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Fall detection monitoring systems: A comprehensive review

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Abstract The increase in elderly population especially in the developed countries and the number of elderly people living alone can result in increased healthcare costs which can cause a huge burden on the society. With fall being one of the biggest risk among the elderly population resulting in serious injuries, if not treated quickly. The advancements in technology, over the years, resulted in an increase in the research of different fall detection systems. Fall detection systems can be grouped into the following categories: camera-based, ambient sensors, and wearable sensors. The detection algorithm and the sensors used can affect the accuracy of the system. The detection algorithm used can either be a decision tree or machine learning algorithms. In this paper, we study the different fall detection systems and the problems associated with these systems. The fall detection model which most recent studies implements will be analysed. From the study, it is found that personalized models are the key, for creating an accurate model and not limiting users to specific activities to perform.

Keywords Fall detection · Machine learning · Elderly care · Healthcare

1 Introduction

An increase of more than 30% in the elderly population is expected by 2050 in 64 countries stated by the United Nations [1]. The World Health Organization, reported that about 28% of people aged 65 fall and about 32% of people aged 70 fall each year [1], [2]. Due to the shortage of nursing homes, more elderly people are required to stay at home [3]. Elderly people who live alone cannot alert anyone for help if a fall occurs due to any serious injuries sustained or if they were unconscious [1]. The definition of a fall is as follows, "an event which results in a person coming to rest unintentionally on the ground or other lower level, not as a result of a major intrinsic event (such a stroke) or overwhelming hazard" [4]. A fall can occur in one second usually it takes between 0.45 and 0.85s; during a fall, the posture and shape of the person changes [5]. These changes are of great importance when detecting a fall [5]. The risks of fall can be divided into two categories, namely, extrinsic, and intrinsic risks [6], [7]. Extrinsic risks are related to environmental factors such as drug usage, slippery floors, poor lighting, loose carpets, unstable furniture, clutter, and obstructed paths; whereas intrinsic risks are related to the characteristics of the person such as age, general clinical condition, mental impairment, sedentary behaviour, impaired mobility and gait due to reduced muscle strength [6], [8], [7]. Extrinsic factors can be prevented by taking precautions, whereas intrinsic factors cannot be prevented [7]. Factors that contribute to the increase in rate of falls is the increase in person age, mortality, morbidity, disability, and frailty [9], [10]. When a fall occurs, it can result in serious damage to a persons health, fear of falling (FOF), loss of independence, no social contacts, lack of movements, and decrease in productivity, which increases the risk of another possible fall [6], [2], [9], [4], [11]. This can result in loss of self-confidence which can lead to social isolation and lower the quality of life [2]. An FOF is linked to an increase of neuroticism and anxiety which results in elderly people avoiding partici-

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pation in any physical activities [2]. The biggest danger of falling is “long-lie” condition, where the fall victim is unable to stand up from a fall and remain on the ground for hours [12]. Long lie can result in dehydration, internal bleeding, physiological and psychological consequence, depending on the seriousness of the injury; and where half of the people who experience long lie die within 6 months [6], [13], [14], [15], [16], [17]. With a fall detection system, the psychological stress and severity of head-trauma during epileptic seizures can be reduced and the cost of treatment is also reduced drastically [18], [5]. Falls can influence the increase in the economic costs which impose a burden on the health-care system [11]. A lot of research has been done on fall detection systems from the 1990s [19].

The cost of being monitored is expensive at health care facilities, where the main purpose of it is to detect whether a person has fallen or not, that’s why fall monitoring systems play an important role in society by allowing people to be monitored from the comfort of their homes or anywhere else resulting in huge savings and eliminating the need for a 24/7 nursing to monitor the person [14], [18]. The first fall detection system was a device with a button known as user-activated devices or Personal Alarm System (PAS), which was usually worn as a wrist band or necklace and it required the user to be conscious when a fall had occurred to press the button and alert the emergency personnel [6], [20], [3]. The problem with the push buttons were that they could not be pressed if the user had lost consciousness or was in a confused state due to panic; and the button could also be accidentally pushed; and the device is not have been worn by the user during a fall [6], [21], [17]. An automatic real-time activity recognition device that can successfully discriminate between activities of daily living (ADL) and fall activities is required. ADLs contain a wide set of actions characterizing the habits of people, especially in their living places e.g. walking, sitting, standing, etc. [22]. These fall detection devices that are available in the market are not satisfactory in terms of high false alarms, high maintenance cost, and they are not ergonomic [7]. Fall detection needs to detect quickly to reduce impact and recovery time; and should inform others quickly to reduce the time people remain on the floor and to neglect any injuries that can occur [20], [4], [23]. A precise, robust, and reliable fall detection system is required for elderly people living independently thus reducing the risks when living alone [19], [20], [23]. There is no standard method for fall detection in terms of what type of sensors that can be used, which features to extract, and which machine learning algorithm performs better [9]. The following is expected from a fall detection system: no intrusion on the users privacy, no restrictions on the users independence, and should not degrade the users quality of life [7].

