however it disregard the type of falling as recognition errors occur when a normal walking person is classified as being falling.

Also, in both [30] and [31], authors used the normalized vertical and horizontal projection of segmented object as feature vectors. So, in [30], a method was proposed to detect various posture-based daily life and unusual events in a typical elderly monitoring application in a video surveillance scenario with a particular interest to the problem of fall detection. The proposed approach provided a useful clue for detection of different behaviors via applying a combination of best-fit approximated ellipse around the human body, projection histograms of the segmented silhouette, and temporal changes of head position. Then extracted feature vectors are fed to a MLP Neural Network for precise classification of motions and determination of fall event. The main advantage of the proposed system in [30] is that is able to detect type of fall incident (forward, backward or sideway), while most existing fall detection systems are only able to detect occurrence of fall behavior. The approach proposed in this research has been applied to a dataset of videos in a simulation environment and nothing has been mentioned regarding time or computations cost/complexity for the system to be applied in real life environments.

Authors in [31] used a similar approach in addition to considering the k-Nearest Neighbor (k-NN) algorithm and evidence accumulation technique to infer human postures for fall detection. Furthermore, they used the speed of fall to differentiate real fall incident and an event where the person is simply lying without falling. Authors concluded that due to evidence accumulation technique, an event will not be instantaneously detected; however it takes on an average of 8 frames to accumulate enough evidence of fall detection.

Falling detection has been tackled from another point of view in [32], where a smart solution has been proposed for patients with heart disease that face continuous examination in the medical center under stress by using particular injections that cause elevated heart rate and boost of body temperature with frequent fainting. The goal of the proposed mobile system in [32] was to enable heart disease patients of moving freely without having to be accompanied by nurses while moving within the medical center. The proposed automatic system provided having all patients continuously monitored and under control and the intervening by caregivers is only when necessary. That has been done via continuously monitoring heart rate and accelerometer data to detect both abnormal cardiac accelerations and abnormal movement of patients. The components of the proposed system are the monitor ECG and accelerometer parts of Alive Heart Monitor [33] sensor, which is a wireless health monitoring system for screening, diagnosis and management of chronic diseases, the Alive Pulse Oximeter Monitor [33] sensor, which is a wearable medical device using wireless technology instead of inconvenient cables for reading oxygen saturation data and transmits the data via Bluetooth wireless technology to a mobile Bluetooth-enabled device, and the IP-camera for indoor monitoring for video surveillance of patients within the healthcare center. The previous components were operated along with the fall detector module that is based on threshold-based algorithms [34], which attempt to identify movements that are potentially harmful or indicative of immediate danger to a patient. The testing of algorithm for fall detection has been successful to trigger no false alarms even when attempting to trigger false positives with normal exaggerated movements, the algorithm generates no alarms. In [35], authors moved to another monitoring method via developing a distributed sensor network that provides health and wellness services to the elderly through a fall detection application that constantly tracks people as they move about the living environment in view of the multiple cameras. At every frame of a person's motion, several features are extracted and fused with features from previous frames. This sequence of features is analyzed using one of several techniques to determine if a fall has occurred. If a fall is detected, the alert procedure is initiated. Authors not only presented the design and preliminary implementation of a distributed smart camera application for fall detection but also another smart camera application for object finder has been proposed. So, the proposed approach in [35] approach is providing a different technique that is based heavily on video data, whereas other solutions, as previously mentioned, require devices that must be worn or attached to objects. The fall detector in the proposed approach relies on features, extracted from video by the camera nodes, which are sent to a central processing node to detect a fall via applying one of several machine learning techniques. On fall detection, alerts are triggered both in the home and to a third party (caregiver or somebody to help).

