From Fall Detection to Fall Prevention: A Generic Classification of Fall-Related Systems

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***Abstract*—Falls are a major health problem for the frail community dwelling old people. For more than two decades, falls have been extensively investigated by medical institutions to mitigate their impact (e.g., lack of independence and fear of falling) and minimize their consequences (e.g., cost of hospitalization and so on). However, the problem of elderly falling does not only concern health-professionals but has also drawn the interest of the scientific community. In fact, falls have been the object of many research studies and the purpose of many commercial products from academia and industry. These studies have tackled the problem using fall detection approaches exhausting a variety of sensing methods. Lately, researcher has shifted their efforts to fall prevention where falls might be spotted before they even happen. Despite their restriction to clinical studies, early fall prediction systems have started to emerge. At the same time, current reviews in this field lack a common ground classification. In this context, the main contribution of this paper is to give a comprehensive overview on elderly falls and to propose a generic classification of fall-related systems based on their sensor deployment. An extensive research scheme from fall detection to fall prevention systems have also been conducted based on this common ground classification. Data processing techniques in both fall detection and fall prevention tracks are also highlighted. The objective of this paper is to deliver medical technologists in the field of public health a good position regarding fall-related systems.**

***Index Terms*—Falls, fall detection, fall prevention, early-fall detectors, classification.**

I. Introduction

Aging is a natural, progressive and heterogeneous process to all living species. In humans, the aging process is characterized by different aspects (morphological, pathophysiological, psychological, social and environmental) that are commonly investigated in "gerontology". At these levels, age is measured by the functional abilities of the person. The health status of an elderly person is therefore the result of the additive effects of aging as well as the attained diseases. This situation will lead the elderly to a state of "unstable incapacity" for "normal aging" [1]. It is characterized by a reduced reaction to the environment and to certain pathologies with obvious decrease of autonomy and integration in Activities of Daily Living (ADL). It has major effects on most of the systems (e.g. nervous, metabolic, sensory, cardiovascular, respiratory, musculoskeletal, etc.). These effects are more observable in the musculoskeletal system in terms of locomotion and mobility [2]. The result is a general physical and functional weakening which will eventually increase the risk of fall incidents.

Falls are considered among the most hazardous incidents that can strike an elderly person. They are the second leading cause of unintentional death estimating 424000 deaths globally [3]. Despite their inevitable risk, falls could be managed, detected and even prevented if proper means are administered to the patient. These incidents require both human and technical interventions. This double support is accounted for "gerontechnology". The outcome of this discipline shall be measured in terms of gain of independence and improved quality of life [4].

Fall-related technology can be contextualized according to two research tracks: (1) Fall Detection (FD) and (2) Fall Prevention (FP). Research in fall detection has been exhaustively explored; however, fall prevention is currently under investigation. in one hand, wearable and non-wearable systems have started to be deployed and gone commercial. These systems use different types of sensors to collect motion and environmental data for further processing and analysis. On the other hand, large reviews and surveys on fall detection and fall prevention also started to appear. It can be noticed that these reviews lack a common ground classification. From this standpoint, the main basis of this article is the elaboration of a common ground classification for existing fall-related systems according to their sensor deployement. The objective is to offer researchers a standpoint from existing FD and FP solutions that have been developed in academic and commercial facilities. The article also gives a state of art on existing fall-related systems in both tracks.

The remaining of this article is organized as follows. Section II formulates the problem of falling. It states the definition of falls and summarizes their major causes and consequences. It also emphasizes the importance of technological intervention in minimizing the consequences of these incidents. Section III proposes a common ground

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three-category classification of fall-related systems based on their sensor deployment. These are categorized into wearable, non-wearable (or context aware) and fusion based systems. Smart-phone based systems are also considered in this classification. A state of the art on fall detection and fall prevention systems is developed in sections IV and V. Section VI concludes the paper.

II. Understanding Elderly Falls

Understanding fall incidents, their causes and their consequences would serve researchers, engineers and health practitioners to develop systems and devices to detect and prevent these hazardous incidents. The goal is to provide the elderly with more independence and an improved quality of life.