There are several fall detection surveys published which cover some aspects of the fall detection model. In [2], an overview of wearable sensors is provided; particularly fall detection systems which incorporates smartphones are covered. The study also conducts an experimental testbed to analyse the performance of the different threshold fall detection algorithms that make use of accelerometer sensors [2]. The results from the testbed indicate that accelerometer techniques for identifying falls are strongly influenced by the fall patterns; and the tests also shows that it is difficult to set an acceleration threshold to achieve high accuracy [2]. In [24], a detailed comparison of wearable fall detection devices and fall prevention systems are provided. This includes the different sensors for detecting falls, the challenges and design issues faced are discussed. A short analysis on camera-based and ambient sensing is provided [24]. The general learning models which are employed in wearable systems are explained and the most popular supervised machine learning algorithms are analysed [24]. A three-level taxonomy which describes the risk factors that are associated with falls, is proposed [24].

In [25], an overview and a comparison of the different systems that make use of acceleration methods, methods that combine acceleration methods with other methods, and methods that do not use acceleration. In [26], a detailed review on context-aware systems and wearable accelerometer fall detection studies are provided; which includes comparisons between the different studies. The challenges in design of the fall detection systems and the issues which affect the systems performance; the trends in the present and future of fall detection systems are identified [26]. Due to the lack of fall data, the problem cannot be solved by using supervised machine learning algorithms [9]. In [9], a taxonomy is proposed for sufficient, insufficient and no training data on falls. A comprehensive overview on the different techniques that can be applied for sufficient fall data and the lack of fall data is described. A review on camera-based and wearable studies for anomaly detection is provided [9].

This study will provide an updated overview on the different types of fall detection systems and the problems associated with each of the mentioned fall detection systems. The study provides in-depth analysis on the different categories compared to previously reviewed papers. The need for personalized systems will be investigated and how it can solve the key problems faced in fall detection system.

2 Model of a fall detection system

In figure 1, the most common fall detection model which is used in many studies, when designing a fall detection system is shown. The model comprises of the following parts which will be discussed below: data collection, feature extraction, feature selection, classifier, and evaluation.

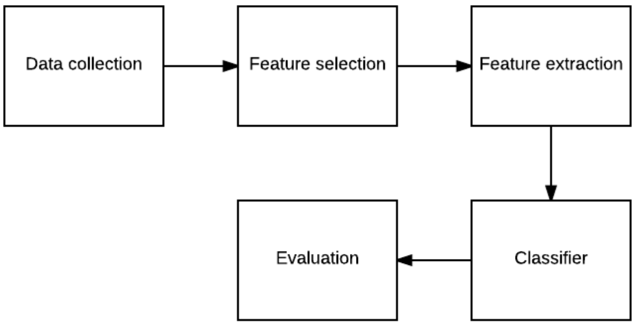

Fig. 1 Fall detection classifier model.

2.1 Data collection

Fall detection starts by the collection of data from sensors. These sensors can be either wearable sensors or ambiance sensor, and camera-based sensors. These sensors will be discussed in more detail, in section 3.

2.2 Feature extraction

Feature extraction is a method where significant attributes are found from the raw data which consists of meaningless information; and it plays a vital part in determining the accuracy of the fall detection system [5], [24], [27]. Fall detection systems require a distinctive feature to represent the different activities and needs to be able to classify falls from ADLs [28]. There are different features, each having relevant characteristics to specific ADLs or fall activity being performed [27]. Features can be group into two categories, namely, time or frequency based features [27]. In wearable device, the most popular features are acceleration magnitude of the accelerometer and angular magnitude of the gyroscope [24]. In camera-based systems the aspect ratio is the most common one; whereas in Doppler and acoustic device the Mel-frequency cepstral coefficient (MFCC) features are the most popular ones. A lot of features are calculated using statistical models such as median, max, min, variance, etc. [27]. Special attention should be applied when selecting features to produce a small descriptive dataset [24]. The dataset descriptive power is impacted by the number of features that the dataset is comprised of [24]. Extracting features are performed on data using a sliding window method [27].

