IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 21, 2019, accepted June 7, 2019, date of publication June 13, 2019, date of current version June 27, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2922708

Research of Fall Detection and Fall Prevention Technologies: A Systematic Review

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This work was supported in part by the Natural Science Foundation of Shandong Province under Grant ZR2018BF014, in part by the Scientific Research Foundation of Shandong University of Science and Technology for Recruited Talents under Grant 2017RCJJ042, in part by the Key Laboratory for Wisdom Mine Information Technology of Shandong Province, Shandong University of Science and Technology, and in part by the National Natural Science Foundation of China under Grant 61502278.

ABSTRACT Falls are abnormal activity events that occur infrequently; however, they are serious health problems among elderly individuals. With the advancements of technologies, falls have been widely studied by scientific researchers to minimize serious consequences and negative impacts. Fall detection and fall prevention are two strategies to tackle fall issues with a variety of sensing techniques and classifier models. Currently, many reviews on fall-related technologies have been presented and analyzed; however, most of them give surveys on the subfield of fall-related systems, while others are not extensive and comprehensive reviews. In fact, the latest researches have a new trend of fusion-based methods to improve the performance of the fall-related systems based on a combination of different sensors or classifier models. Adaptive threshold and radio frequency-based systems are also researched and proposed recently, which are seldom mentioned in other reviews. Therefore, a global taxonomy for current fall-related studies from four aspects, including current literature reviews, fall detection, and prevention systems based on different sensor apparatus and analytic algorithm, low power techniques, and sensor placements for fall-related systems are conducted in this paper. Several research challenges and issues in the fall-related field are also discussed and analyzed. The objective of this review paper is to conclude and provide a good position of current fall-related studies to inspire researchers in this field.

INDEX TERMS Adaptive algorithm, classification algorithms, fall detection, fall prevention, low power techniques, sensing techniques.

I. INTRODUCTION

Due to the declining of birth rate and the increasing in life expectancy, population ageing has become a common problem worldwide. As reported by the World Health Organization (WHO), the population of elderly people aged 60 or over will increase to about 20 billion by 2050 from 900 million in 2015, which accounts for 22% of the world's population [1]. However, ageing is always associated with decreasing functionalities, such as physical, sensory and cognitive disabilities, which increase the risk of falling. It is reported that approximately 28-35% of the elderly aged 65 or over fall each year. The risk of falling will rise as the age increases. It is reported that elderly adults aged 70 or over who fall each year will increase to 32-42% [2], while they suffer moderate or severe health injuries, such as bruises, hip fractures or head trauma, etc. Falls also bring out psychological burden, economic pressures and even impact the caregiver's quality of life [3]–[5]. Earlier responses to the elderly's falls might decrease the serious consequences.

Fall detection and fall prevention are two important strategies to tackle the issue of elderly's falls, and they have been studied over the past two decades. Especially, fall detection methods have been exhaustively explored by researchers. These systems use different types of sensors to collect useful signals for further processing and analysis, while various analysis algorithms are used to process the collected data. Generally, most of the fall detection systems detect shock caused by the body impact using accelerations.Article by Brown [6] considers only the large acceleration impact. It is one of the first fall detection studies. To improve the performance of fall detector, others combine with more

The associate editor coordinating the review of this manuscript and approving it for publication was Fatih Emre Boran.

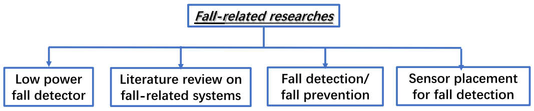

FIGURE 1. Taxonomy for the study of fall-related researches.

sensors or apply complex machine learning-based processing methods. For example, [7] and [8] combine a tri-axial accelerometer and gyroscope to detect fall. Authors in [9] proposed a multimodality fall detection, it is a three-step detection strategy consisting of multiple signal sources, including an accelerometer, audio and images techniques. While articles [10] and [11] use machine learning to effectively detect falls. Except for above research aspects, many other fall-related technologies have also been involved, for example, fall prevention methods, low-power technologies for fall detector, the selection of optimal sensor location for high accuracy fall detection, etc.

Currently, many literature reviews on fall-related systems constantly emerge, however, most of them focus on a narrow scope or a specific category, for example, some only consider one subfield implementation of fall-related systems as studies by [12]–[14], while others mainly provide knowledge about principles, issues, trends, and challenges of current systems as [13], [15], [16]. Generally, most of those reviews are not overall overviews on fall-related researches. To address these gaps,this article examines current technologies and proposes a comprehensive classification on fall-related systems, which is a category scheme with multiple layers framework. Top classification layer of our proposed global taxonomy is drawn mainly based on the research directions of current fall-related studies, including researches of fall detection or fall prevention (pre-impact fall detection) algorithm, low-power technologies for fall detectors, sensors placements for fall detection and literature reviews on fall-related systems as shown in Fig. 1. Meanwhile, other layers of the taxonomy mainly exhibit the subclassifications of each main class. Among the general category, fall detection or fall prevention studies, which are the current hotspots, are explored and highlighted from two perspectives, including the sensor apparatus usages and analytical approaches, respectively. This article aims to show researchers an overall classification of the existing fall-related systems and deliver them a good position regarding current fall-related researches.

To search latest fall-related studies for our proposed taxonomy, potentially relevant articles on fall-related researches were identified through a search in PubMed, PubMed Central, IEEEXplore, Citeseer, Web of Science, and Scopus with combination of keywords, including criteria: (fall detect* OR detect* fall* OR fall alerts OR fall risk OR fall recognition OR fall monitor* OR fall predict OR fall prevent* OR pre-impact fall*) OR/AND (real-world OR older* OR biosensor* OR review OR low-power OR energy-efficient OR placement). Besides, previous fall-related papers we have read were also included in this step. Totally, about

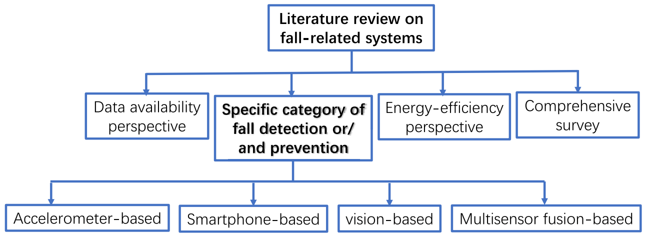

FIGURE 2. Taxonomy for Literature Reviews on Fall-related Systems.

1260 papers were collected and retrieved by the query, and the final 150 papers were selected. This systematic search aims to provide an overview of the published papers on the following discussed topics. And these papers will be analyzed and concluded in the following subsections.

The rest of the article is organized as follows. Section 2 gives a detailed survey on the existing review papers on fall-related systems. In section 3, we present comprehensive reviews on fall detection and fall prevention methods based on sensor apparatus and analytical approaches, followed by the detailed discussion of the state of the art on them. The classification of low-power technologies and the sensors placements for fall detection are concluded and presented in section 4 and section 5, respectively. We discuss the current research challenges of fall-related systems in section 6. Section 7 concludes the paper and points out the possible future directions.

II. SURVEY ON THE EXISTING REVIEW PAPERS ON FALL-RELATED SYSTEM

As mentioned above, review papers on fall-related systems are one of research angles of the current fall-related researches for the elderly. Several review papers on fall-related systems have been published, which refer to four different aspects of the fall-related systems as shown in Fig. 2, including data availability perspective, low-power implementation technologies [20], specific category of fall-related systems based on different technologies, such as accelerometer-based [17], [18], smartphone-based [13], [19], vision-based [14], multisensor fusion-based [15] systems, etc. Of course, comprehensive surveys have also been done by many studies. In this section, current review papers on fall-related systems are surveyed systematically, which is seldom done by others.

A. SYSTEMATIC REVIEWS ON SPECIFIC CATEGORY OF FALL DETECTION OR/AND PREVENTION

In current fall detection/prevention studies, such as articles by [15] and [16], existing fall detection/prevention systems are broadly categorized into three different classifications according to the deployed sensors, including wearable devices, ambient sensors and vision-based sensors. Accordingly, many previous review papers are published from these specific classifications, for example, review papers on accelerometer, smartphone or vison-based fall detection/prevention systems, meanwhile, others focus on hybrid multisensor fusion-based fall detection methods. In the following, each specific category is discussed respectively.