A. Background on Elderly Falls

Falls are defined by Kellog International working group as *"inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects"*. According to the WHO, the magnitude of falls is increasing worldwide. In fact, approximately 28-35% of people aged of 65 and over fall each year increasing to 32-42% for those over 70 years of age [3]. These numbers are likely to grow with age, frailty level, pathological history and living conditions (e.g. falls happen more often in nursing homes or long term institutions). The frequency of falls is also affected by the growing number of elderly. It is estimated that by the year of 2050 one or more in each group of five people will be aged 65 years or above [5]. This demographic change will induce a high rate of fall related injuries (e.g. falls lead to 20-30% of mild to severe injuries and are the cause of 10-15% of all emergency visits [3]). Thus, this increasing weight of demographic change levies new challenges on socio-economic levels if appropriate measures are not taken to tolerate the impact of this inevitable ageing and its associated fallouts.

B. Causes of Falls

The causes of falls are often the result of complex interactions among many factors. Skelton et al. in [6], have identified more than 400 factors that contribute to a fall. Campbell, Borrie et al. in [7], said that elderly falls result from the effect of additive factors. Thus, screening the factors may help reduce the risk of falling. In fact, the risk of falling and the number of factors are linearly correlated [8].

Risk factors are often classified in three dimensions. There are factors related to the behavior, other factors are connected to the health status of the elderly and finally factors linked to the environment (extrinsic factors). The first two dimensions can be merged together. They score the factors associated to the person (intrinsic factors). Falls happen because of the interaction among these dimensions as illustrated by Fig.1. The more the link between these factors is identified, the more medical professionals are able to reduce the risk of falling. For the rest of this section, we will consider the two-dimensional classification of the risk factors.

Fig. 1. Three-level impact of fall consequences.

TABLE I
Classification of Fall Risk Factors According to Their Measurability

	Fall risk factors	Measurability
Factors related to the person	- Age	Measurable
	- History of falls	Measurable
	- Acute or chronic pathologies (e.g. Parkinson's, osteoporosis, diabetes, etc.)	Non-measurable
	- Neurological functions	Non-Measurable
	- Gait, balance, lower limbs joint function, muscle strength	Measurable
	- Cardiovascular status (e.g. blood pressure, heart rate, rhythm)	Measurable
	- Cognitive functions (Visual acuity)	Measurable
	- Fear of falling, independence, efficacy	Non-measurable
Factors related to the environment	- Outdoor environment (e.g. uneven paving, ice)	Non-measurable
	- Indoor environment (e.g. loose carpets, sloppy floors, cumbersome furniture)	Non-measurable
	- Foot wear, clothes	Non-measurable

C. Determining the Risk of Falling

To determine the risk of falling, measurable screening of risk factors must be conducted using adequate assessment tools and systems. Nashwa et al. in [5] divide the risk factors according to their origin and controllability. Rose et al. in [9], categorize the falling risk factors whether they can be modifiable or not. Based on these two review papers, risk factors can be modifiable and controllable. However, in order to quantify the risk of falling, we propose a more beneficial organization of the risk factors based on their measurability as we present in table I. Thus, the involvement of each risk factor to induce a fall incident can be measured.

D. Consequences of Falls

Falls have adverse consequences on many levels. They do not only affect the person himself by increasing his dependencies, but also impact his environment. The five-dimensions classification proposed by Nashwa et al. in [5] can be simply reassembled into three groups that can be related to the person, the environment and the government. Fig. 2 illustrates the new hierarchy based on which plans can be established to reduce fall consequences.

E. Need for Help

For all the above reasons, the need for help arises. The burden of this health problem lies foremost on the shoulder of

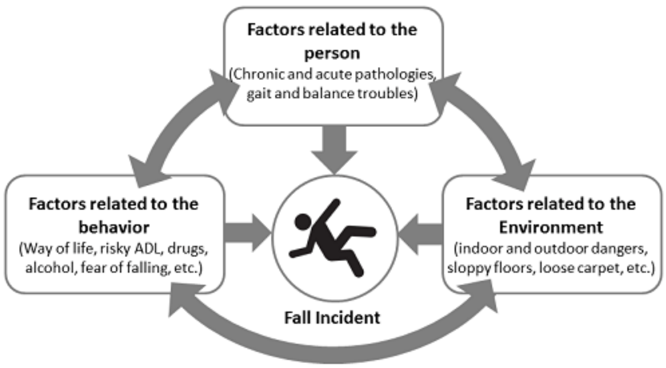

Fig. 2. Three-dimensional classification and interaction of fall risk factors.

societies and governments. It is also the role of the scientific communities to find solutions that are facing societies. From a scientific point of view, the problem of falling is approached by two research tracks. The first track is Fall Detection (FD) that has been aggressively investigated by researchers, scientists and industrialists through the past two decades. The main focus is to reduce the response and rescue time to reach the victim after a fall. In fact, lying on the floor for more than one hour is associated with many diseases (e.g. dehydration, pneumonia, hypothermia) and eventual death within 6 months [10]. The second track is Fall Prevention (FP). This track gathers the efforts made to detect the possibility of a fall. Research in this track is still in its early phases. The focus is mainly on predictive analysis of gait and balance parameters.