2.3 Feature selection

The more features a database has, the more descriptive it becomes, and it becomes difficult to find meaningful relationships among the classes as the feature space grows exponentially; and the performance of the machine learning algorithm is also dependent on the feature space [19], [5], [24], [27]. By finding features which describes the data better and discarding the redundant features, we can improve computational speed and prediction accuracy [19], [24]. The method of selecting features from an N dimensional feature space is known as feature selection [17]. The feature selection algorithms are used to detect and discard features that provides minimum contribution to performance of the classifier [27]. Feature selection provides the following advantages it reduces the cost of pattern recognition process, reduce the dataset, and provides better accuracy [19], [17]. There are two categories of feature selection methods, namely, filter methods and wrapper methods. Filter methods or ranking method make use of search algorithms to score the different features and rank the features from the best to the worst [24], [27]. Filter methods make use of statistical tests such as T-test, F-test, Chi-squared, etc. The wrapper method takes combination of different features and compare the combinations of features based on the classifier results, where the classifier is part of the selection process [24], [27]. The combination of features is chosen based on that which provides an accurate model for classification [24], [27]. The disadvantage of wrapper methods is that it requires a huge amount of processing power and it is very time consuming [27]. Instead of selecting features, all the features that are extracted are combined to create new features using principal component analysis (PCA). The PCA is an unsupervised linear transformation method, which useful variable reduction procedure widely adopted in many fields and is a common technique for identifying patterns in data of high dimension and expressing the data in such way as to highlight their similarities and differences [22], [1]. A PCA algorithm provides an orthogonal transformation of a large feature space, into a new set of values made of linearly uncorrelated variables called principal components which results in a significantly smaller feature space and decreases in dimensionality [22], [1].

2.4 Classifiers

The fall detection classifiers can be divided into two parts, threshold-based or rule-based and machine learning algorithms [2], [18], [4].

2.4.1 Threshold or rule-based

The most popular classification method used in fall detection studies is the threshold analytical method [9], [29]. The basic principal for the threshold analytical method is that a possible fall could be detected based on the sensors captured value; which is compared to the reference value [9], [29]. A threshold method is a flowchart where each node is tested where the outcomes result in each branch. Fall detection that make use of accelerometer sensors, uses a threshold parameter to detect falls such as absolute acceleration magnitude or wavelet acceleration sum-vector and compares it to a predefined value [1]. The predefined value is calculated and determined from a fall signal [1], [18]. Fall training data is required to compute the threshold value using domain knowledge's or data analysis techniques [9]. The advantage of threshold is that it is easy to implement, power budget, and computational power [22], [2], [29]. The problem of threshold systems is that they lack limited recognition ability, not precise enough, difficult to determine the predefined value and it results in high false rates from running or jumping which results in low accuracy [1], [29], [8]. The performance of the fall detection methods is affected by the selection of the fall indicators and detection thresholds [30]. Thresholds results in low accuracy which makes researchers to focus more on machine learning classifiers which achieves higher accuracies.

2.4.2 Machine learning

Classifiers obtained a greater performance compared to threshold classifiers when using an accelerometer sensor [18]. Machine learning algorithms have complex implementation when compared to the threshold implementation, it is based on decisions using posture calculation which result in a higher fall detection rates [29]. The advantage of machine learning algorithm is that the different falls could be customized; and high accuracy is achieved when compared to the threshold methods; and it can manage anomalies (such as noise and incompleteness) well; and it can detect patterns in signals [4], [29]. The disadvantage of machine learning algorithm is that it requires huge amounts of representative training data, it is complex and requires heavy processing [4], [29], [31]. Machine learning algorithm can be divided into two groups supervised and unsupervised learning algorithm.

2.4.2.1 Supervised

Supervised learning algorithm make use of labelled data for training the system and the outputs of the system is controlled [24], [27]. Certain classifiers can perform better on certain activities [27]. Classifiers can be combined such as voting machines or comparator machines [18]. A hybrid framework which make use of both threshold based and machine learning algorithms is implemented in the study [4]. Popular supervised machine learning algorithms include Naive Bayes, k-Nearest neighbour, support vector machine, hidden Markov model, and artificial neural network.