Similarly, the object finder uses a boosted cascade of classifiers to visually recognize objects either on user's request or automatically when an object is moved. However the main drawback with the object finder proposed module is not being able to locate an object out of view of any camera. So, for future work they considered incorporating RFID-based object localization into the system. In 2009, authors of [36] presented an approach, called iFall, for a fall detection alert system using common commercially available electronic devices (smart phones) to both detect the fall and alert authorities. The proposed prototyped application is designed using the Android HTC G1 smart phone with an integrated tri-axial accelerometer. Data from the accelerometer is 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 cellphone 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 users response. If the user does not respond, the system alerts pre-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 speaker-phone. If a social contact confirms a fall, an appropriate emergency service is alerted. Similarly, in 2010, authors in [7] proposed a system utilizing mobile phones as the platform for pervasive fall detection system development via combining both the detection and communication components. The minimum requirement for such a mobile phone platform is also the presence of a simple accelerometer sensor (integrated in the smart phone). The proposed prototype pervasive fall detection system, named PerFallD, was designed and implemented on an Android G1 phone mobile platform to conduct fall detection. The application works as a background daemon, so if a fall is detected, the daemon service transmits a signal that triggers an alarm and starts a timer. If the user does not manually turn off the alarm within a certain time period, the system automatically and iteratively calls and/or texts contacts (up to five contacts) stored in the emergency contact list according to their priorities. PerFallD has been proved to be available in both indoor and outdoor environment. Authors of PerFallD suggested enhancing its performance by integrating it with some extra protection devices, e.g., airbag based fall protector to reduce fall impacts and prevent fall related injuries. Concerning fall detection approaches based on the technology of smart phone devices and regarding the argument that elderly people may not accept such mobile phones, authors claimed that elderly people may prefer to have a single phone with self-contained fall detection functionality than to carry a separate fall detection device on their bodies. One main advantage of using a smart phone, is that the user is more likely to carry the phone throughout the day since it seen as indispensable in daily living, whereas users may forget to wear special micro sensors [37].

Generally, many authors proposed approaches for capturing images of people and then detect visual fall based on image processing techniques. However, such approaches still having challenges and limitations on pervasive detection affordability and acceptability. That’s due to many reasons such as the detection area is limited within monitoring environment, which is costly to build up. Also, the people’s privacy is compromised. Moreover, visual fall detection is inherently prone to high levels of false positive (a fall might not be a real fall, but a deliberate movement towards the ground) as most of current systems are unable to 100% discriminate between context-base events such as real fall incident and an event when person is lying or sitting down abruptly. Furthermore, existent fall detection systems tend to deal with restricted movement patterns and limited normal scenarios like walking; however in real indoor environments various normal /abnormal motions occur.

Table 1: A summary of the surveyed fall detection research work

| Reference | Proposed approach | Contributions | Challenges |
|---|---|---|---|
| [7] | *PerFallD*: A Pervasive Fall Detection system using mobile phones | Uses Android G1 phone mobile platform to conduct fall detection, the system automatically and iteratively calls and/or texts emergency contacts according to priorities on fall detection, available in both indoor and outdoor environment | Mobile phones limited battery and affordability, false alarms, integrating the system with some extra protection devices, e.g., airbag to reduce fall impacts |
| [12] | Wearable fall detection monitoring system for the elderly | Distinguishes between fall and non-fall events, provides visual, audio, and tactile fall alerts | Some actions have not been successfully distinguished to be falls/non-falls, as a wearable device, old people tend to forget wearing it, produces false alarms |
| [13] | Wearable fall detection monitoring system based on TEMPO 3.0 sensor nodes [14] | Applies both tri-axial accelerometers and gyroscopes, improves fall detection accuracy, reduces both false positive and false negative alarms | Facing difficulties in differentiating actions that need context information |
| [15] | *WAMAS*: Wearable Accelerometric Motion Analysis System | Measures head motion via 3-axis sensors attached to both corners of eyeglass frames and two more above the hips at the waist, warns the wearer of pre-fall behavior | As a wearable device, old people tend to forget wearing it, needs lighter weight, digital input, voice output improvements |
| [16] | *SPEEDY*: a wrist wearable watch-like fall detector | Easy to wear, smaller than the system proposed in [15], analyzing walking activity | The complexity of the fall detection algorithm, not all fall situations are detected with the same certainty, as a wearable device, old |