Generally, accelerometer-based fall detection is mostly studied by many researchers, this is similar to the reviews on accelerometer-based systems. For example, Bagala et al. [17] presented an overall evaluation of accelerometer-based fall detection algorithms. Totally, 13 different published algorithms were implemented and compared by analyzing different parameters, thresholds, and the phases of a fall, such as beginning of the fall, falling velocity, fall impact and orientation after the fall, based on a database of real-world falls. Preliminary results showed the performances of those algorithms tested using real-world fall data were much lower than they were tested under simulated environment, which definitely indicates it is important to evaluate the proposed fall detection system in real-world conditions. Aziz et al. [21] made an accuracy comparation of 10 accelerometer-based fall detection algorithms, 5 of which used threshold-based methods while the other 5 used machine learning-based approaches to detect falls. These threshold-based methods detected falls using input features of the minimum value of the peak Vector Sum (VS) or/and the smallest value of the VS, while five machine learning algorithms, including logistic regression, Naïve Bayes, Nearest Neighbor, Decision Tree and Support Vector Machine (SVM) were trained with input features of the means and variances of the X, Y, and Z accelerations acquired from the waist-mounted accelerometer. The final comparison revealed machine learning-based fall detection methods have better overall performance than threshold-based algorithms. Meanwhile, SVM-based fall detection was proved to provide the highest combination of sensitivity and specificity. Article by Bourke et al. [18] presented the performance evaluation of 21 existing proposed fall detection approaches with varying degrees of complexity for a waist-mounted accelerometer-based system. Three different features were extracted, including velocity, impact and posture to train the classifiers, while they were tested based on a comprehensive dataset containing normal activities of daily living (ADL), simulated falls and also continuous unscripted ADL. Different combination of impact, posture and velocity were tested. Results showed the algorithm with ''impact+posture+velocity'' achieved 100% sensitivity and specificity, and was the most suitable fall detection method. Pierry et al. [22] also made a survey and evaluation of different fall detection methods, which were grouped specifically based on accelerometers, including only acceleration-based methods, acceleration combined with other sensors-based methods, and non-acceleration-based methods. Experiment results showed fall detection with accelerometer had best performance, as it collected vital signals in generating accurate analysis. Obviously, above studies mainly made performance evaluation of accelerometer-based fall detection systems, however, most of studies used simulated falls to test the related algorithms, while only [17] evaluated algorithms based on real-world fall data, which is essential for the algorithm evaluation.

Smartphones always have built-in sensors such as 3-axis accelerometers, gyroscopes and magnetic, high performance microprocessors, etc. which make smartphone a very good platform to detect or prevent a human fall. Habib et al. [13] reported a comprehensive survey on smartphone-based fall detection and fall prevention. They gave three taxonomies from three different operation phases of the system: sense, analyze and communicate. For example, they illustrated a taxonomy of smartphone-based fall detection and prevention systems based on their sensing mechanism and placement of sensor, which included context-aware and body worn-based systems. They also classified them into threshold-based and machine learning-based fall detection and prevention algorithms on the basis algorithms of the analysis phase. Furthermore, a detail comparative analysis was made based on their functional and architectural properties and quantitative features. Finally, the article presented some challenges that limited the performance and the usability of the systems. Casilari et al. [23] presented a thorough review and comparison on Android-based fall detection systems considering different criteria such as the system architecture, the used sensors, the detection algorithm or response time to a fall event. However, to get an accurate fall detection decision, there were some challenges to be considered, such as effective evaluation methods and a reference framework, the actual applicability of Android devices, for example, the sampling frequency setting of the built-in sensors, position placement of the Android devices and the limited battery, and etc. Comparing with [13], [23] made an overall survey on both smartphone-based fall detection and prevention systems, which was a much more comprehensive taxonomy for smartphone-based systems.

Currently, cameras are increasingly installed in subject's home, which can be easily used to detect falls. And they are usually classified as vision-based systems. Accordingly, some literature reviews focusing on this type of methods have been studied and published. For example, Zhang et al. [14] presented a comprehensive review on fall detection systems and algorithms aiming at automatically detecting a human fall from vision-based perspective. In this article, vision-based fall detection approaches were classified into three different categories, including single RGB camera-based, multiple camera-based and depth camera-based fall detection methods. Single RGB camera-based fall detection methods commonly use shape related features, inactivity detection and human motion analysis as the clues for fall detecting. For multiple RGB cameras-based fall detections, the calibration of the system is essential to reconstruct the object. However, this operation is a time-consuming process. For depth camera-based fall detection methods, the distance from the top of the person to the floor, the last frames in a coordinate and shape characterization are common features for such detection approaches. Furthermore, five publicly fall datasets available were introduced in this study to provide researchers useful benchmark datasets for public algorithm verification, which is important for fair comparison of different methods.

Combination of different data sources processed by a multisensor fusion algorithm can potentially improve the performance of a fall detection system. As presented in [15], authors concluded the challenges and issues of multisenosr fusion-based fall detection. They categorized and described current multisensor fusion algorithms into three generations, including wearable sensors fusion, context-aware sensors fusion and wearable/ambient sensors fusion. Each categorization was described in detail. However, cost efficiency, conflicting output, data correlation processing framework and computational power were challenges that should be analyzed and taken into consideration.

B. LITERATURE REVIEWS ON FALL-RELATED SYSTEM FROM ENERGY-EFFICIENCY AND DATA AVAILABILITY PERSPECTIVE

As shown in our previous work [24], energy consumption of a fall detector dramatically impacts whether users use the system, and further affects the quality of the services. High energy consumption implies frequent battery recharging or replacement, which is disastrous for the elderly person to do this. Energy-efficiency technologies can help to alleviate this issue and extend the use time of fall detection system. Wang et al. [20] made a comprehensive review on low-power technologies for wearable telecare and telehealth, which were concluded and classified into two classes, including hardware and firmware-based methods. For each category, the article detailedly elaborated recent developments and researches about how to realize these approaches. For low-power hardware designs, they mainly focused on the selection of appropriate hardware, such as appropriate electronic components or hardware framework, while low-power firmware methods employed event-driven, duty cycle, feature selection or sensor selection to reduce the energy efficiency of the system. Commonly, an energy-efficient system usually combines multiple low-power technologies mentioned above to optimize and prolong the battery life of the whole system.

From the data availability aspect, obviously, falls are infrequent and diverse subject events, which seldom and random occur during the elderly's daily life. Therefore, there lacks sufficient real-world fall data, especially, during fall detection study, it is a fatal issue when training the classifiers or setting the thresholds. Though major published studies have been verified by laboratory simulations, the performances of fall detection algorithms are greatly affected when they are tested with real-world as clearly stated in [17] and [25]. Broadley et al. [25] evaluated current fall detection algorithms from real-world data perspective. Total twenty-two fall detection articles that had been tested using real-world data in their research were recorded and discussed involving the data collection and preparation, data processing methods and the criterion of the performance measures. Examining results showed the performance of these approaches were inconsistent and the number of real-world falls was commonly small. Khan et al. [26] presented a classification for the current fall detection studies from the availability of fall data aspect, which had two high levels of sufficient training data for falls and insufficient or no training data for falls. For each taxonomy, fall detection systems were implemented with different classification methods, which were investigated and discussed detailedly by authors. Moreover, they also pointed out the method of treating a fall as an abnormal activity to be a plausible direction, while personalized fall detection solution in supervised classification of falls is hard.

C. COMPREHENSIVE LITERATURE REVIEWS ON FALL DETECTION OR/AND FALL PREVENTION

Currently, many literature reviews also have been done from fall detection or/and fall prevention perspectives. However, most of them still lack of a comprehensive classification. In this subsection, we analyzed and concluded current review papers from three aspects, including fall detection, fall prevention, as well as both fall detection and prevention angles.

From fall detection aspect, Mubashir et al. [16] made a comprehensive survey on fall detection systems and the related algorithms, which were mainly divided into three parts, including wearable-based, ambience-based and vision-based fall detection approaches. Each category was further distinguished according to the detail technology it referred to, for example, wearable-based methods further included posture and motion-based devices. They also summarized and discussed the properties of these approaches. Finally, a brief comparison of different approaches was made, and they found a robust fall detection system should simultaneously consider both sensitivity and specificity for practical application. Existing issues of current fall detection researches are concluded, for example, ethical issues of confidentiality and privacy, the dependency risk on the individual body, adequate, overall and public fall dataset of real-world for experiment and evaluation. Mohamed et al. [27] also classified fall detection algorithms into three categories, and summarized the merits and demerits of each classification approach, however, authors considered the video-based method was the best choice due to its versatility. The article by Chaudhuri et al. [28] gave a systematic assessment on the current fall detection systems, which contained 57 recorded papers using wearable systems and 35 non-wearable systems. In this paper, authors analyzed and categorized fall detection studies from the aspect of system evaluation, which was different from the former survey papers. Results of comparison showed only 7.1% wearable-based systems monitored the elderly in real-world environment during evaluation procedures, while no non-wearable-based fall detection studies used the elderly as subjects in a lab or a real-word setting. Obviously, latest research hotspots, scuh as adaptive, Radio Frequency (RF)-based and adaptive-based detection methods are seldom mentioned in above mentioned reviews. Recent public surveys on fall detection have also been published, such as publications by Lapierre et al. [29] and Vallabh et al. [30]. Lapierre et al. in [29] provided a general classification on fall detection. In this article, 118 studies were included and analyzed from the characteristics of the applied technologies, including the types of sensors (based on which systems were classified into wearable-based, ambient-based as well as combination of wearable and ambient technique), common algorithms to detect fall, the evaluation standards and outcomes. In discussion section, they put forward that the results of these 118 articles should be reconsidered due to the simulated conditions and the lack of the elderly adults for evaluation. Similarly, Vallabh et al. [30] also divided fall detection systems into wearable-based, ambient-based, and camera-based systems. For each classification, they made a systematic analysis and conclusion on the most recent system implementations. Meanwhile, the disadvantages or limitations of them were also discussed. Finally, they considered and proposed personalized fall detection approach to be the trend to create high accuracy and adaptive to new human activities, for which the lack of real fall data of the elder would not be an issue.