For a k-Nearest neighbour (k-NN) also known as a lazy learner, which classifies a new feature vector based on the classes of the other training feature vectors [7], [10], [24]. Each time a new feature vector is inserted into the classifier, all the training feature vector sets are compared to the new feature vector in terms of Euclidean distance. From the Euclidean distance, the shortest distance will be determined, what centroid the feature vector has joined and in what class it lies [18], [10], [24]. The value k determines the number of centroids that are available for each class. Special attention should be applied to determine the value of k; if a smaller value k is selected the variances increases and the results are less stable; and a large k value will result in an increase in biasing which will reduce the sensitivity [7]. The disadvantage of this classifier is that the time complexity increases as the training data increases.

The Support Vector machine (SVM) uses a kernel trick as it transforms the inputs, which are features extracted, into a higher dimensional space using a non-linear mapping in which an optimum hyperplane is found separating two classes from a given training dataset [15], [32], [33]. The basic idea is to find a separating hyperplane that corresponds to the largest possible margin between the points of the different classes [34]. A hyperplane is used to separate the two classes by creating a decision boundary (maximum margin hyperplane) [24]. Optimization of separating hyper plane is done by maximizing the distance between the hyperplane and the nearest data points [34], [32]. The maximum margin hyperplane is learnt based on the support vectors, which the classifier uses to classify the new feature vector [15], [24].

A Hidden Markov Model (HMM) is a statistical Markov model. An HMM, is made up with different number of states. A typical model for a fall detection system is a continuous HMM model, where each state is connected to one or more states. An HMM consist of the following parts: a transition probability distribution matrix which is used to determine the probability of one state reaching another state in one single step, an observation symbol probability distribution matrix which is used to determine the output of a state based on the input feature and an initial state distribution matrix which is used to determine what the initial state is. The system is trained by using a Baum-Welch training algorithm. The class is determined using a Viterbi algorithm [35]. The disadvantage of HMM it is computationally expensive and requires many model parameters [4].

2.4.2.2 Unsupervised

Unsupervised learning algorithm make use of unlabelled data for training the system [24]. This type of learning algorithm can be trained on only fall data or non-fall data [9]. The classifier can be trained on with new activities on the fly. Popular unsupervised classifiers include: one class support vector machine, and nearest-neighbour.

One class support vector machine (OCSVM) converts the data to a feature space which is surrounded by a hypersphere; and it searches for the appropriate hyperplane that splits a portion of the input data from the rest of the data by the sign of the distance to the hyperplane (f(C) >0 or f(C) <0) [36], [37], [38]. The classifier makes use of hyper-plane as a decision boundary to classify the binary data [36]. The advantage of OCSVM is that it describes the data in a flexible way; since it does not need to ensure that the data follow a certain distribution [14], [38].

Nearest-neighbour (NN) is a data driven method, and which is simply a k-NN classifier where k is equal to 1[15], [39]. The basic concept of NN is to allocate the incoming record to the class that has a record closest to the incoming record [39]. The Euclidean distance is computed for the incoming record with each of the stored record, where the minimum distance between the incoming record and stored record is used [15], [37]. If the minimum distance is higher than a threshold value, the incoming record is considered an anomaly [15], [37]. The performance of NN will suffer if the data has regions of varying densities [37].

2.5 Testing and evaluation of the system

Typical testing of the system is to perform leave-one-out method or cross validation method [4]. The dataset can also be split into 70% for training the classifier and 30% for testing the classifier [27]. Statistical tests are done to determine the overall performance of the classifier [24]. The classification model can produce the following four possible outcomes [18]: 1. True Positive (TP) when a system properly detects a fall when fall has occurred. 2. False Positive (FP) when a system detects a fall when no fall has occurred. 3. True Negative (TN) when a system detects no fall when no fall has occurred. 4. False Negative (FN) when a system detects no fall when a fall has occurred. False negatives are falls which remained undetected and false positives are ADL activities which were classified as falls [2]. The following below, are most popular methods for measuring the performance of the classifier.