| Reference | Proposed approach | Contributions | Challenges |
|---|---|---|---|
| | | | people tend to forget wearing it |
| [18] | An accelerometer mote based on the design of the *Ivy* [19] sensor networked infrastructure | Small and lightweight device worn on the waist, detects the location of the falling person via RF signal strength | Design should consider customization as amplitudes and frequencies of movement vary with the size and weight of the wearer |
| [23, 24] | An intelligent home monitoring unit based on ZigBee wireless sensors | Continuously monitoring day-to-day life appliances, Foresee unusual changes both physiologically and physically, Reducing false alarms and predicting the irregular behavior. | Apply the classification model to regular and irregular sensor activity patterns, consider incorporating elderly concurrent activities and highly structured behavioral patterns in the proposed behavior recognition model |
| [25] | A hierarchical-based architecture for healthcare monitoring applications in Wireless Heterogeneous Networks. | Wearable (built into a fabric belt) sensor systems, environmental sensor network for outdoor elderly/chronic-patients monitoring, group-based monitoring and assistance, adaptive security factors for data transmission | Fabric-belt wearable sensor system, performance issues of Bluetooth security and polynomial-based encryption |
| [26] | Collaborative multi-sensors based system for adaptive body posture analysis | Collaborative sensors based detection of body behavior modes and accidental falling incidents, adaptive adjustment model to detect elderly body postures | Sensors distributed over the body that transmit positions, cannot correctly determine the situation of body after collision, applying additional gyroscope sensors to reconstruct the falling situations |
| [27] | Vision-based fall detection system for the elderly | Models human motion and audio track of the video using HMMs, avoids false alarms via using the impact sound of a falling person | Hard to estimate moving object trajectories, inaccurate detection depending on the relative position of the person and camera, occluding objects, requires using omnidirectional camera |
| [28] | Omnidirectional vision-based surveillance system | Analyzes aspect ratio of the moving object's bounding box, uses omnidirectional camera to avoid blind spot | Disregards the type of falling |
| [29] | Omnidirectional video camera based surveillance system | Uses 'unusual inactivity' as a clue for fall detection, uses a coarse ellipse model and a particle filter to | No audio information considered |

| Reference | Proposed approach | Contributions | Challenges |
|---|---|---|---|
| | | handle multiple sources of illumination | |
| [31] | A video surveillance application for elderly monitoring using a dataset of videos | Uses normalized vertical and horizontal projection of segmented objects as feature vectors, uses k-NN algorithm and evidence accumulation technique to infer human postures for fall detection, uses the speed of fall to distinguish real fall event | Delay in fall detection due to evidence accumulation technique |
| [30] | A video surveillance application for elderly monitoring using a dataset of videos | Detects type of fall incident (forward, backward or sideway), uses horizontal projection of segmented objects as feature vectors | Time and computations cost/complexity for the system to be applied in real life environments are not proven |
| [32] | A mobile system for monitoring heart disease patients while moving freely in indoor environments | Continuous ECG and accelerometer data monitoring, detects both abnormal cardiac accelerations and abnormal movement of patients, wireless communication among system components, limited false alarms | Special purpose system based on the *Alive* [33] wireless health monitoring sensors |
| [35] | A distributed sensor network for constantly tracking the elderly through a fall detection application | Proposes additional smart camera application for object finder, applies machine learning techniques for fall detection, alerts are triggered both in the home and to a third party on fall detection | Incorporating RFID-based object localization devices into the system |
| [36] | *iFall*: An Android application for fall monitoring and response | Uses Android HTC G1 smart phone with an integrated tri-axial accelerometer, uses adaptive threshold based on user provided parameters, an automatic notification is raised on fall event alerting social contacts via SMS and alerting emergency service | Mobile phones limited battery and affordability, false alarms |

## IV. FALL DETECTION AND PREVENTION COMMERCIAL SOLUTIONS

Recently, the number of proposed fall-detection systems developed has increased dramatically [2]. In an aging society, the elderly can be monitored with numerous physiological, physical, and passive devices.

Many monitoring and fall prevention commercial products are now available in the market, each with its pros and cons. Sensors can be installed in the elderly wearable or hand-held device or even in elderly resident room at home or health care facility for continuous mobility assistance and unobtrusive fall prevention. In the last years, there have been many commercial solutions aimed at automatic and non-automatic detection of falls such as the wearable fall detectors that are based on combinations of accelerometers and tilt sensors.