Unlike fall detection technology, fall prevention (also called pre-impact fall detection) has been identified as an effective strategy [31] to prevent falls, which can activate the configured fall prevention apparatus to reduce physical injuries. Hu and Qu [31] conducted a systematic survey on pre-impact fall detection technologies. Authors analyzed and discussed current pre-impact researches from multiple aspects, including detection apparatus, indicators, algorithms, types of falls for evaluation, and also the performance of pre-impact fall detection. They also reported the limitation of current technologies, appropriate selection of fall detection indicators, as well as the lack of real fall data were three existing limitations of current pre-impact fall detection systems. Study work by [32] mainly presented a comprehensive search on sensor technologies for fall prevention among institutionalized geriatric patients. Four specific issues including fall prevention interventions, effectiveness of fall prevention systems on fall rate, false alarms rate and also user's experiences, such as feedbacks or possible alerts to the patients and nurse, were addressed and discussed detailedly. Results showed there was no evidence that current sensor technologies to prevent falls of people in indoor care environment would reduce fall rates. Only one study among the final selected 12 articles in this paper reported false alarm rate up to 16%, however, this rate was too high. Therefore, effective detection methods should be focused to make intervention successfully. Sun and Sosnoff in [33] also made a survey to assess the current sensing technologies that were used for fall risk assessment in elderly people. They extracted and analyzed the sensing techniques used for fall assessment, information about fallers and types of fall, the extracted features, and also fall prediction models of all selected 22 studies. Results indicated that sensing technologies of inertial sensors, cameras, pressure sensors and laser sensors were four potential approaches for high accuracy fall risk assessment in older adults, however, due to the variation in signal measurements, parameters selection and modelling methods, a diverse range of diagnostic accuracy was reported when they were used for activity assessments. Therefore, a clinical meaningful fall risk diagnosis should be proposed, which reconsiders the functional evaluation and user experience. Oladele et al. [34] also presented a comprehensive literature survey on fall prevention, which aimed to clarify the usefulness of information technologies in fall prevention.

As shown in [35], fall-related technologies can be split into fall detection and fall prevention. Both of them apply different types of sensors to sense related signals for further fall detecting or preventing. However, reviews on fall detection or prevention discussed above only investigate one special fall technologies for the elderly. Currently, many comprehensive reviews consider both fall detection and fall prevention. For example, Delahoz and Labrador [36] presented the state of the art in fall detection and fall prevention systems. They concluded the general model of both systems, and a three-level classification of falling risk factors. They also made a thoroughly review and comparison of current fall detection and fall prevention approaches. Hawley et al. [37] in 2014 provided a systematic review on fall detection, prevention and monitoring of the elderly adults. They considered intrinsic factors such as independence, requirements for safety to be important motivation to use such technique, while extrinsic factors including usability, costs etc. were also important to support users' attitudes. The article by Chaccour et al. [35] is another comprehensive review on both fall detection and fall prevention system. In this study, both fall detection and prevention systems can be divided based on sensor technologies into a 4-level classification, the top layer of which included wearable-based, non-wearable, and fusion or hybrid-based systems (new category added in this taxonomy). Authors gave a detail discussion on fall detection and prevention systems with respect to the sensors deployment, data processing and analytical approaches. Based on their analysis, fall detection/prevention researches should consider exploiting gait and balance assessment to provide reliable solutions for elder adults.

Obviously, most previously mentioned surveys mainly emphasize on the analysis of fall detection or/and prevention systems from a specific research aspect, even some make comprehensive surveys, they miss current significantly novel categories, such RF-based, fusion-based, personalized/adaptive fall detection methods, each of which can be considered as a category as the proposed taxonomy in this paper. In this paper, an overall review on both fall detection and prevention is done based on recent studies from sensor deployments and their analytical algorithms.

III. GENERAL CLASSIFICATION OF FALL DETECTION/ PREVENTION

According to our proposed top layer taxonomy for the studies of fall-related researches, study of fall detection or/and fall prevention is another research hotspots, which has been exhaustively explored by current researchers in recent years. However, as it is shown in above section, current literature reviews on fall detection and prevention systems mainly focus on a narrow scope but lacking of a comprehensive

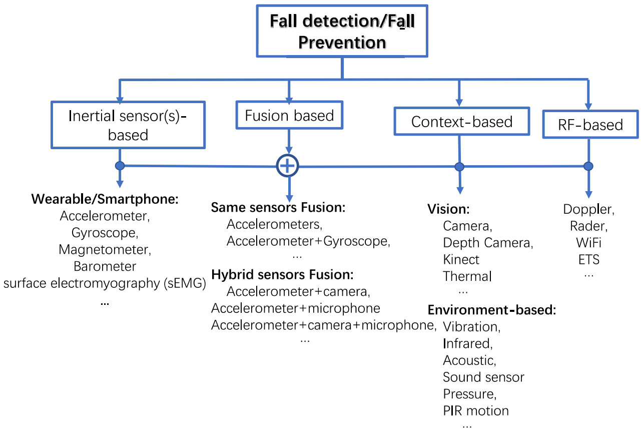

FIGURE 3. Taxonomy for fall detection and fall prevention from sensor apparatus aspect.

classification. Additionally, more novel approaches have appeared after those mentioned reviews were published, which can be considered as new categories, for example, RF-based methods, sensor fusion-based methods, and personalized/ adaptive methods. Therefore, a further complementary taxonomy on fall detection and fall prevention is proposed in this paper by extending the above classification for the study of fall-related researches. Especially, we propose two global classification schemes on fall detection and prevention from the sensor apparatus and analytical algorithm standpoints, respectively.

A. SENSOR APPARATUS-BASED CLASSIFICATION SCHEME

As it is shown in previous studies, fall detection system usually detects the body impact to trigger an alarm, while fall prevention system extracts the gait information to get early fall alert. However, both fall detection and prevention system always use accelerometers, gyroscopes, pressure sensors, video/depth camera, microphone, or/and radio frequency, etc. to determine falls or fall risks, in other words, they usually apply similar types of sensor apparatus with different numbers, which is the same idea as drawn from current literature studies [32], but they have different final objectives. Therefore, in our paper, fall detection and fall prevention are considered to have the same categories from the sensor apparatus angle, which is a global classification scheme for fall detection/fall prevention.

In the proposed scheme, four major classes are reported and presented based on sensing apparatus used in the existing fall detection and fall prevention systems as shown in Fig. 3, they include inertial sensor-based, context-based, RF-based and sensor fusion-based fall detection/fall prevention. Worthy mentioning, the classification drawn in Fig. 3 is totally based on current literature publications. In the following subsubsections, each category is illustrated and explained thoroughly.

1) INERTIAL SENSOR(s)-BASED FALL DETECTION AND FALL PREVENTION

It is known that most falls are always accompanied by sudden body changes, such as severe crash, significant body orientation or inclination changes, which can be sensed and measured by Micro Electro-Mechanical devices, such as accelerometers, gyroscopes, or other types of sensors like barometers or magnetometers, etc. Normally, one or more above sensors are placed on different body parts of the elderly to measure the abrupt changes of human body, which are further used to detect or identity falls from normal ADL. Except for above reasons, features of miniaturization, portability, low-cost and real-time make inertial sensor(s)-based systems to be potential and popular devices among the elderly for practical services. Majority of current fall detection and fall prevention researches apply inertial sensors to collect body information so as to detect or prevent fall events. 2-/3- axial accelerometers or/and gyroscopes are commonly used sensors in most studies, other inertial sensor apparatuses are also used in some studies to increase the accuracy of fall detection or prevention. Current studies on inertial sensor-based fall detection and fall prevention systems are summarized and concluded in our paper as shown in Table 1.