III. Classification of Fall-Related Systems

The literature reviews on fall related systems lack a common ground classification. In the track of fall detection systems, we analyzed four review papers. Each study provided a different classification approach based on the understanding of the problem of falling and the anticipated contribution. Noury et al. in [11] and [12], classify fall detection studies according to the detection techniques of the shock impact or the post-fall phase. Mubashir et al. in [13] used a three-category approach based on the physical deployment of the sensors. They classified the systems as wearable based devices, ambient based and camera based. They also provided a brief summary on the fall detection studies in each category. Pierry et al. in [14] considered a survey and evaluation of real-time accelerometry based fall detection techniques. Their classification was therefore based on methods that measure acceleration, methods that combine acceleration with other sensor data and methods that do not measure acceleration at all. It can be noticed that Pierry et al. were very specific in their classification which was based on accelerometers. This type of classification doesn't provide a common reference for the variety of sensors that can be deployed on wearable systems. Igual et al. in [15] provided a general classification. They divided fall detection systems into wearable devices and context-aware systems. The latter considered mostly of image processing and computer vision techniques using camera based devices and ambient sensors. At the time when those papers were published, the fusion systems had not significantly appeared and consequently they were considered a category. For instance, none of the previously mentioned reviews considered solution where wearable and ambient sensors are combined together to detect falls. These are known as fusion or hybrid systems. Recently, a survey on challenges and issues in multisensor fusion approach of fall detection systems provided a three-category classification [16]. The authors based their classification on wearable, ambient and vision sensors much like Mubashir et al. [13]. In their article, the fusion concept is only considered within the same category. For instance, they considered fusion of accelerometers and gyroscopes while both of these sensors are wearable. The emphasis of fusion systems proposed by our classification combine different sensor technologies.

In the track of fall prevention, three articles were investigated. The most relevant classification was found in [17]. The review paper provides an overview of wearable and non-wearable fall prevention systems used for gait analysis; however, the focus was on clinical applications only. The other two reviews were more specific. For instance, Weijun et al. in [18] provided a review on gait analysis using wearable systems highlighting their applications in sports, rehabilitation and clinical diagnosis. They also conducted a brief research on the types of sensors used in these systems and their working principles. Abdul hadi et al. in [19], reviewed foot plantar pressure measurement systems highlighting the types of sensors involved and their current applications particularly in sports and rehabilitation.

Large reviews on both fall detection and fall prevention were also found. Nashwa et al. in [5], provided a review of trends and challenges in fall detection and fall prevention systems. The paper offers exhaustive narrative information regarding both systems without any obvious classification. Another recognized survey by Delahoz and Labrador [20] is much more explicit. Their article classifies fall detection and fall prevention systems based on two categories: wearable systems and external sensors systems. The paper provides a qualitative evaluation based on different criterions (e.g. type of sensor, falling factor, cost, etc.). In their classification, vision systems are considered as external systems controversially to Mubashir et al. [13]. Other related surveys such as [21], focus on fall detection and fall prevention systems that use the smart phone as a sensing device.

A. Proposed Global Classification Scheme

Based on the previous classification issues, we propose our global common reference scheme for better understandability of fall-related systems. The goal of this classification is to provide researchers in this field a global reference scheme on fall-related systems. According to this scheme, emerging fall-related systems can be easily identified and classified. The proposed scheme is a three-category based classification shown in fig.3. The entities drawn in fig. 3 and the connection between them are based on literature studies.

In this scheme, fall-related systems are divided in two big groups: Fall detection systems and fall prevention systems. The first group uses the fall impact to trigger an alarm whereas the second group extracts features of gait and balance. Due to