Also, several products, attempting to address the problem of fall detection and help elderly people requesting help when fall, are already existed on the market and have reached commercialization [38–40]. Most of the already available products provide pendant or wristband help button in order for the patient to be able to call for help when fall and become totally helpless [12].

Figure 3 depicts pendant and wristband help button facilities. Critical problems are associated with those solutions like non-automatic buttons is often unreachable after the fall and old people tend to forget wearing them frequently [41]. Moreover, most automatic wearable devices produce many false alarms.

Other hand-held, movement-sensing, and anti-wondering solutions have been proposed with their own contributions as well as having several drawbacks facing each of them. This section presents and summarizes several modern commercial sensors and research approaches and prototypes, which tend to improve the quality of life and assist the elderly and their caregivers for preventing falls and consequent injuries in the elderly.

### a. Wearable and hand-held solutions

Many proposed approaches, based on the technology of accelerometers and gyroscopes, have been proposed for tackling the fall detection and prevention issue. The accelerometer is a device that can detect the magnitude and direction of acceleration along a certain axis [12].

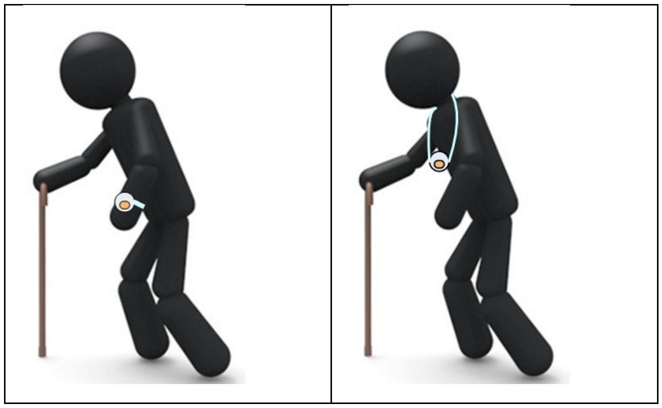
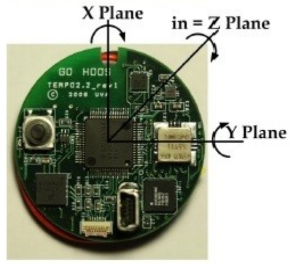


Figure 3. Pendant and wristband help buttons

Using tri-axial accelerometers with applying thresholds, is one of the most common and simple methodology for objectively monitoring a range of human movements as well as fall detection [32–44].

So, any motion that exceeds some threshold value of acceleration will be considered a fall. As when a person falls, their orientation often changes from vertically standing to horizontally lying on the floor. Hence, analyzing post-fall orientation, in addition to acceleration threshold, is an important approach to be considered. Also, taking the dot product or cross product of the axial accelerations to obtain the cross product magnitude and angle change is considered as more advanced fall detection approach [45]. Researchers generally agree that optimal fall sensor placement on the body is at the waist [44, 46]. The gyroscope, which is a device measures orientation, consists of a spinning wheel whose axle is free to take any orientation [43]. Like an accelerometer gyroscope can measure the orientation along one or multiple axes. Using gyroscopes with a similarly-placed gyroscope that measures pitch and roll angular velocities with applying a threshold algorithm to angular change, velocity, and acceleration, can be successful in fall and tilt detection [43, 47].

Figure 4 (a) shows the TEMPO (Technology-Enabled Medical Precision Observation) 3.0 sensor node for tri-axial accelerometer and Figure 4 (b) illustrates the placement of two TEMPO 3.0 nodes [13, 14].



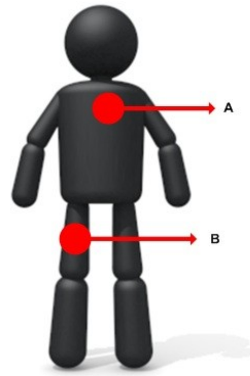




Figure 4. Tri-axial accelerometer TEMPO 3.0 sensor node [13, 14] and placement

Figure 5. Airbag based fall-detection system for preventing fall-related injuries [48]

In [48], a wearable airbag has been developed that incorporates a fall-detection system using both acceleration and angular velocity signals to trigger airbag inflation, as shown in Figure 5 [48, 49]. The fall-detection algorithm was devised using a thresholding technique with an accelerometer and gyro sensor. The fall-detection algorithm could detect signals 300 ms before the fall. This signal was used as a trigger to inflate an airbag to a capacity of 2.4 L. Although the proposed system can help to prevent fall-related injuries, further development is needed to miniaturize the inflation system.