Listed inertial sensors no matter in custom-built devices or general development board, or even in smartphone/wristwatch are used to sense the motion changes of the monitored body to detect the abrupt changes, analyze gait, monitor the body orientation or/and assess the muscle control signals, while they are always tied to the body. When a fall occurs, body changes can be sensed and used to detect a fall. Many fall detection studies use single type of wearable inertial sensors to achieve, for example, Shahzad et al. [38] achieved an accelerometer-based fall prevention system in 2017, then they further proposed a high accuracy fall detection approach using only accelerometer. Gyroscope was also used as measuring sensor for fall detection or prevention as shown in Bourke and Lyons [64], Su et al. [65], and etc. Meanwhile, Lu et al. [68] and Chaccour et al. [69] used only pressure sensor(s) to detect or prevent falls. Further, there are also only electromyography or inclinometer-based fall detection or prevention system. However, among those listed inertial sensors, but not limited to those sensors, accelerometer is the most popular and widely used sensor in fall detection/prevention systems as shown in Table 1. As accelerometer can sense and extract multiple significant parameters for fall detection/prevention, and can be feasible, fast, real-time and effective solutions to detect falls. What is more, as shown in Table 1, it is clear that accelerometer-based fall detection or prevention systems have high performance than those systems using pressure, electromyography, or inclinometer sensor.

Inertial sensors-based fall detection and fall prevention studies are one of the most current hotspots and trends. They have many advantages, such as portable while easier to be implemented, few privacy issues, high accuracy, real-time and etc. Nevertheless, there are still some limitations in such approaches. Firstly, elderly to be monitored are required to wear such device on his/her body, which is uncomfortable and disastrous, as it is an intrusion for users. Second, sensor placement and external noise will affect the performance of

TABLE 1. Current studies on inertial-based fall detection and fall prevention systems.

Sensor Types	Fall Detection			Fall Prevention		
	Article & Year	Sensor & location	Performance	Article & Year	Sensor & location	Performance
Accelerometer	Shahzad (2019) [10]	Smartphone: accelerometer(waist)	Acc[a]: 97.81%	Shahzad et al. (2017) [38]	Triaxial Accelerometer (lower back between the L3-L5 vertebrae)	Not given
Accelerometer	Yacchirema et al.(2018) [39]	3-axis accelerometer (waist)	Acc: 91.67%, Pre[b]: 93.75%	Otanasap (2016) [40]	3-axis accelerometer(Chest)	LDT[c]: 365.12 ms Acc:99.48% Se[d]:95.31% Sp[e]:97.4%
Accelerometer	Suriani et al.(2018) [41]	Triaxial accelerometer (hip, back of thigh and foot)	Acc:81.2-88.7%	Martelli et al. (2014) [42]	two parallel and adjacent treadmills	LDT: 351±123 ms Acc:95.4%
Accelerometer	Putra et al. (2018) [43]	ADXL345 accelerometer (waist, chest)	F-scores: chest:98% waist:92%	Simila et al (2014) [44]	3-D-accelerometry (low-back)	Acc:60.8-87.2% Se:42.1-89.5% Sp:62-96.6%
Accelerometer	Kostopoulos et al.(2015) [45]	Smartwatch: accelerometer(wrist)	Acc:89.74% Se:92.18% Sp:87.29%	Liu et al. (2014) [46]	3-axis accelerometer(waist)	Acc:90-100%
Accelerometer	Others: [47]–[58]			Others: [59]–[63]		
Gyroscope	Bourke et al. (2008) [64]	Bi-axial gyroscope(waist)	Sp:100%	Su et al. (2016) [65]	Two gyroscopes (waist and right thigh)	Acc:97.5-98.8% Se:98.1% Sp:98.8%
Gyroscope	Almeida et al. (2007) [66]	MG1101 MicroGyro	Not given	Fino et al. (2015) [67]	three uniaxial gyroscopes(trunk, left and right shank)	Se:76.1-89.4% Sp:76.7-100%
Pressure	Lu et al. (2016) [68]	barometer (neck)	Se:94% Sp:90%	Chaccour et al. (2016) [69]	resistive pressure sensors(smart shoe)	Risk level for scenarios happens to fall between 0.256 to 0.27
Pressure	Light et al. (2015) [70]	foot pressure array (underneath a foot)	F-Measure: 0.643-0.888 Precision: 0.0.658-0.889 Recall:0.659	Verghese et al. (2009) [71]	pressure sensors	Slower gait speed: risk ratioper 10 cm/s decrease 1.069, 95% confidence interval 1.001-1.142
Electromyography	Han et al. (2017) [72]	a bidirectional EMG network (forearms)	Positive predictive rate:81.8% Se:69.2%	Rescio et al. (2018) [73]	sEMG sensors (Gastrocnemius and Tibilias muscles)	LDT: 770 ms Se:91.3% Sp:89.5%
Electromyography	Xi et al. (2017) [74]	sEMG electrodes (Left lower limb)	Se:98.7% Sp:98.59%	Leonoe (2017) [75]	Ag/AgCl electrodes (lower limb)	LDT:775 ms Se:89.1% Sp:87.1%
Electromyography	Others: [76]			Others: [77]–[79]		
Inclinometer	Sun et al. (2016) [80]	Single axis inclinometer (under feet)	Detection rate:85.4%	—		
Inclinometer	Sun et al. (2015) [81]	plantar inclinometer (under feet)	Detection rate:92%	—		

[a]Accuarcy, [b]Precision, [c]Lead Detection Time, [d]Sensitivity, [e]Specificity.

the system. Furthermore, fall is a rare event, which leads to a lack of real-world fall data to give proper thresholds or training related classifiers, further bring out poor fall detection/prevention performance.

2) CONTEXT-BASED FALL DETECTION AND FALL PREVENTIONS

As mentioned above, many review studies categorized current fall-related systems into wearable-based, ambient-based

TABLE 2. Current studies on context-based fall detection and fall prevention systems.

Sensor Types		Fall Detection			Fall Prevention		
		Article & Year	Sensor & location	Performance	Article & Year	Sensor & location	Performance
Ambient environment	Audio signal	Droghini et al. (2017) [82]	acoustic sensor(floor)	F1[a]:98.66% -100%	—		
		Irtaza et al. (2017) [83]	microphone	Acc:97.41%			
		Others: [84]–[88]					
	Pressure pad	Chaccour et al. (2015) [89]	piezoresistive pressure sensors(floor)	Se:88.8% Sp:94.9%	Morgado et al. (2012) [90]	resistive pressure sensor array(floor)	Fall profile can easily be predicted with system.
		Muheidat et al. (2010) [91]	Sensor Pad (floor)	Acc:96.2% Se:95% Sp:85%	Mcgrath et al. (2012) [92]	high density pressure mat(floor))	CHAT and MOP have reliability to discriminate fall from non-fall
		Others: [93], [94]			Others: [95], [96]		
	PIR motion	Fan el al. (2017) [97]	Infrared array sensor(Wall)	F1:0.9-0.99 Pre:0.97-1 Re:0.83-1	Nishiguchi et al. (2013) [98]	Infrared laser	Effective tool to identify high risk elderly individuals
		Others: [99]–[101]			—		
Vision	Video camera	de Miguel et al. (2017) [102]	Camera module (height:2-2.25 m)	Acc:96.9% Se:96% Sp:97.6%	Kutchka et al. (2016) [103]	Custom-designed embedded smart camera(wall)	Not given
		Fan et al. (2017) [104]	Eight cameras (mounted around room)	Acc: 95.2%	Li et al. (2017) [105]	RGB Camera and line-laser shoes	Notice obstacle in advance, reducing the risk of falls
		Others: [106], [107]			Others: [108]		
	Depth camera	Zhao et al. (2018) [109]	Microsoft Kinect v2/ Orbbec Astra depth camera	Acc:92.3% Se:86.6% Sp:98.1%	Li et al. (2018) [110]	Kinect sensor 2.0	LDT:867.9 ms Se:100% Sp:81.3%
		Kong et al. (2017) [111]	Depth camera	Acc:97.1% Se: 94.9% Sp:100%	Xu et al. (2017) [112]	multiple Kinect cameras	DT:333 ms Acc:91.7%
		Akagunduz et al. (2017) [113]	Depth videos	Acc:89.63% -100%	Dubois et al. (2014) [114]	Microsoft Kinect camera	Accurate enough to be used in real fall prevention applications
	Thermal	Rafferty et al. (2016) [115]	thermal vision sensors (Ceiling)	Acc:68%	Song et al. (2017) [116]	thermal imagery camera	Acc:99.7%
		Vadivelu et al. (2016) [117]	Thermal sensor	Acc:99.61%	—		

[a]F1-score.

and vision-based fall detection/prevention systems. However, in this paper, ambient-based and vision-based fall detection/prevention are considered as context-based category. As both methods detect fall by sensing environment information to track the movement of the body. In this category, external sensors such as microphone, pressure sensor, infrared sensor, camera, thermal sensor and etc. are attached around the surrounding where the individual stays in, such as bedroom, bathroom or a home to detect or prevent falls. Current studies on context-based fall detection and fall prevention systems are listed in Table 2.