The recall or sensitivity measures the ability of a fall detection algorithm to correctly identify falls over the entire set of fall instances [18], [11], [24].

$$recall = \frac{TP}{TP+FN} \tag{1}$$

The precision measures the ability of a fall detection to correctly identify falls over the entire set of instances classified as falls. The precision measures the ability of the classifier to return the fall results were correctly classified [18], [24].

$$precision = \frac{TP}{TP+FP} \tag{2}$$

The specificity measures the ability of a fall detection algorithm to correctly identify ADLs over the entire set of instances classified as ADLs [18], [12], [11], [24].

$$specificity = \frac{TN}{FP+TN} \tag{3}$$

Accuracy is measured the portion of fall results that were correctly classified amongst all outcomes [18], [24].

$$accuracy = \frac{TP+TN}{TN+TP+FP+FN} \tag{4}$$

The F_1-measure combines the precision and sensitivity indicators [16], [24].

$$F_1 - measure = \frac{2 \times precision \times recall}{precision + recall} \tag{5}$$

The receiver operating character (ROC) theory has been used to properly define threshold values based on constraints on the system sensitivity and specificity [22]. By adjusting the threshold value, the ROC curve is created [15]. From the curve, the threshold point is selected where the maximum geometric mean of the sensitivity and specificity is selected from equation 6 [15].

$$geometricmean = \sqrt{specificity \times sensitivity} \tag{6}$$

The area under the curve (AUC) is the recover operating characteristic (ROC) curve and tells the performance of the classification model [40], [41]. The closer the AUC is to 1 the better the performance of the classification model is.

3 Fall detection sensors

Fall detection systems are also known as context-awareness systems should be able to recognize, interpret, and monitor different activities the user performs and be able to detect fall events [7]. There are different types of fall detection methods which includes camera-based, acoustic-based, and wearable sensors [11]. Each method of fall detection consists of numerous sensors, but none of these sensors provides 100% accuracy, but each sensor has its own advantage [42]. Table 1, shows the general characteristics of these sensors types.

3.1 Wearable sensors

Due to the increase in wearable telemedicine technology, solving these problems becomes easier [10]. The growth of Micro-Electro-Mechanical System (MEMS) resulted in miniaturized, more compact, and low cost [7], [43]. They can be easily integrated to other available alarm systems in the vicinity or to the accessories that the person carrier e.g. smartphones or smart watches which can achieve a kind of non-intrusive and non-invasive diagnosis and monitoring [7], [10], [44], [45]. The wearable sensors are connected to the subject of interest (SOI) [5].

Wearable devices make use of embedded sensors to calculate the motion of the monitored body in any unsupervised environment, period of inactivity, and the posture of the person [21], [2], [5]. The first automatic fall detection system is a wearable device that is placed on the user to detect falls which make use of acceleration or rotation information [46]. Wearable sensors can detect a fall by analysing the impact of the body with the ground, and taking the body orientation post and prior to a fall has occurred [47]. Wearable sensors are not affected by the environment or by privacy concerns [11]. Collecting activity data from wearable sensors is not restricted to laboratory environment, which allows collection of real world activities [12]. Wearable device can be implemented using micro-controller or smartphones.

3.1.1 Using smartphone for activity monitoring

Smartphones are now equipped with MEMS sensors which can be used to perform unobtrusive fall detection monitoring; and smartphones are already integrated in the daily life of users [22], [2], [9], [43]. The increase in growth of technology has made smartphones more popular and more commonly used than any specific fall detection equipment, they are non-invasive, portability, cost-effective, easy to carry; and work both indoors and outdoors [2], [9], [48]. Figure 2 shows a list of different high precision sensors that are nowadays available on the smartphone. The biggest advantage of smartphone is that it has most of these sensors integrated into it, which does not require no extra device [22], [1]. The biggest problem of smartphone devices used in fall detection is the fact that the devices lack battery draining; and have limitations in memory and real-time processing capabilities [1], [2].

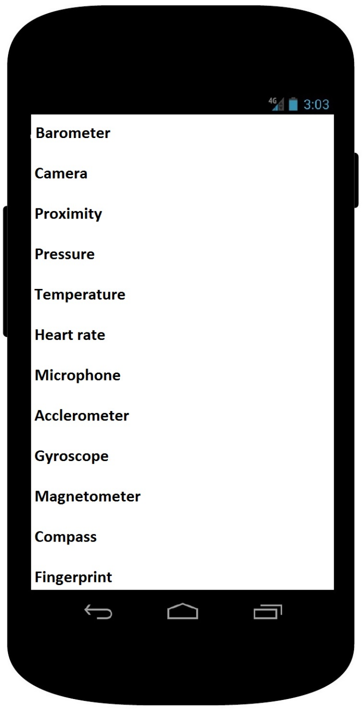

Fig. 2 Available sensors on smartphone devices.