For addressing the issue of falling in the elderly, several commercial devices already exist on the market such as the iLife fall detection sensor by AlertOne [38]. The iLife sensor is a self-contained, battery operated, wireless fall sensor worn on the body with a belt clip to detect falls or abnormal body movements and automatically call for assistance without end-user intervention; it also has a manually activated button for summoning help. However, the commercial iLife device has been found out to have several weakness points, compared to another research based proposed device such as the device proposed in [12]. The iLife sensor uses only accelerometers and thus only acceleration based algorithms, however device proposed in [12] applies a hybrid approach of both accelerometer and gyroscope. Other differences are that the iLife system has only one LED for visual confirmation of activation; it has no audio or tactile alert for the seeing/hearing-impaired and does not facilitate a cancel feature as in [12].

b. Movement-sensing solutions

On the other hand, concerning the commercialized fall monitoring and prevention products, another classification is to categorize products into movement-sensing monitoring solutions and anti-wandering solutions. Figure 6 summarizes the main products under each category that will be further discussed in more details.

b.i Weight-sensitive reverse pressure pads

For bed, chair, and toilet fall monitoring, there are weight-sensitive reverse pressure pads. When connected to a fall/mobility monitor, the pressure pad will trigger the monitor, or the wireless transmitter if using a wireless system monitor, when weight is removed from the pressure pad.