For ambient-based system, acoustic, vibration, and pressure signals are collected to track the body within the sensor's view. Mel-Frequency Cepstral Coefficient (MFCC) features of acoustic signal can be extracted to capture the movements of the user, which are further used to classify fall and ADL, such as approaches proposed by Droghini et al. in [82] and Irtaza et al. in [83]. Falls and ADLs always show different vibration patterns, which is the basic theory of such category system. Vibration signal can be collected by various pressure sensors (piezoresistive or resistive) [89], [91] or sensor pad/mat [90], [92] on the floor, which are always used in both fall detection/prevention system. Infrared sensors have also been used in fall detection [97] and prevention systems [98]. Most notably, both audio and pressure signals are commonly used to detect falls, however, it is clear that audio-based approaches have better performance than pressure-based methods. Meanwhile, both pressure and infrared sensors have been applied for fall detection and fall prevention, but Infrared sensors are more preferred by researchers in recent years. In addition, compared with inertial-based system, ambient devices are the least intrusive as they are always unobtrusive and have minimum interaction with the individual, which also implies few privacy and security issues. However, in this category, there are still plenty of problems making this type method not to be the best choice. Coverage of this category is one of the most serious difficulties. Ambient-based systems always place sensors only indoors or in one room, which brings out dead spaces or blind spots in fall detection/prevention, in other words, these methods have limited detection range. Moreover, they also make an assumption that only one individual stays in the room. Besides, ambient sensors are easier affected by external environment, for example, other falling materials in the monitoring room, floor types, and various noise, which affect the performance of the system and produce many false alarms.

With the popularity of cameras in our daily life, cameras are embedded into fall monitoring system gradually to acquire information, which are also considered as context-based fall detection/prevention systems. Many studies using capture system to tract the head trajectories, body shape changes, or body posture of the monitoring subject to detect or prevent falls. These capture systems can be RGB camera(s), depth camera(s) (Kinect), thermal sensor(s), or even multiple cameras combination. The most simple and common vision-based method applies a single camera, such as de Miguel et al. [102] used k-Nearest Neighbours (kNN) algorithm to analyze the silhouette change over time with a camera module, which is the cheapest system among this category and is easy to setup, however, the performance of such approach needs to be further improved due to the limited area coverage. Multiple cameras are used in many studies to cover a wide detection area, for example, Fan et al. [104] applied 8 cameras mounted around the room in the proposed method to improve the performance of fall detection system. Depth information from camera(s) can increase the accuracy of the system. As depth camera(s), such as Kinect can be used to calculate the distance between the person and the floor to improve the performance of the system. For instance, both articles of Zhao et al. [109] and Li et a. [110] tracked the key joints of the body using depth camera to detect or prevent falls. Moreover, thermal sensors are also widespread used in fall-related researches, which have high accuracy up to 99.7%. Compared among the above mentioned detection means, depth camera-based methods attract much more attentions of current researchers. Obviously, camera can record the body image continuously, which can be applied to monitor the body behavior for fall detection/prevention without disrupting the normal life of the individual. Moreover, due to the development of technologies, the price of camera decreases rapidly, therefore, it becomes popular and is increasing utilized in elderly's daily life, which promote camera-based fall-related system to be a plausible research direction. However, there are many disadvantages in this category. Firstly, camera-based system always applies complex computer vision and image processing techniques to monitor the individual, which requires considerable computing and storage capacity to run the real-time algorithm. Second, acquiring real falls image/video of the individual is difficult, as this always refers to privacy issue, which is a serious issue for most people. Thirdly, camera(s) in systems are always fixed at fixed placements, which means limited capture space can be monitored. What is more, for such category system, installation and calibration of cameras are also difficult to operate.

3) RF-BASED FALL DETECTION AND FALL PREVENTION

Obviously, radio frequency can also be classified into context-based system. However, in this paper, RF-based methods are taken out due to the type of signal, size of data, and the special sensor apparatus, meanwhile, recent development and trend in this category are also considered. These technologies track the fluctuation of radio frequency signals or wireless channel state information (such as WiFi, Bluetooth) to detect or predict falls, as the strenuous body movement speed brings out abnormal changes on RF signals. RF-based system can be categorized into two classes as concluded in Table 3, including radar frequency-based and wireless channel-based system. To detect falls, Tian et al. [118] analyzed signals collected from multi-antenna Frequency Modulated Continues Wave (FMCW) radio and extracted complex spatio and temporal features to train Convolutional Neural Networks (CNN). Tang et al. [121] proposed a FMCW radar-based fall prevention system, they constantly measured the distance between radar and surrounding environment and analyzed the relationship between body motion and the radar frequency to predict falls. Wireless channel state information-based fall related system estimates fast changes in wireless signal caused by different human activities, they can be WiFi or Bluetooth. Wang et al. [124] proposed a novel fall detection system based on WiFi devices. They demonstrated that wireless channel state information can distinguish fall and fall-like activities successfully. Apparently, radar frequency signal is ubiquitous, based on which automatic fall detection can be achieved conveniently without user's involvement, that is to say, this method is nonintrusive. However, RF-based technology also has coverage issue, wireless network is always deployed within the limited range of the house.

4) SENSORS FUSION-BASED FALL DETECTION AND FALL PREVENTION

Preliminary studies have demonstrated single sensor-based fall detection system often has low accuracy or/and high false

TABLE 3. Current studies on RF-based fall detection and fall prevention systems.

Sensor Types	Fall Detection			Fall Prevention		
	Article & Year	Sensor & location	Performance	Article & Year	Sensor & location	Performance
Radar frequency	Tian et al. (2018) [118]	multi-antenna FMCW radio (wall or cart)	Re:94% Pre:92%	Tang et al. (2017) [119]	FMCW radar (Shoe)	feasibility of fall prevention using wearable radar
	Jokanovic et al. (2017) [120]	radar	Acc:80.2-95.7%	Tang et al. (2016) [121]	FMCW radar (shoe)	feasibility of fall prevention using wearable radar
	Shiba et al. (2017) [122]	microwave Doppler sensor	Acc:95% TP:94% FP:97%	Visvanathan et al. (2012) [123]	Radio Frequency Identification device	Not given, but in timely manner
WiFi channel	Wang et al. (2017) [124]	WiFi device	Se:92% Sp:92%	—		
	Wang et al. (2017) [125]	802.11n NIC	Pre:90-94% False alarm: 13-15%			

alarm, it needs additional information to improve the accuracy of the system. Homogeneous or heterogeneous types of sensors can be fused together to improve the performance of fall detection/prevention systems. Current studies on sensors fusion-based systems are listed in Table 4. For homogeneous sensors fusion, they can be similar or the same types of sensors, such as fusion of inertial sensors, fusion of ambient sensors, etc. Fusion of inertial sensors among triaxial accelerometer, triaxial gyroscope and triaxial magnetometer was proposed to detect falls by de Quadros et al. in [11]. Leone et al. [128] combined electromyography and accelerometer information to detect pre-impact falls, more than 750ms lead detection time was allowed before a fall happened. Certainly, different types of sensors can also be combined together to exploit different data sources for fall detecting or preventing, which is called as heterogeneous sensors fusion method in this paper. For instance, in our former study [9], a multimodality-based fall detection scheme based on accelerometer, microphone and camera was proposed and verified. For fall prevention, Rantz et al. [139] showed a comprehensive fall prevention approach based on heterogeneous sensors fusion of pulse-doppler radar, a microsoft Kinect, and 2 web cameras. Results demonstrated that there was significant performance improvement when system combined several types of sensors together to provide multiple data sources, as sensors fusion-base system was able to provide sufficient information on human activities or gait balance characteristics. Currently, with the recent development in science technologies, more novel sensors spring out and can be combined together to improve the performance of the system, which is a trend in such domain. However, few fall detection or prevention devices or systems are used in real-life of the individual so far, though there are many works have been done. This is because of the lacking of high accuracy fall detection approaches, in other words, sensor fusion-based methods still face low performance issue. Except for this, they also have other limitations, for example, information redundancy, robust fusion algorithm.

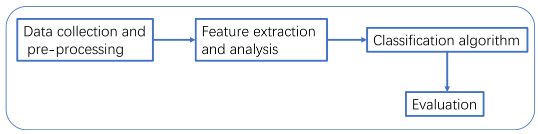

FIGURE 4. An example general model of fall detection/prevention from analytical algorithm aspect.

B. ANALYTICAL ALGORITHMS-BASED CLASSIFICATION SCHEME

Generally, smart sensors are attached to/near the body parts of the individual to measure significant signals, which are used to distinguish falls from ADLs with some classification algorithm. A general example of fall detection/prevention system model from analytical algorithm perspective is shown in Fig. 4. Totally, four component parts are associated with this model, in which data collection and pre-processing is the first step of the system. It collects data from various sensors as mentioned and discussed in the above section. The collected data directly or indirectly reflect the body motions. Then data pre-processing methods such as Kalman filters, mean filters, or advanced integration method are used to remove noise and external impact. In fall-related systems, distinctive features are significant attributes to distinguish fall and non-fall, which should be extracted from the raw data. And they play vital roles in fall detection/prevention algorithm. For example, the most popular features of inertial-based systems are the magnitude of the acceleration and the angular velocity. In context-based system, aspect ratio of image, MFCC features are common extracted features. After feature extraction and analysis, the chosen classification model is trained with the extracted features to detect/prevent falls. Actually, models used in current fall detection or fall prevention systems can be further divided into three classes based on the applied

TABLE 4. Current studies on sensors fusion-based fall detection and fall prevention systems.