3.1.2 Different types of wearable categories

Wearable fall monitoring systems are grouped into three groups: fall alert, fall risk assessment, and impact prevention [4]. Fall alert or PERS (personal emergency response system) is implemented to alert medical personnel or caregivers to provide assistance to user in an event of fall [4], [11]. Fall risk assessment is the study of fall in terms of the cause of it, and detecting which patients should be monitored based on their movements [4]. Impact prevention or FIPS (fall injury prevention

Table 1 Characteristics of different fall detection methods

Method	Price	Continuous monitoring	Battery problem	Obtrusive	Privacy	Monitor multiple people	Easy setup	Affected by the environment
Wearable	Cheap	Yes	Yes	Yes	Yes	No	Yes	No
Ambient	Medium	No	No	No	Yes	No	Yes	Yes
Camera	Expensive	No	No	No	No	Yes	No	Yes

system) is used to detect a fall event before it happens, and triggers a protection or prevention device to protect the user [4], [11]. An Example of FIPS is the detection of falls in the pre-impact phase where an activate protection devices can be used, such as an inflatable airbag or other projection device, to avoid any injuries from the fall [30], [49]. PERS prevents a long-lie by notifying caregivers when a fall is detected, since some falls are too hard to get up from or the user is in an unconscious state [11]. PERS is the most popular type of system and more research being conducted into it. PERS can be split into posture and motion devices [47]. Only PERS system will be analysed, and not FIPS as it relies on pre-fall data to detect a possible fall and is shown to achieve a low accuracy in [4].

3.1.3 Different wearable sensors

Wearable sensors include but are not limited to tilt switches, accelerometers, gyroscopes, pressure sensors, magnetometers, and microphones [4]. Each sensor has different characteristics and can operate independently or in conjunction with each other.

3.1.3.1 Accelerometer

Accelerometer sensors are the most popular and widely used sensors for detecting fall accidents and sensing body motions; as it has high accuracy, even in noisy measurements a well-read acceleration measurement down to 0Hz [5], [11], [36], [42], [43]. Accelerometers are feasible, effective, fast, easy to set up and operate, simple, lightweight, low-power, and cost-effective solutions for fall detection systems [20], [18], [50]. In [25] a study was conducted to detect what type of wearable sensor can accurately detect falls based on sensors that use acceleration, acceleration integrated with other sensor methods, and no acceleration sensors. The study concludes that using sensors which can sense accelerations are good at detecting falls; whereas methods that did not use acceleration are less accurate and can lead to many false alarms [25]. Falls can be detected by applying different signal evaluation techniques on accelerometer data [1]. The most popular feature extracted from the accelerometers is the Signal Magnitude Vector (SMV) which is given below,

$$SMV = \sqrt{x^2 + y^2 + z^2}, \tag{7}$$

where x, y and z are the acceleration values along the X, Y, and Z axis of the accelerometer [45], [25]. A fall acceleration signal comprises of peaks and valleys, and fall activities usually associated with large SMV peaks [42], [47]. Fall decision which make use of only SMV and considers only the abrupt peaks in the acceleration which result in high FP, due to the sudden movements which occur when performing complex movements, such as sitting down fast, and jumping [2], [47]. Most acceleration-based studies use a threshold-based algorithm for detecting a fall which result in high false alarms, in order to reduce false alarms, machine learning algorithms can be implemented [43].

The placement of sensors also plays a vital role as it can directly impact the accuracy of the fall detection techniques [25]. In [51] different positions on the human body is tested to identify the best position for the accelerometer. The following positions were tested: head, waist, and wrist to detect falls [51]. The acceleration information measured was compared to a threshold to detect a fall [51]. The results show that placement of the accelerometer sensor on the person head and waist achieves a sensitivity of 97-98% and specificity of 100% when using a simple threshold algorithm [51]. Investigation in [4], to determine what phase of a fall and placement of the tri-axial accelerometer on the body will achieve the best accuracy. Hybrid framework which make use of rule-based knowledge and a two-layer Gaussian classifier was implemented [4]. The following accuracies were obtained at different phases of a fall: 86.54% for pre-impact, 87.315% for impact, and 91.15% for post-impact [4]. The paper found that the side of the waist is the best position for the sensor during post-impact, followed by head, wrist, and front of waist, thigh, chest, ankle, thigh, and upper arm [4]. The reason for not achieving 100% accuracy in the post-impact phase include signal loss, post-impact and high impact ADLs were classified incorrectly [4]. If falls are analysed during post-impact phase, the chest is not suitable placement since the data transmission path of an alert signal could be blocked by the user's body [4]. The following sensors placements result in false positives by not being able to differentiate falls among sitting and standing: head, upper arm, wrist, ankle, and chest [4]. Placing the sensor close to the person centre of gravity makes the sensor less sensitive to spurious movements.