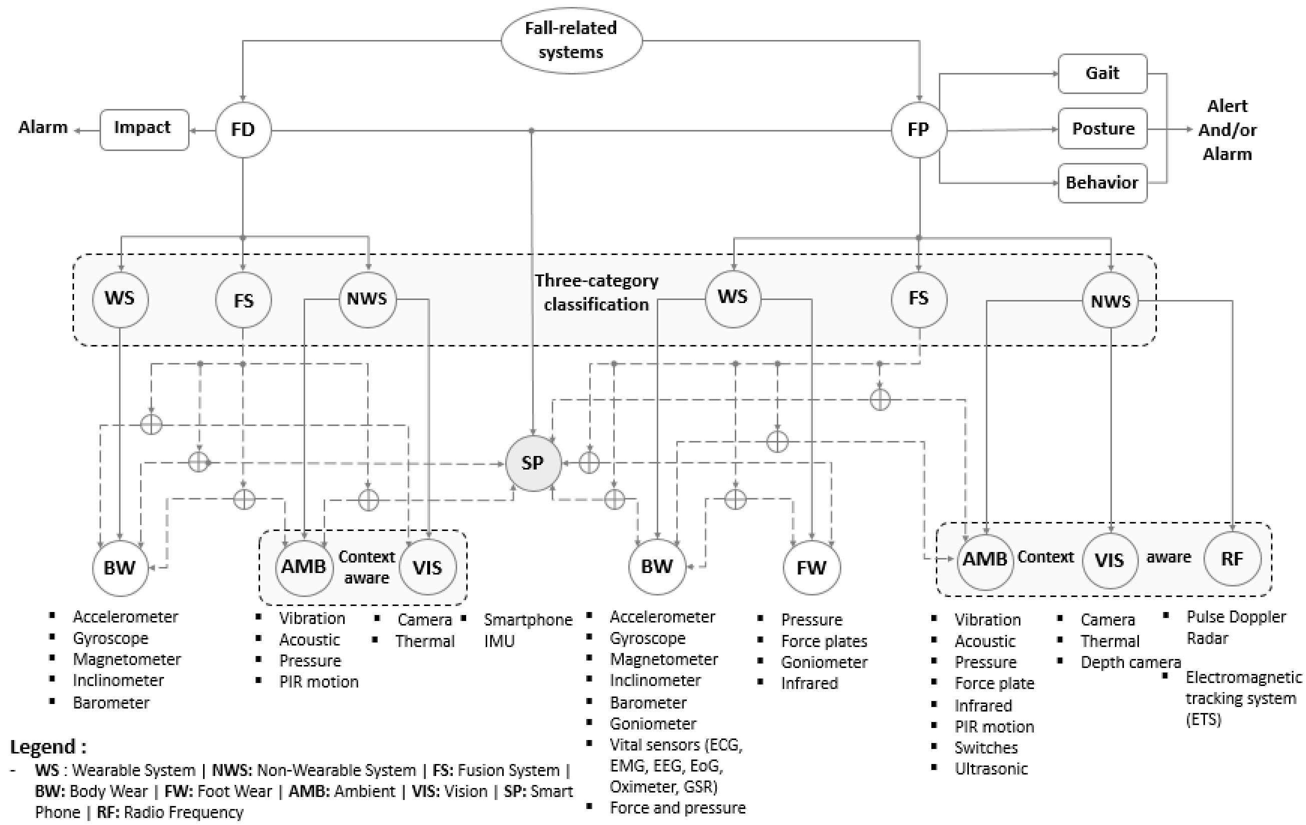

Fig. 3. A three-category based global classification scheme of fall-related systems.

the large amount of studies and to the lack of a global classification, fall detection and prevention systems can both be divided with respect to their sensor-technology deployment according to three categories:

- Wearable based Systems (WS).
- Non-wearable based Systems (NWS).
- Fusion or hybrid based Systems (FS).

Controversially to Mubashir et al. [13] and to Igual and Medrano [15], camera systems are a sub-category of the non-wearable systems mush like Delahoz and Labrador [20] who named this category as external sensors. Furthermore, due to the emerging fusion solutions, fusion based systems category is also added to this classification. At this level of the scheme, both groups have the same classification, however, when screening existing solutions and studies, FD and FP systems exhibit major differences. In fact, the deployment of sensors in wearable systems is typically attached to the body. These can be named as Body Wear (BW). For fall prevention systems, sensors can be found on the body or inside the sole of a shoe. These can be named as Foot Wear (FW). Another difference is the type and number of sensors used in wearable fall prevention systems. In fact, motion data must be collected from body segments and joints to study the human gait. Vital signs monitors are also added to this category for their relevance in providing intrinsic data to estimate the risk factor.

