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

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].

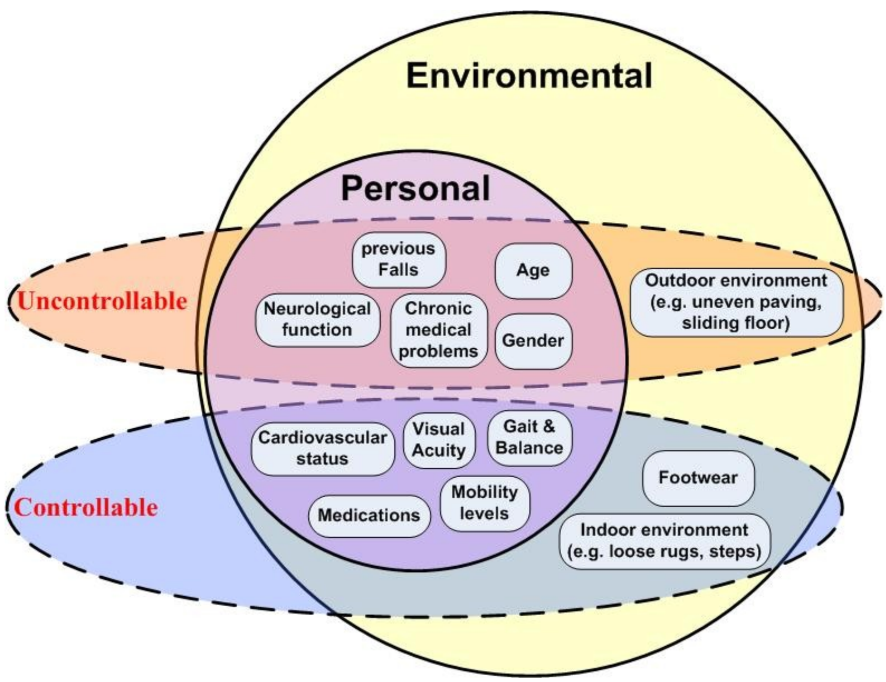

Figure 1. Categories of common reasons causing falls

b. Consequences

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.

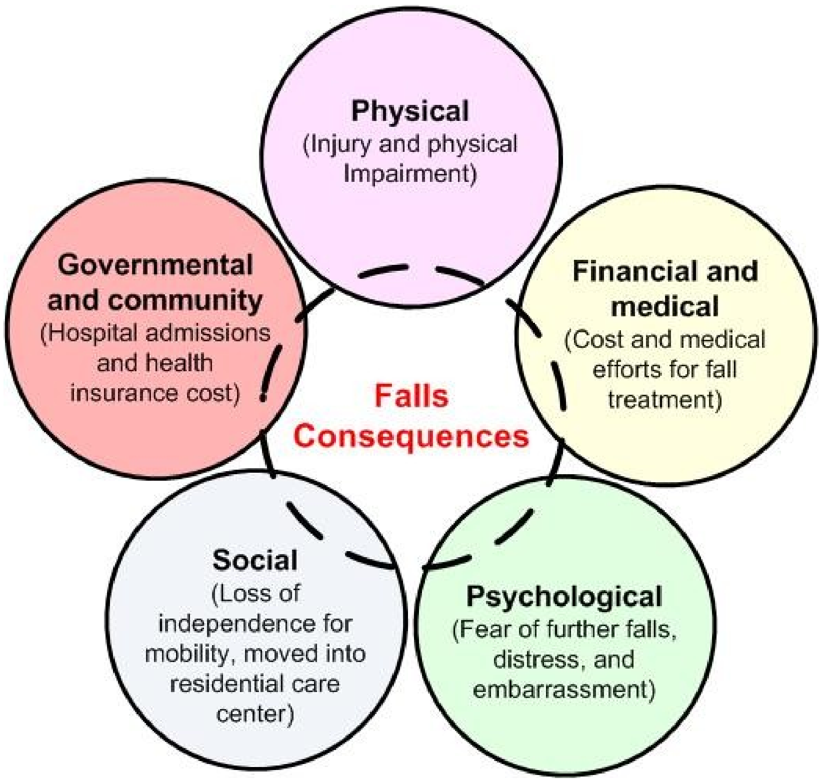

Figure 2. The main consequences related to elderly falling

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

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

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

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

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

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
		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

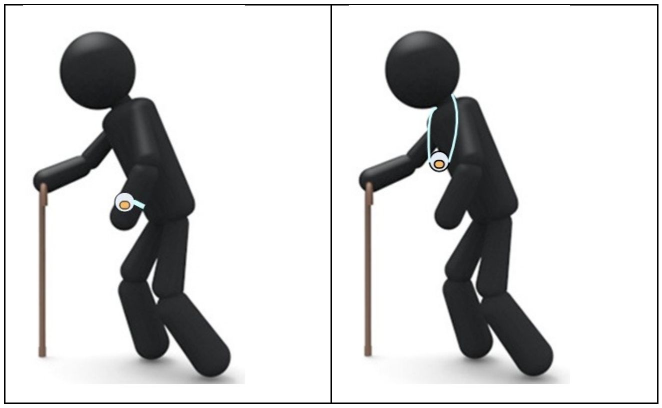

Figure 3. Pendant and wristband help buttons

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].

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.

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,

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

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

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

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