The disadvantage of accelerometer sensors is prone to elevators and high-speed cars or trains [20]. The output of the accelerometer does not only consist of acceleration but also gravity, which can create errors when calculating the angles resulting in high false positives [10]. Accelerometer systems lack the adaptability together with insufficient capabilities of context understanding [34], [12]. Accelerometer methods require high sampling rate, which can result in fast battery draining [34]. In [52] it was investigated that threshold based algorithms implemented on smartphone suffers a limitation from the accelerometers. The assumptions from smartphone fall detection system is that the hardware sensors measure acceleration with sufficient precision which is not the case [52]. The sensors from different manufactures record values in significantly different ranges for identical test sensors, which makes it impossible to set a reliable threshold value [52]. The accuracy of the system increases when accelerometer is incorporated with other sensors such as gyroscope, magnetometers, and barometers, the accuracy of the system increases [1].

3.1.3.2 Gyroscope

The most common feature extracted from the gyroscope sensor is the magnitude of the resultant angular velocity(w), which is given below,

$$w = \sqrt{w_x^2 + w_y^2 + w_z^2}, \tag{8}$$

where w_x , w_y and w_z are the angular velocity along the X, Y, Z axis of the gyroscope [10]. There are limited studies that only make use of gyroscope sensor to detect a fall.

In [53], a study was conducted to understand the use and the contribution a gyroscope sensor has when classifying physical activities. Accelerometer and gyroscope data were collected and fed into different classifiers [53]. The study concluded that by adding the gyroscope sensor to the system can improve the accuracy, the reason being that gyroscope data makes use of the objects orientation which most activities consist of; since the accelerometer only measures the linear motion along specified directions [53]. There are a lot of studies which combines both accelerometer and gyroscope together [29], [10], [54], [55].

The disadvantages of low cost gyroscopes are that they suffer from time varying zero shifts. This introduces significant errors when calculating the angular acceleration and angular position, using differential and integral operations [29], [10], [54]. If the noise is not removed and the data is accumulating, the error can be huge [29]. The Kalman filter algorithm with dynamic information of the target is required to remove the noise, in order to estimate the angle [29]. The gyroscope is also only available in higher grade smart phones [33].

3.1.3.3 Health sensors

In [56], fall is detected using electromyogram (EMG) sensors; which measures the muscle control signals. When a fall occur, there is a change in heart rate, which can be used to detect a fall. In [45] an accelerometer and cardio-tachometer is used to analyse and detect falls. When a person falls down, the state of person heart-rate can increase anxiety [45]. When a fall occurs the heart rate can be used to detect how seriousness of the fall is [57]. The disadvantage of using health sensors, it difficult to place on, and they can interfere when performing ADLs.

3.1.3.4 Wearable Camera

Compared to wearable sensors, wearable cameras provide a much richer set of data including contextual information about the environment, which includes analysis of a variety of activities including falls [20], [23]. The wearable camera system monitored is not limited to confined areas, and it can extend to wherever the subject may travel [23]. Wearable cameras do not affect the privacy of the user since it only records the surroundings of the user environments; and the system processes everything locally on the device and nothing gets transmitted anywhere [23]. In [20] the study make use of a camera system is worn on the user waist, which can provide continuous monitoring and is not limited to certain areas as compared to static cameras. Advantages of this system is that the privacy concerns are removed as opposed to the static cameras [20]. The wearable camera system uses edge orientations and histograms to detect falls; which can work effectively both indoors and outdoors, but it is highly invasive for subjects [8]. The wearable camera records the surrounding environment, which will make other people around the user uncomfortable, as it will seem as it is recording other people.

3.1.3.5 Ambient sensors as wearable sensors

Ambient sensors such as pressure sensor and microphone can be attached on the user footwear to detect falls [13], [58]. The advantage of attaching ambient sensors on wearable items, it can provide outdoor monitoring, and it is not limited in coverage area; since it is attached on the user. The disadvantage of the system it is influence by the environment. In table 2, a summary of the different wearable fall detection studies is shown.