The non-wearable systems category is the same for both groups with a minor difference in fall prevention. Sensors in this category are either Ambient (AMB), Vision (VIS) or Radio (RF). The reason for taking out the vision and the radio systems from the ambient sub-category is the size of the data and the level of processing that can be achieved within these systems. Moreover, the type and size of the sensors used in vision and radio devices are different from those used in ambient sensing. These sub-categories can be baptized by the name context-aware systems due to their ability to sense and process data from the environment. Data collected from these systems are more dependent on the main context (FD or FP). For instance, ambient sensors are more variant in fall prevention systems to provide behavior analysis and activity monitoring while radio frequency systems are much adequate for gait analysis only.

Fall detection and fall prevention systems can benefit from the fusion of wearable and non-wearable sensors to provide more accurate analysis in terms of detection and prevention. Fusion systems (FS) are set in both categories. In this case, data is collected from different sensors for analysis. This category is poorly investigated in the literature of fall prevention systems; However, this option must be considered when taking fall prevention out of the laboratory to elderly homes.

Due to the emerging smart phone sensing technologies, we have integrated in our proposed classification the Smartphone (SP) category. This category is represented as a floating entity because smartphone systems can be located at any level of the classification. They can be considered as wearable or non-wearable that are capable of sensing,

TABLE II
TYPICAL SENSORS USED IN WEARABLE FD AND FP SYSTEMS

Sensor	Measurement
Accelerometer	Acceleration, velocity, position
Gyroscope	Angular velocity, flexion angle
Magnetometer	Orientation
Barometer	Change of pressure
Goniometer	Flex angle
Inclinometer	Tilt angle
Ultrasonic	Distance, clearance
Force and pressure	Vertical force, pressure

processing and communicating. Existing smart-phone systems are either stand-alone or combined with other wearable or non-wearable sensors for both fall detection and fall prevention. According to [21], smart-phone based systems are not yet been deployed as stand-alone systems in a non-wearable context.

B. Sensors Deployment in FD and FP Systems

Based on the proposed global classification in Fig.3, the sensor type and number are mainly dependent on the context of the application (FD or FP). These sensors are deployed in wearable, non-wearable and fusion systems.

1) Wearable Systems Sensors: In the context of fall detection, sudden changes in body motion parameters such as acceleration, orientation or inclination may be interpreted as fall-like incidents in case of elders. To measure these parameters, sensors must be tied to the body. Wearable based systems widely use inertial sensors such as accelerometers, gyroscope, inclinometers or other types of sensors like barometers and magnetometers, to detect abrupt surges in human gait, assess balance and monitor displacement [22]. Practically, accelerometers and gyroscopes are Micro Electro-Mechanical System (MEMS) devices that can measure acceleration and orientation (e.g. pitch, roll, yaw or angular momentum) of a body part along a certain axis. These sensors are basically utilized when identifying different types of falls: falls from sleeping, fall from sitting, fall from walking or standing, and fall from standing on support tools such as ladder or stairs [20]. Most often, 2-axial or 3-axial accelerometers and gyroscopes are found in almost all studies.

In the context of fall prevention, wearable sensors are used to analyze human gait. Compared to the types of sensors used for fall detection, fall prevention systems use a wider range of motion sensors. These sensors can be placed on different body parts in order to measure the characteristics of the human gait (e.g. feet, knee, hips, waist, chest, etc.) [18]. These systems use in addition to inertial sensors extensometers, force sensors and goniometers. Moreover, wearable sensors can be deployed on body and foot wears. The list of sensors use in wearable systems are listed in table II.

These listed sensors can be directly linked to human locomotion as they provide input to extract gait characteristics and detect abnormal changes in behavior depicting a potential fall. But, changes in behavior can also originate from intrinsic factors related to the pathophysiological history of the patient (e.g. muscle fragility, diabetes, heart diseases, hypertension, etc.). These factors are highly correlated with falls [9]. In this context, recent advances in MEMS technology have led to the development of new types of non-invasive healthcare sensors to monitor health signals. For example, blood glucose, blood pressure and cardiac activity can be measured using techniques such as infrared sensing, optical sensing and oscillometry [23]. These sensors are listed in table III.