Sensor Types	Fall Detection			Fall Prevention		
	Article & Year	Sensor & location	Performance	Article & Year	Sensor & location	Performance
homogeneous	de Quadros et al. (2018) [11]	triaxial accelerometer, triaxial gyroscope, triaxial magnetometer	Acc: 99% Se:100% Sp:97.9%	Howcroft et al. (2017) [126]	Pressure sensing insoles, accelerometers	Acc:0.57-0.75 F1:0.636-0.778
	Wu et al. (2018) [127]	Triaxial acceleration, Triaxial angular velocity	Se:94.8% Sp:95.2%	Leone et al. (2017) [128]	4 electromyography probes, Accelerometer t-shirt	LDT: 750 ms Se:>75% Sp:>75%
	Ejupi et al. (2017) [129]	tri-axial accelerometer, barometric sensor	Acc:82-96%	Hemmatpour et al. (2017) [130]	Accelerometer, Gyroscope	Acc:83-90%
	Lu et al. (2016) [131]	Infrared sensor Pressure sensors	Se:81.2-88.2% Sp:99.4-100%	Majumder et al. (2014) [132]	iPhone, 4 pressure sensors	Acc:97.2%
	He et al. (2017) [133]	triaxial accelerometer, triaxial gyroscope	Acc:95.67% Se:99% Sp:95%	Thella et al. (2016) [134]	Accelerometer, gyroscope	LDT: 150 ms
Heterogeneous	Kepski et al. (2018) [135]	Accelerometer, Kinect depth camera	Acc:98.9-99.45% Se:98.2-100% Sp:99.22%	Lin et al. (2017) [105]	Line-laser(sie of shoes), camera(top side of shoes)	System can be used to prevent falls in indoor environment
	Ramezani et al. (2018) [136]	WiFi, Accelerometer (ground)	Acc:95%	Ejupi et al. (2016) [137]	Kinect, Inertial sensor	Feasibility of a sensor-based self-assessment for fall risk
	Li et al. (2017) [138]	Tri-axial accelerometer, micro-doppler radar, Depth camera	Acc:91.3%	Rantz et al. (2015) [139]	pulse-Doppler radar, a Microsoft Kinect, 2 web cameras	Correlated (p<.01) with the Kinect. Radar velocity is correlated (p<.05)
	Zhang et al. (2013) [9]	Accelerometer, microphone, camera	Acc:94%	—		

classification algorithm, including threshold, non-threshold and fusion-based analytical algorithms, as shown in Fig. 5. This classification is based on current literature publications, too. In the following subsubsections, each category will be illustrated and explained thoroughly.

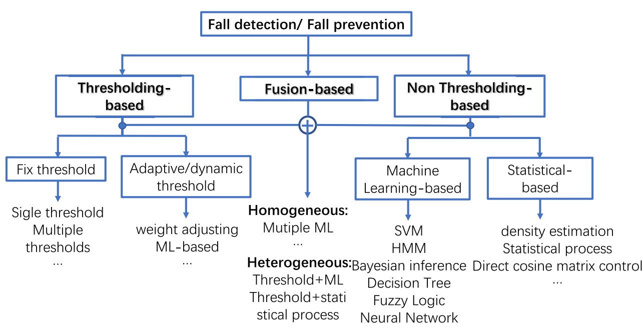

FIGURE 5. Taxonomy for fall detection and fall prevention from analytical algorithms perspective.

1) THRESHOLD-BASED FALL DETECTION AND FALL PREVENTION

Currently, most fall detection and prevention studies apply threshold-based approaches to detect/prevent falls. Fall events can be detected or prevented by comparing the collected data with a setting reference value (threshold). However, threshold set in the algorithm significantly affect the performance of the system. A high threshold value brings out large amount of fall missing issues, while a low threshold value causes false alarms. Therefore, appropriate thresholds should be chosen and set. Actually, current threshold-based approaches can be further classified into two groups: fixed threshold(s) and adaptive threshold(s)-based methods as concluded in Table 5.

Due to the low computational complexity, fixed threshold-based method has been widely applied by current fall

TABLE 5. Current studies on threshold-based fall detection and fall prevention systems.

Sensor Types	Fall Detection					Fall Prevention				
	Article & Year	Sensor& location	Features	Experiment & subjects	Performance	Article & Year	Sensor & location	Features	Experiment & subjects	Performance
Fixed Threshold(s)	Razum et al. (2018) [140]	Accelerometer (waist)	SVM, Euler angle	16 young (15 to 44 years)	Se:86% Sp:80.1%	Hemmatpour et al, (2018) [141]	Accelerometer, gyroscope (lower trunk)	Hjorth parameters, energy measurements,SVM, etc	31 users (18-68 years)	Acc:93.5% Se:90.9%
	Pham et al. (2018) [142]	Accelerometer	SVM, ΔSVM, angle	5 youngs (22-23, males)	Acc:92% Se:93.3% Sp:91.4%	Sivaranjani et al. (2017) [143]	Tri-axis Accelerometer, gyro sensor	Angular velocity, acceleration	Not given	High Acc, Sp, Se
	Abdelhedi et al. (2016) [51]	3-axes Accelerometer	SVM, angle	Not mention	Se:89.5-96% Sp:97-98%	Thella et al.(2016) [134]	Accelerometer, gyroscope	SVM, SMA, angle	Not given	LDT: 150 ms
Adaptive/Dynamic Threshold(s)	Wuet al.(2018) [127]	3-axis accelerometer 3-axis angular velocity	acceleration and angle velocity	10 young (20 to 27 years)	Se:90% Sp:92%	Otanasap (2016) [40]	3-axis accelerometer(Chest)	SVM, acceleration mean value, standard deviation of acceleration, et al.	6 youngs (19-21 years)	LDT: 365.12 ms Acc: 99.48% Se:95.31% Sp:97.4%
	Ren et al. (2016) [144]	3-axis accelerometers	SVM, angle	15 youngs	Acc:96.83%	—				
	Cao et al. (2012) [145]	Smartphone: 3-axes Accelerometers	SVM, BMI	20 participants (20-50 years)	Se:92.75% Sp:86.75%					

detection and fall prevention studies. For example, Razum et al. [140] selected optimal threshold values for two features of sum vector magnitude and euler angle to distinguish falls from ADLs based on the receiver operating characteristics (ROC) curve, which has been commonly applied in former studies. Two optimal thresholds were selected and analyzed for three situations of each feature separately and the combination of two features, respectively. The best results were obtained when sum vector magnitude was set to 4.1 g, while Euler angle between the direction of earth gravitational field and the vertical axis of sensor was set to 70 degree. Abdelhedi et al. [51] also proposed a threshold-based approach to discriminate falls from ADLs. In the proposed method, two fixed thresholds of sum vector magnitude were set to 0.6 g and 1.8 g respectively to detect free fall phase and impact phase, while feature of body tilt was set to 60 degree to detect inactivity phase. Sivaranjani et al. [143] predicted falls by analyzing data collected from both gyroscope and tri-axial accelerometers. The collected signals of acceleration and angular velocity were analyzed and compared with fixed threshold values (± 3 g, 0.5 rad/s) to determine pre-fall and inflate the airbag. Clearly, for above discussed algorithms, pre-defined thresholds should be determined firstly, however, it is commonly confirmed empirically in most publications. Furthermore, as shown above, different thresholds are set in different publications though they are used for the same detecting parameters. This is because each individual has different characteristics, such as age, sex and physique etc., which affect the setting of the fixed thresholds. Therefore, fixed threshold-based fall detection system cannot perform well for different individuals. In other words, fixed thresholds for one may be unsuitable for others to ensure high fall detection performance of the system.

TABLE 6. Current studies on non-threshold-based fall detection and fall prevention systems.