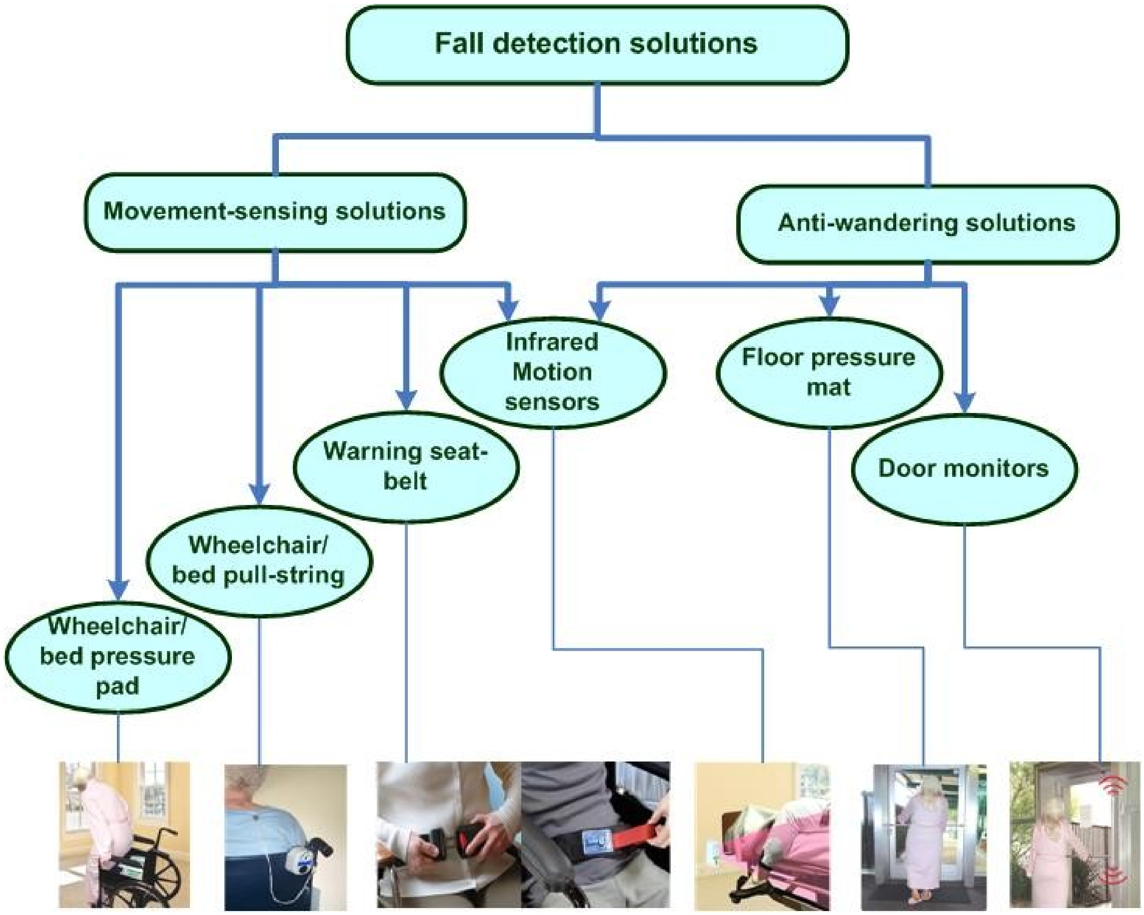



Figure 6. Categories of commercialized fall monitoring and prevention products

When a wireless system monitor is used, it sends a signal to the central monitor unit informing the caregiver of the activated reverse pressure pad. Most of the time, an optional wireless alarm light is also available for this system. The main drawbacks of reverse pressure pads based fall monitoring systems are related to maintenance issues, where it's not advisable to fold or immerse pressure pads in any solutions and they should be wipe-cleaned only by using disinfectant wipes or anti-bacterial cleaner, in addition to the cost of frequent replacing for pads when the warranty period expires [50]. Figure 7 shows an example of weight-sensitive reverse pressure pads.

b.ii Wheelchair/bed pull-string monitor

The pull-string fall monitor attaching a string to patient clothing which alerts caregivers when the patient tries to get up. It features a magnet-positioned cord, so when the resident attempts to get out of their chair, the tension on the pull string cord causes the magnet to pull away from its position, causing the fall alarm to sound, alerting the caregiver of the resident's departure. Adjust the cord stop to the desired pull-string length for the resident's comfort and also to prevent false alarms [50].

Figure 8 shows an example of wheelchair pull-string monitor. The main drawback of pull-string fall monitoring device is that sometimes elderly people feel uncomfortable having some cord/string attached to their clothing in addition to that the pull cord can somehow get tangled. As well, there still a possibility of false alarms even with a suitable length of the device cord as it can be detached by mistake from patient clothing.

b.iii Non-restraint wheelchair seat-belts

These wheelchair seat-belts are available in two types, namely Easy-Release-Buckle and Quick-Release-Hook and Loop wheelchair seat-belts. Both types of wheelchair seat-belts are not designed to restrain or hold individuals in position in their chairs, whereas to reduce falls by triggering a fall monitor mounted to the chair to signal a caregiver pager when the easy release buckle is unbuckled or the Hook and Loop strap is opened and inform the caregiver of which resident's seatbelt was opened. Wheelchair seat-belts can also be set up as a wireless fall monitoring system that trigger the wireless system to signal a caregiver pager directly with no central monitor required. Moreover, an optional wireless alarm light is also available for this system. The main drawback of wheelchair seat-belts based fall monitoring is the limited applicability to wheelchairs only. Figure 9 shows an example of wheelchair pull-string monitor [50].

c. Anti-wandering solutions

c.i Door alarm bars

The function of the anti-wandering door alarm system is based on two components, namely the door alarm bar and the resident's wristband. So, when the resident hangs the door alarm bar, attempting to wander too close or through the exit or doorway in the care facility, this will act like plugging the resident's wristband in door alarm bar. Accordingly, the door alarm sounds audibly and visually.