TABLE III
VITAL SIGNS MONITORING DEVICES

Sensor	Measurement
Pressure	Blood pressure
CO2 gas	Respiration
Electrocardiography (ECG)	Cardiac activity
Electroencephalography(EEG)	Brain activity
Electromyography(EMG)	Muscle activity
Electrooculography (EoC)	Eye movement
Galvanic skin Response (GSR)	Perspiration
Oxymeter	Blood oxygen
Thermal	Body temperature

TABLE IV
TYPICAL SENSORS USED IN NON-WEARABLE FD AND FP SYSTEMS

Sensor	Measurement
Motion PIR	Motion
Infrared	Motion /identification
RFID	Location tracking/identification
Pressure and load	Force, weight
Magnetic Switches	Actions (opening/closing
Microphone	Sound height, impact
Vibration	Impact, vibration
Ultrasonic	Distance, clearance, motion
Camera	Activity, identification

Moreover, new technologies in sensing fabric also known as e-textile are currently being deployed on garment, in fabric and ultimately in fiber [24]. This technology is more flexible and comfortable compared with other wearable sensors in measuring human gait and posture [25].

2) Non-Wearable Systems Sensors: In non-wearable systems, sensors are deployed in the environment. The main effectiveness of this arrangement is when obtrusiveness is rejected from the subject as he refuses to wear any device on his/her body. The purpose of such systems is to be able to track human daily activities (ADL) and to detect abrupt changes in motion. Furthermore, the detection area of these solutions is limited to the range covered by the sensor [26], the reason why their usability is restricted to indoor premises only. Common sensors used in this category are pressure, motion PIR, vibration, acoustic, and infrared sensors.

In the context of fall prevention, sensors used for gait and balance analysis are usually deployed inside clinics or gait labs. Practically, these systems share similar components as in fall detection context-aware systems, however they have different objectives. The purpose of non-wearable systems is to monitor ADL during which gait and balance parameters are assessed. As a result, these sensors are more appropriate for elderly homes and healthcare facilities where falls are more likely to happen. In this case, real-life scenarios are more evaluated. According to [27], changes in daily activities are early indicators of cognitive and physical decline which is correlated to gait deficits and eventual fall. Thus, these systems are able to identify abnormalities,

TABLE V
CLASSIFICATION OF FALL DETECTION SYSTEMS WITH RESPECT TO THEIR DATA PROCESSING TECHNIQUES AND SENSOR DEPLOYMENT

Classification of fall detection systems and data processing techniques	Data processing techniques		Non-wearable systems (NWS) or Context-aware systems		New	New
		Wearable systems (WS)	**Ambient systems (AMB)**	**Vision systems (VIS)**	**Fusion systems (FS)**	**Smartphone systems (SP)**
Analytical methods (ANM)	Thresh-holding (TH)	[29] [30] [31] [32] [33] [34]	[35] [36] [37]	[38] [39] [40]	[41]	[42] [43]
	Principal Component Analysis (PCA)			[44]		
	Fisherś discriminant ratio					[45]
	Fuzzy logic		[46]	[47]	[48]	
	K-Nearest neighbor		[49]	[50]		
	Gaussian mixture model (GMM)		[51]	[26]		
	Rule based techniques and transformations - Shape analysis - Direct Linear Transform (DLT) - Wavelet transform - Histogram of Oriented Gradient (HOG) - Fast Fourier Transform (FFT)	[53]	[54] [55] [56] [37]	[57] [40] [58] [59]	[60]	
	Hidden Markov model		[61] [62]	[63] [32]	[64]	
	Pattern recognition		[65]			
	Bayesian filtering		[66]			
Machine learning methods (MLM)	Support Vector Machine (SVM) and DAGSVM	[67] [68]	[69] [55] [51]	[70] [71]	[72]	[73]
	Neural network classifier	[74] [75]		[76] [77]		[78]
	Multilayer perceptron	[53] [75]				
	Decision tree	[29]		[39]		[78]
	K-Nearest Neighbor (KNN)	[79]	[35] [56]	[80]		

track any changes in gait parameters and detect emergency events.

Camera sensors belong also to non-wearable systems, but they differ by their processing techniques to detect or predict falls. Cameras are fixed on the ceiling for wide area coverage. Recently, they become increasingly utilized in elderly-care facilities due to the available low-cost and high-quality images. Moreover, multi-event triggers can be easily analyzed using these systems. Non-wearable sensors are listed in table IV.

3) Fusion Systems Sensors: Fusion systems don't have dedicated sensors. As their name indicates, various types of wearable and non-wearable sensors can be fused together to provide a multichannel source of data upon which one or more fusion algorithms is applied. According to [16], this novel approach can potentially offer a significant improvement in reliability and specificity of fall-related systems. A multisensory fusion approach is more likely to answer the needs of independent living for elderly people. The opt for a fusion based approach is the flexibility of adjusting the system for a wider context (e.g. wider sensor network, implementation of fall detection and fall prevention strategies, design of a patient-based monitoring process, scalability, etc.).