Sensor Types	Fall Detection					Fall Prevention				
	Article & Year	Senso r &loc ation	Features	Algor ithm	Perfor mance	Article & Year	Sensor & location	Features	Algor ithm	Perfor mance
Machine learning	Yu et al. (2018) [146]	3-axial accele rometer	accele ration signal	HMM	Se:100% Sp:99.8%	Rescio et al, (2018) [73]	sEMG (Gastrocn emius and Tibilias muscles)	Integrated EMG, Co-contraction Index, Mean absolute value, etc	Linear Discrimin ant Anal ysis clas sifier	LDT: 770 ms Se:91.3% Sp:89.5%
	Zhou et al. (2018) [147]	Microwa ve radar, optical camera	Time-fre quency sig nal,short time fourier transform	CNN	Acc:99.85%	Zhen et al. (2016) [148]	3-axis Accelero meter, 3-axis gyroscope, 3-axis magnetomet er(waist)	mean of resultant acceleration, minimum of resultant acceleration, angle θ	SVM	LDT: 268 ms Se:99% Sp:96.5%
	Min et al. (2018) [149]	Webcam (1.6m ab ove the ground)	Space relation, hu man shape aspect ratio, human centroid height	Faster R-CNN	Pre:94.4% Re:94.9% Acc:95.5%	Steffan et al. (2017) [150]	3-axis Accelero meter, 3-axis rotational, rate, absolute orientation	3-axis acceleration, 3-axis rotat ion rates, 3D orientation θ	multilayer Perceptron neural networks	F1:82%
	Min et al. (2018) [151]	Microsoft Kinect sensor	Minimum height of the given joint, Max joint vertical velocity	SVM	Acc:92.05%	Aziz et al. (2014) [152]	3-axis Accelero meter, gyroscope (waist)	means and variances of X-, Y-and Z-axis acceler ations, veloci ties angular velocities	SVM	Se:>95% Sp:>90% LDT: >250 ms
Statistics process	Wu et al. (2017) [127]	3-axis accele rometer 3-axis angular velocity	accele ration, angle velocity	Hotell ing's T2 sta tistic	Se:94.8% Sp:95.2%	Hu et al, (2014) [153]	eight-camera capture system	head vertical acceleration, upper arm and trunk vertical velocity,sh ank frontal velocity, head frontalangular velocity	ARIMA -based statistical	LDT:620-710 ms Se:94.7% Sp:99.2%

Clearly, fixed threshold-based methods have low recognition ability, and always result in high false alarms. Dynamic or adaptive threshold-based fall detection and prevention methods have been proposed to solve these problems. Wu et al. [127] proposed an adaptive threshold method to detect falls based on a multivariate control chart. This adaptive threshold method had high detection performance as it considered individual historical data, that is to say, this constructed fall detection was a person-specific method. In article by Ren and Shi [144], different user groupings, including different gender, age, height and weight, were analyzed to refine personalized threshold for high accuracy fall detection system. Adaptive threshold methods were also proposed for fall prevention. In article by Otanasap [40], they proposed a pre-impact fall prevention system using adaptive threshold model, which automatic adjusted threshold based on motion history of the user. Obviously, experiment results concluded in Table 5 clearly show personalized or adaptive thresholds-based fall detection/prevention systems considering user's characteristic and other influence factors have high performance than these fixed threshold-based systems. We believe this category is a inevitable trend for the widespread use and extension of the system in real life.

2) NON-THRESHOLD-BASED FALL DETECTION AND FALL PREVENTION

Non-threshold-based methods always use complex algorithms to distinguish or predict falls from ADLs. They mainly apply machine learning algorithms or statistics process algorithms as concluded in Table 6.

For machine learning-based methods, commonly used algorithms in fall detection or prevention system are kNN, Support Vector Machine (SVM), Naïve Bayes, Hidden Markov Mode (HMM), random forest, fuzzy logic, etc. For instance, Yu et al. [146] developed a HMM-based fall detection algorithm using a single 3-axial accelerometer. Raw acceleration signals were analyzed using Gaussian distributions for hidden states to train HMM models. In article by Zhou et al. [147], three CNNs were used for fall recognition by training three feature sets extracted from capture information of wave radar and optical cameras. The combination decision of the three CNNs gave the final fall detection results. SVM is another popular machine learning technique, which needs to find a hyperplane to ensure the largest margin between different classes. SVM is also used to distinguish falls from ADLs, as published in Min et al. [151], they extracted 32 features from data collected by Kinect sensor to train the proposed classifier. Apparently, machine learning techniques can also be used to predict falls, for example, SVM-based preimpact fall detector was proposed by Zhen et al. [148] and Aziz et al. [152]. Neural networks were constructed by Steffan et al. [150] to prevent falls. Certainly, there are many other machine learning-based fall detection and fall prevention methods which have not been mentioned in this paper. Obviously, from Table 5 and Table 6, it is clearly observed that the performance of machine learning-based fall detection system is higher than that of threshold-based system by training classifiers with extracted features.

Statistics process can also be used to detect or prevent falls. Wu et al. [127] applied Hotelling's T2 statistic to detect falls, while Hu and Qu [153] proposed ARIMA-based statistical process-based pre-impact fall detector. Actually, both machine learning and statistics-based fall detection/prevention algorithms have been widely studied, as they can achieve high accuracy than threshold-based fall detection/prevention methods. However, they are complex computing processes and commonly require high computing volume compared to threshold-based approaches, which are the main limitations for these methods.

3) FUSION-BASED FALL DETECTION AND FALL PREVENTION

Both threshold and non-threshold-based systems have their advantages and disadvantages. Threshold-based method is always light-weight algorithm and is easy to be implemented in wearable detector, however, the performance is hard to ensure. Non-threshold method can improve the performance of the system effectively compared to threshold-based method, however, it requires high computing capability and storage volume in general. Recently, fusion method combining threshold or/and non-threshold method has sprung up to increase the accuracy of the system, which integrates the advantages of the combined methods. Based on current studies, fusion-based methods can be divided into homogeneous and heterogeneous-based approaches as listed in Table 7. For homogeneous fusion-based methods, they can be multiple threshold algorithms voting to determine falls as proposed by Poonsri et al. [154]. Combination of machine learning methods can also be used to increase the accuracy of fall detection system as proposed by Cheng and Jhan [155]. Meanwhile, homogeneous fusion-based method has also been applied to prevent falls. Su et al. [65] showed three hierarchical classifiers based on Fisher discrimination analysis to predict falls. For heterogeneous fusion-based approach, the combination of threshold and Non-threshold method have been put forward to distinguish or predict falls. Currently, multiple combination strategies, such as combination of threshold and multiple kernel learning SVM [10], or threshold and kernel density estimation [48], etc. were proposed to reduce false alarms. Comparison among Table 5, 6 and 7, it is clear fusion-based fall detection/fall prevention system has high performance than single threshold or non-threshold-based method. Therefore, we also consider fusion-based method to be one of future study directions.

IV. CLASSIFICATION OF LOW-POWER TECHNOLOGIES FOR FALL DETECTION

Since a wearable fall detector is typically powered by a battery, energy-efficient approach is essential for such service. However, traditional studies usually commit to the accuracy of fall detection, but neglect the fact that fall detection algorithm always runs on a microcontroller with limited computing, storage and energy resources, which decide the limited usage time of the detector.

Currently, some researches on low-power fall detector have gradually been put forward. As we all know, the elderly performs ADLs for most of the time, while falls seldom occur. Therefore, in our former study [24], an energy efficient scheme of using a low sampling rate during most of time, but a high sampling rate when there is a possible fall to increase the performance of fall detection algorithm was proposed, which was called a segmented sampling rates scheme. This proposed low-power fall detection method was verified to improve both energy efficiency and detection accuracy. Article by Wang et al. [158] also concentrated on adjusting the sampling rate to get the goal of energy efficiency. The proposed low-power fall detection algorithm dynamically adjusted the sampling rate of the sensor and managed wireless transmission to reduce power consumption. Testing results showed the proposed energy-efficient algorithm achieved slightly better than the algorithm without using low-power idea. Solaz et al. [159] presented an energy-aware fall detection integrated circuit, which included a Programmable Truncated Multiplier (PTM). It combined the power-reduction

TABLE 7. Current studies on fusion-based fall detection and fall prevention systems.