Figure 7. An example of weight-sensitive reverse pressure pads [50]

Figure 8. An example of wheelchair pull-string monitor

Figure 9. An example of wheelchair non-restraint seat-belts [50]

The caregiver can silence the alarm using a caregiver key. This system can also be used with a central monitoring unit that alarms at a nurse's device and displays the doorway and resident that set off the door alarm [50]. Figure10 shows an example of the anti-wandering wristband based door alarm system. The main drawback of the door alarm based fall monitoring is that it's only functioning when the resident hangs the door alarm bar, attempting to wander through the doorway. However, if the resident gets up from his/her bed and tried to wander in the room within a distance sufficiently far from the doorway, the alarm will not be triggered.

c.ii Weight-sensing floor mats

This fall monitoring system is based on sensing floor mats that alarm when stepped on. Weight sensing floor mats, which may be placed at the side of a bed, hallway or in a doorway, trigger fall monitors, central monitors or caregiver pagers to alert when weight is placed on the floor mat meaning that a resident arises or attempts to depart. So, on the contrary of the reverse pressure pad that activates when weight is removed from it, weight-sensitive pressure floor mats are weight-sensitive floor coverings that activate when stepped on. The available weight-sensing floor mats can be configured in three different ways; cordless with wireless transmitter fall monitor, corded with wireless transmitter fall monitor, and corded with corded local fall monitor floor mats. The first type works wirelessly with central monitors and caregiver pagers with no cords to trip on with cordless products, and caregivers may freely place them in the bedside or doorways. The second type wirelessly signals a caregiver pager and/or the central monitor allowing caregiver paging directly from the floor mat with no central monitor required and an optional wireless alarm light is also available for this system. The third type provides a configuration where the floor mat plugs directly into the fall monitor [50]. Figure 11 shows an example of weight-sensing floor mats placed at the side of a bed and in a doorway.

The main drawback of the weight-sensing floor mats based fall monitoring is that they are effective in detecting movement over ground-area where they are placed, however they may be suited as one component of a more comprehensive fall prevention monitoring system in conjunction with other measures such as other motion sensors/detectors, like ultrasound, passive infrared (PIR) sensing units, etc.

Figure 10. An example of the anti-wandering wristband based door alarm system

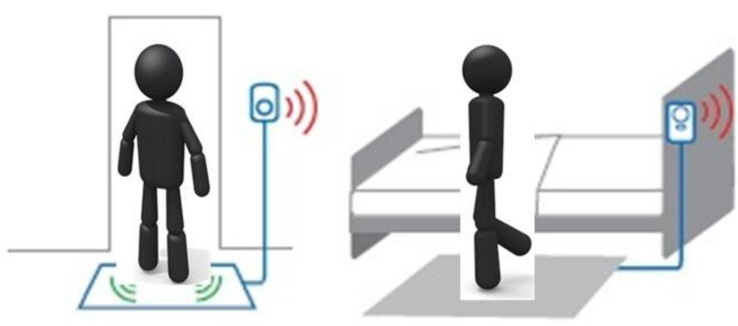


Figure 11. an example of placing weight-sensing floor mats

c.iii Anti-wandering wireless motion sensors/detectors

(1) Wireless passive infrared (PIR) fall alarm monitor: The PIR sensor, which is used as ”motion detector”, is a compact fall monitor that has a detecting area to report movement when the passive infrared field is interrupted. When positioned along the bedside the fall monitor will alarm as the resident attempts to vacate the bed. When positioned by a door the fall monitor will alarm as the resident approaches the doorway, which may help to prevent the resident from moving and accordingly falling [50].

(2) Wireless fall alarm monitor, receiver, and pager: Another type of PIR motion detectors, which provides noise reduction in health care centers by moving the alarm noise outside of the room via having a detecting area of the fall monitor to report movement when the passive infrared field is interrupted. The first way to achieve moving the alarm noise outside of the room this is that instead of sounding at the motion sensor itself, the motion sensor sends a wireless signal to the receiver, which can be located to alarm inside or outside the room where the motion sensor is located. Another option is that the motion sensor sends a wireless signal to the caregiver pager allowing the caregiver to be notified wherever they are without disturbing residents [50]. The main drawback of all types of PIR motion detectors is false alarms when the resident is sleeping and moving his/her leg, hand, cover etc. to interrupt the PIR device field in an unintended manner. Figure 12 shows an example of PIR motion sensor wirelessly signaling the caregiver pager on detecting resident’s movement.