Fusion systems are currently being exploited in both fall detection and fall prevention areas. In fall detection, these systems can extract data related to posture, inactivity, presence, body chape, head change etc. In fall prevention, these systems are able to provide rich source of data on human gait and balance characteristics to compute the falling risk. Fusion systems are solely deployed in gait assessment labs. Efforts to export these technologies into homes are currently being made. These are known as "Abient Assisted Living". Despite the advantages that fusions systems may offer to the falling problem, some challenges need to be overcome (e.g. integration into smart homes, real-time analysis, computational power, processing scheme, cost). Examples of studies are provided in tables V and VI.

C. Data Processing Techniques in FD and FP Systems

Fall data processing techniques are dependant on the parameters extracted from the sensors. Wearable, non-wearable and fusion systems for both FD and FP can benefit from techniques using Analytical Methods (ANM) or Machine Learning Methods (MLM).

D. Analytical Methods

Analytical methods are based on traditional techniques that use statistical models for gaining interpretation on data for prediction (e.g. linear regression, time series, transformations, etc.). Among these methods are thresholding techniques (TH) that is if a fall is reported when peaks (fall impact), valleys or other shape features in data signals are detected. Such methods are commonly used in wearable fall detectors with inertial sensors to distinguish between posture (inactivity) and basic motion patterns (activity). Ambient based systems use event sensing techniques through vibrational data that can be useful for monitoring, tracking and localization. Camera based systems use image processing techniques that extract spatiotemporal features (e.g. ratio of silhouette height, weight, orientation of main body axis, width, skin color) to

TABLE VI
LITERATURE REVIEW ON FUSION FALL PREVENTION SYSTEMS

Article	Methods				Experiments and results		
Ref.	Sensor (class)	Sensor location (Obtrusiveness)	Features analyzed	Data Processing technique	Experimental environment	Subjects	Results
Wearable Systems (WS)							
[81]	Triaxial Accelerometer (BW)	Waist (Medium)	acceleration signals from a Directed Routine	Logistic regression models	Clinic	Elders	Sensitivity = 71% Specificity = 73%
[82]	Triaxial Accelerometer (BW)	Waist (Medium)	acceleration and angular velocity	Hidden Markov Model	Lab	Elders	Recognition rate = 90% to 100%
[83]	Accelerometer Gyroscope (BW)	Waist (Medium)	acceleration signals from a Directed Routine	Logistic regression models	Clinic	Elders	Sensitivity = 71% Specificity = 73%
Non-Wearable Systems (NWS)							
[84]	Pressure mat (AMB)	Floor (Low)	CoP (Mean & RMS distance) sway ML-AP (velocity, length, frequency)	TH (ANM)	Elderly home	Dwelling elders	Inter correlation coefficient $>$ 75%
[85] [86] [87]	Kinect (VIS)	Vicinity (Low)	Joint and CoM (position, speed, acceleration) walking speed direction of Progress	Multiple additive regression trees (MART) (MLM)	Lab + Home	Middle-aged Adults	Correlation with pressure sensor = 80%
[88] [89]	Force plate (AMB)	Floor (Low)	GRF and CoP	Multivariate multi-scale Entropy (ANM)	Lab	Young volunteers	Symmetry of stride in normal people Designed force plate = AMTI force place
Fusion Systems (FS)							
[90]	Smartphone Accelerometer Oximeter + PIRMotion pressure mat door contact Power detector (SF+AMB)	Waist (Medium)	Impact orientation + Contact recognition (ADL)	TH + DBN	Setup (ice skating) + Apartment	Young volunteers	**Fall detection** SEN =90% SP= 100% Accuracy = 94% **Fall prevention** Probability of Fall Alarm (FA) function of ADL + fall event (FE)
[91]	ECG, GSR + Contact switches + Zigbee node (BW+AMB)	Wrist, finger + Home appliances sensing units (Low)	Emotion + behavior (activities)	Naive Bayes + K-mean clustering + TH	Apartment	Elders	**Emotion** Accuracy = 84% **Wellness indices** β1 and β2 $<$ TH=0.5 $\rightarrow$ assistance

identify lying or standing posture in the scene. Other image processing techniques use vector analysis to detect abrupt motion. Therefore, various analytical strategies can be adopted to classify fall from non-fall events.