Sensor Types	Fall Detection				Fall Prevention			
	Article & Year	Features	Algorithm	Performance	Article & Year	Features	Algorithm	Performance
Homogeneous	Poonsri et al. (2018) [154]	orientation, aspect ratio, centroid distance between frames	Multiple Threshold voting	Acc:91.38% Se:97.92% Sp:60%	Su et al, (2016) [65]	Average absolute signal magnitude variation, Correlation coefficient, Average absolute value	Three hierarchical classifiers based on Fisher discrimination analysis	LDT:326-374 ms Se:98.1% Sp:98.8%
	Cheng et al. (2013) [155]	Acceleration values of x-, y- , z-axis, intensity of triaxial acceleration, integration of acceleration intensity	Cascased-Adaboost +SVM	Acc:95.35-98.48% Se:97.92% Sp:60%	Martelli et al, (2014) [42]	linear acceleration of all the body segments	Independent Component Analysis and a Neural Network	LDT: 351 ±123 ms Acc: 95.4%
Heterogeneous	Khojasteh et al. (2018) [156]	Detect a peak, 8 features (Impact Duration Index, Maximum Peak Index, etc.)	Threshold +classifier (Feed forward NN, DT, SVM, etc.)	Acc:88.6-95.2% Se:83.3-100% Sp:88.2-95.6%	Otanasap (2016) [40]	Acceleration amplitude, acceleration mean value, standard deviation of acceleration, etc	Statistic process +threshold	LDT: 365.12 ms Acc:99.48% Se:95.31% Sp:97.4%
	de Quadros et al. (2018) [11]	Total acceleration (TA), Vertical acceleration(VA), total velocity, total displacement, vertical displacement(VD), Mean and maximum of VA, VD, etc.	Threshold +Madgwick's decomposition)	Acc:91.1%	Kutchka (2016) [103]	Pixel time process, mean and variance of each gaussian	Haar cascades +histogram of oriented gradients (HOG)+SVM	Not given
	Shahzad et al. (2018) [10]	acceleration vector magnitude, average absolute acceleration magnitude variation, Impact duration index, Max peak index, etc.	Threshold +multiple kernel learning SVM	Acc:91.7-97.8% Se:95.8-99.5% Sp:88-95.2%	Fino et al. (2015) [67]	Magnitude of angular velocity, heading angle	threshold +trapezoidal integration	Se:76.1-89.4% Sp:76.7-100%
	Li et al. (2018) [157]	Magnitude of the body change, instantaneous activity intensity, angle, head's movement speed	Threshold + SVM + D-S evidence theory	Acc:95.83-98.33%	—			
	Medrano et al. (2017) [48]	Nearest neighbor distance, change in orientation, final velocity, distance of the body's displacement during the fall	Threshold +kernel density estimation	Se:97.9% Sp:96.7%				

benefits of the standard truncated multipliers with the benefits of programmability. Yuan et al. [160] proposed an interrupt-driven low-power fall detection algorithm based on a digital accelerometer (ADXL345). ADXL345 supports various interrupts, which were used in the proposed fall detection algorithm to trigger different fall phases. The special capability of it allowed adaptive status changes of MCU between the deep sleeping mode and the working mode according to interrupts, which is the key idea of power saving for the proposed fall detector. The article by Gia et al. [161] investigated energy efficient fall detector in different configurations and operating conditions from hardware (such as the choice of micro-controller, motion sensor, and transmission module) and software (such as the choice of sampling rate, transmission distances and transmission condition) perspectives, and they presented the optimal hints for the implementation of low-power system. In article by Rahmani et al. [162], authors analyzed multiple factors that can reduce the power consumption of the system, such as micro-controller, 3D accelerometer sampling rate and Bluetooth technology. Wang et al. [163] proposed an optimal low-power fall detector that contained triaxial accelerometry and barometric pressure sensor. They mainly used a combination of both hardware and firmware-based method to reduce the power consumption of the fall detector, such as the selection of ultra-low-power components, voltage scaling, reasonable working modes configuring, etc.

It is clear that various low-power technologies can be used to optimize the energy consumption of fall detection system, however, most of them only use a simple energy-efficient method, such as low-power hardware selection, auto-tuning of wireless communication module. Hybrid energy-efficient schemes are future trends, which combine multiple low-power technologies together to optimize the overall power consumption of the system.

V. CLASSIFICATION ON SENSOR PLACEMENTS FOR FALL DETECTION

The number and placements of the wearable sensors, such as accelerometers or/and gyroscopes on the body have different effects on the performance of fall detection, which have been explored by some studies. Jacob et al. [164] presented a simple fall detection approach using one accelerometer and two gyroscopes, which were placed on three different positions along the thoracic vertebrae to find and verify the best placement location. T-4 was indicated to be slightly better. Suriani et al. [45] studied the optimal sensor placement for lower activities. Accelerometer was placed on hip, thigh, and foot to collect data for experiment verification. Hip was proved to be the best location to detect falls. Ntanasis et al. [49] also investigated the optimal sensor placement for fall detection. Sensor locations such as the head, chest, waist, wrist, thigh, and ankle were studied and evaluated, among which the waist and the thigh were two optimal locations for high accurate fall detection. Article by [165] focused on the impact of accelerometer number and locations on the performance of fall detection system. 21 corresponding attributes were extracted for accelerometers located on the waist, chest, thigh and ankle, and were trained by the proposed classification model for fall recognition. Chest was proved to be the best location for advanced posture recognition. Meanwhile, authors also compared the accuracy of accelerometer-based fall detection and posture recognition with four different located sensors. Study of [42] was another study focused on the best subset of body segments for fall prevention. An ad-hoc designed machine learning algorithm was proposed and tested with the recorded data of different subsets of all body segments to determine the minimum number of segments to get a good detection performance. Experiment results showed the information collected by all the different body segments is redundant for pre-impact fall detection, only the kinematics of upper and lower distal extremities are adequate signals for high performance of pre-impact fall detection.

Obviously, the determination of the number and appropriate placements of the wearable sensors can improve the performance of fall detection and fall prevention system. Current related studies mainly compare previous algorithms with information collected by different sensors located on different body segments to decide the best sensor locations, however, different studies draw different conclusion as shown above description. This is maybe because placing sensors on different body segments affects particular posture recognition, which further reduces the performance of fall detection algorithm. Others focus on the influence of the sensor number to gain a high performance. However, different number of sensors bring out information redundancy issue. Further system modeling on the body segments can be researched to solve above issue.

VI. DISCUSSION

A global study for fall detection and prevention has been conducted by summarizing all fall-related technologies using variety of sensors and analytical solutions. However, no matter what types of sensors or analytical solutions have been used, there are still some limitations that need to be urgently analyzed and considered.

1) Most of previous studies on fall detection or prevention make an ideal assumption that training data for the system are available and sufficient to construct system model. Actually, falls are abnormal events that happen infrequently and diversely in real-life scenario, therefore, fall data is rather scarce and is difficult to acquire. However, in previous studies, data used to train and verify classifier model is always collected from simulated falls by young people in a laboratory environment or a controlled setting, which may be different from actual fall data of elderly. The classifiers trained with those data may suffer from high false alarm or fall missing rate when they are applied into practice. In some studies, few real fall data is collected and available in their system, however, on the one hand, the collected data is still insufficient to train classifiers, on the other hand, the real data is not publicly

available, which cannot be accessed or used to compare with other implementations. We believe it is benefit for the future research to incorporate real data of various falls into a public dataset.

2) It has been proved that fusion-based fall detection and prevention systems, combining with variety of sensors or analytic algorithms, work better than those single-based system. However, fusion-based method integrating multiple data sources has redundant information, which increases the computational complexity and system cost. In this case, determination of the number of components to reduce redundant information and synchronization of various sensors is inevitable to improve the overall performance of the system.

3) The main objective of current fall-related researches is achieving high performance. However, there lacks of general evaluation framework among different methods. Most studies collect their own simulated activities data in special environment across volunteers with different characteristics, which is impossible to be reproduced. Therefore, it is difficult to verify the given evaluation results or give a fair comparison. As it is discussed earlier, age, gender, height and other external factors affect collected signals, however, these influences on proposed algorithms are not presented in most studies. General evaluation framework should be discussed and presented for different algorithm comparison.

4) False alarm is also considered by fall detection/prevention system, which is ignored by current studies. To reduce false alarms, classifiers in fall-related systems should adapt and self-learn new activities to reduce false alarms, as the user has different characteristics compared with volunteers in training phase, the collected simulated data and the real-time running data may have different motion trend and strength, which increase the false alarms of the system. Therefore, personalized/adaptive fall detection/prevention system that has adaptive ability is a new trend to detect or predict fall.

VII. CONCLUSION AND FUTURE WORK

Fall detection and fall prevention systems play important roles in elderly's daily life. Currently, various sensors are deployed to determine or predict falls from ADLs, while sensor-fusion method is one novel trend to improve the performance of the system, as it combines multiple data sources from the related sensors. From analytical algorithm perspective, threshold-based method is a classical and basic approach by comparing with a reference value, while machine learning-based method has been widely researched to increase accuracy of the system. However, combination of threshold or/and machine learning-based method has sprung up to improve the performance of the algorithm.

In this presented paper, we conduct a comprehensive review among the latest studies on all fall-related technologies, which is a four-layers classification. The top layer contains four classes, including current literature reviews on fall detection or/and prevention, comprehensive classification schemes for current fall detection and fall prevention researches, and also summary current low-power technique and sensor placement of fall detection system. It is a systematic study refers to all the fall-related technologies. Especially, two classification schemes for fall detection and fall prevention systems are proposed and conducted from sensor apparatus and analytical algorithm perspectives in detail. Each sub-category is systematically studied. Specially, from sensor apparatus perspective, RF and fusion-based systems are considered. Meanwhile, from analytical algorithm aspect, algorithm fusion-based methods including homogeneous and heterogeneous-based approaches are presented and discussed detailedly. Furthermore, current challenges and issues in fall-related systems are considered and analyzed, including lacking of real-world fall data due to various reasons, cost and information redundancy of fusion-based system, lacking of general evaluation framework, as well as high false alarm issue, all of which should be solved for future research.

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