A major problem with both existing commercial products and academic research is that they have deficiencies that hinder pervasive fall detection. For example, for most existing products, the base station must be installed somewhere indoors and the portable sensor must be attached to the patient or to the location where the patient usually resides. Hence, once the base station receives the signal from the sensor indicating a fall, it can automatically communicate with a preset emergency contact using the phone/pager. However, the maximum distance between the sensor and the base station is always limited.

So, fall detection can only be conducted within a small indoor environment. So, it would be ideal, though more expensive, solution to combine several of the previously discussed motion detection system components for achieving more extended connectivity among monitoring devices in addition to have them collaboratively and accurately send an alarm for the caregiver on the movement of an elderly resident in order to accordingly help that resident and prevent him from falling.

Figure 12. Wireless signaling between PIR motion sensor and the caregiver pager

## V. CONCLUSIONS AND FUTURE DIRECTIONS

Increased awareness of the occurrence of falls among the elderly and enrollment of efforts to prevent or diminish such events are highly needed in order to improve the quality of life for elderly people and provide them with convenient fall detection and prevention techniques.

Despite the considerable achievements that have been accomplished on the field of providing multiple solutions for elderly fall monitoring, detection, and prevention in the recent years, there are still some clear challenges to overcome. Typically, drawbacks previously stated while surveying various types of research and commercial fall detection and prevention solutions, are considered as open issues that have to be considered for further research. Also, regarding detection of falls using camera-based surveillance and image processing techniques [30], there still some difficulties to overcome. One of those difficulties is the fact that visual fall detection is inherently prone to high levels of false fall detection as what appears to be a fall might not be a real fall, but a deliberate movement towards the ground. In other words, most of current systems [28, 51–53] are unable to discriminate between real fall incident and an event when person is lying or sitting down abruptly. Also, existent fall detection systems tend to deal with restricted movement patterns and fall incidents to be detected, whereas in real indoor environments various normal/abnormal motions occur. Other systems, as in [54], used the audio information or using 3D trajectory and speed of head to infer events. These mechanisms tend to be more complex and need extra additional costs. Moreover, using the accelerometer sensor technology integrated in smart phones for fall detection has numerous advantages in cost and capability of the system [36]. However, unfortunately, it may be difficult to convince users to mount the phone to various body parts in order to improve fall detection rate [55]. Also, actions such as raising the phone to the user's ear to start a call and lowering the phone from the user's ear to end a call may highly affect the phone's ability of having correct fall detection. So, the software applications must dynamically adjust to different locations and methods of carrying the phone. This requires the software to classify acceleration parameters of general use to identify the correct parameters for the fall detection logic.

Furthermore, the area of behavior determination, which is focused on building a behavioral profile of the aging patient and monitoring deviations appearance from the model, is still widely open for further research work. Behavior determination is heavily based on activity recognition and location tracking that detects a typical behavior, which might be caused by decreased health status, progressing disease, or emergency situation [56–58]. Another challenge is that despite understanding to a great extent the causes of most falls, there is still no many methods to accurately predict that a fall event is likely to occur.

Generally, all monitoring algorithms and approaches for fall detection and prevention relying on only one data provider (movement-sensor, camera, accelerometer, etc.) have their own limitations and do not ensure 100% reliability [6]. In fact, preventing falls and injuries is difficult because they are complex events caused by a combination of intrinsic impairments and disabilities with or without accompanying environmental conditions. Algorithms for fall detection for several environments and the subject's physical condition were rather troublesome; however, a combination of movement sensors and signal-processing technologies can provide more accurate and precise fall detection and prevention approaches. Data fusion based on multi-sensing technology [59–61] offers many challenges for providing more accurate approaches for fall detection and prevention. Multi-sensor data fusion is the area focusing on creating multi-modal systems, which receive data from several providers and perform correlation or fusion upon it in order to increase the accuracy and reliability of the proposed systems. Moreover, combining multi-sensing data fusion technology with prediction technologies such as Machine Learning and

Artificial Intelligence approaches will support developing intelligent fall prevention system based on fall prediction.

Finally, elderly people in long-term care centers or aging persons with cognitive impairment, who have not widely considered in this survey, are as well at high risk of falling and more specialized technology solutions must be developed specifically for these populations.

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