1) Machine Learning Methods: Machine learning methods rely on complex algorithm to get close insight on data to predict output decisions. Starting from observation and then classification, wearable, ambient and camera based fall detectors can benefit from techniques such as Support Vector Machine (SVM), Regrouping Particle Swarm Optimization, Gaussian Distribution of Clustered Knowledge, Multilayer Perceptron, Naive Bayes, Decision Trees, ZeroR, and OneR to gain insights in to the data to detect and even predict future falls. An investigation on the performance of the afore mentioned classification techniques is detailed in [28].

The following sections IV and V, provide the state of the art of some existing FD and FP systems. An explicit search was conducted deploying the main databases like Google Scholar, IEEEXplore, PubMede. Studies are sorted according to their number of citations, the year of publication ($>$ year 2000), the type of sensor deployment and their application of various analytical and machine learning methods.

IV. FALL DETECTION SYSTEMS

A fall detection system is defined by Raul et al. in [15] according to its purpose. It is an *"an assisting device whose main objective is to alert if a fall event has occurred"*. Nashwa et al. in [5], define fall detection systems according to their functional components (sensing and communicating). We believe that a global definition is required. Thus, we propose our definition of a fall detection system as ***"an assisting device that is capable of sensing, processing and communicating alarm data in the event of a fall under real-life conditions effectively"***. Our intention in this definition is to emphasize not only the structure and the purpose but also the practical use of a fall detection system. In other words, a fall detector is effectively fit into an application if it is put into test in real-life scenarios. Besides the aspects that a fall detection system has in mitigating the consequences of fall such as reducing the response time, it must prove reliability and confidence to be adopted. These are accounted for the number of false positives and false negatives generated by the device. Fall detectors are classified according to their sensor deployment and their data processing techniques in table V.

V. Fall Prevention Systems

Fall detection systems have helped reduce the consequences of falls (long lie, fear of falling); however, they didn't stop them from happening. Thus, the problem of falling can be rather tackled using prediction systems. The context of fall prevention amounts to identify the risk factors inducing a fall incident. This is usually done by caregivers through questionnaires, diaries or phone calls; but the data collected is sometimes incomplete and not always reliable [20]. Person-related fall risk factors assessment consists of extracting and analyzing human biomechanical parameters of gait (e.g. stride and step length, time, Center of Pressure (CoP), etc.) and balance (e.g. static and dynamic sway, Ground reaction forces (GRF), etc.). Gait and balance parameter are assessed using either semi-subjective or objective assessment tools. The first are usually conducted by clinicians and often use functional performance traditional scales (e.g. Berg Balance, Performance-Oriented balance and Mobility Assessment (POMA)) to evaluate gait and balance. Results are scored in a semi-subjective way. In contrast, objective assessment tools with advanced sensor technologies provide a large amount of reliable information on patients' gait and balance. These tools are deployed in a gait laboratory with specific technical skills to run them. However, these tools are performed in clinical settings and their cost is high for home use. Given the fact that elders prefer to stay in their own home comfort [27]; efforts must be put to export gait and balance assessment into homes. Many studies were carried with these tools to estimate the risk of falling. Examples of fall preventions are surveyed in table VI.

VI. Conclusion

Aging is inevitable, whether it ends with no, mild or severe pathologies, it is always decent to age with good quality of life. Efforts to reach this objective do not lie on the medical force alone; it is therefore the joint effort between health professionals and scientists to address public health issues. From this standpoint, we have tackled in this review article an old-recent problem in the field of public health: the problem of elderly falls. The subject was undertaken according to two research tracks: (1) fall detection and (2) fall prevention. The article gave a basic understanding on elderly falls, their intrinsic and extrinsic causes and their consequences. The main contribution of this paper is a four-level common ground classification where fall related-systems were categorized into wearable, non-wearable and fusion according to their sensor deployment. The proposed common ground scheme provides a global overlook over the systematic studies related to elderly falling which hasn't been seen in previous reviews with an emphasis on fusion systems. Smartphone based solutions were also considered in this classification.

On one hand, fall detection systems were summarized and organized with respect to their sensor deployment and their data processing techniques. On the other hand, fall prevention systems were also surveyed; however more details were accorded to existing solutions given the current efforts in this research track. Future directions in fall-related systems may consider exporting gait and balance assessment tools into homes while providing reliable and low cost solutions for the elderly. Moreover, these systems must be able to contextualize the problem of falling in real life situations where the reliability and the confidence of the systems are evaluated. Future solutions must also consider merging systems for indoor and outdoor protection with minimum obtrusiveness to the patients. Finally, using our proposed generic classification scheme, scientists and medical technologists can draw new fusion-based fall solutions.

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