3.1.4 Disadvantage of wearable sensors

3.1.4.1 Placement and intrusion

The major disadvantage of wearable devices includes intrusion, undesirable placement of device, neglect, or not wanting to wear them, and inconvenience to the users movement [7], [5], [32], [33], [40], [47], [66], [67]. Neglect or forgetting to wear the device, can resulting a wearable device an ineffective solution [34], [21], [66]. The undesirable placements of sensor on the user body, can cause obtrusiveness, inconvenience and uncomfortable when performing ADLs [34], [14], [21], [5]. Wearable devices which are placed on the belt around the hip, cannot be worn when changing clothes; and sleeping which results in the inability to monitor when a person is getting up from the bed [34], [51]. The addition of extra sensors causes the user to feel uncomfortable and lead to certain degree of inconvenience [33]. One solution, is to allow the user to choose the placement of the device, and the device should perform on-body sensor localization to detect the location of the device on the user [55]. This will eliminate undesirable placements. To make it convenient to the user, trouser pocket location can be used for placing device [48]. Bathroom has a high occurrences of falling down, which make it difficult for a person to wear a device in the bathroom, since these systems are affected by water, and make it uncomfortable when bathing [17], [68].

3.1.4.2 Power

Wearable sensors are all battery powered, which means it cannot be used when the device is recharging or batteries will have to be replaced [7], [16], [67]. The battery problem can be compensated by implemented using low sampling frequency scheme together with a hierarchical scheme methodology [1]. This will also reduce computational complexity of the system thus saving processing time [1]. To make the system usable , a smaller number of sensors is preferable on the user [4]. The advantage of keeping the number of sensors to a minimum is that it can cope with resource constraint issues such as battery power, storage, computational power, and network bandwidth [4].

3.1.4.3 Hardware and software

Wearable device are limited to the hardware and software [47]. Each smartphone device has fixed number of sensors built in, to add more sensors, the smartphone is required to be upgraded. A basic sensor that is available in all smartphones is the accelerometer sensor. Compared to microcontrollers where the software is fixed; the software of the smartphone can be updated anytime. Smartphones can address the problems of a low-power microcontrollers where classification algorithms are constrained to limited memory and processing power. Most microcontrollers systems implement only threshold classification, whereas smartphones can implement machine learning algorithms.

3.1.4.4 Generates a lot of false positives

Wearable sensors generates a lot of false alarms when performing daily activities, which can lead to frustration of users [34]. The reason for poor accuracy and high false positives using accelerometers of lack of adaptability with the lack of context understanding [44]. False positives can be limited by implementing communication between the user and the device. If a fall has occurred the user is communicated to first, to determine if a fall has occurred. If the user does not respond within a specified time period, the emergency service is communicated [69].

3.2 Ambient sensors

Ambient device make use of event sensing by collecting and examine the environment which is used to track the elderly person's movement, through the use of externals sensors which are attached around the surrounding environment such as a home or close to the subject [2], [5], [8], [45]. Other application that ambient sensors provide is indoor localization and security [5]. The advantage of ambient devices is that user does not to need to wear the device or remembering to put it on, it is passive and unobtrusive [29], [47]. The ambient devices are non-intrusive and it is invisible to the elderly which would not affect the user privacy [19]. Ambient devices are cheaper; but less intrusive compared to camera-based systems [47].

3.2.1 Vibration detection

Ambient devices, that make use of vibration data where the detection of falls is based on the characteristics of vibration patterns [20], [47]. Vibrations can be used to

Table 2 Summary of wearable sensors studies

Study	Sensors	Placement	Features	Algortihm	Results
[47]	Smartphone compass, accelerometer, proximity,gyroscope	Trouser Pocket	Mean, standard deviation, principal component analysis	Decision tree, support vector machine	Accuracy: 90%
[18]	Accelerometer	Chest	Wavelet coefficients	Comparator system	Accuracy: 99%
[13]	Accelerometer, pressure sensor	Shoe	Pressure, orientation of the foot	State machine	NA
[48]	Smartphone accelerometer	Trouser pocket	SMV, Z axis	High level fuzzy Petri net	Accuracy: 90%
[59]	Electromyography	Lower limb tibialis, Gastrocnemius muscles	Co-Contraction Indices	Decision tree	Sensitivity: 83.2% Specificity:72.4%
[4]	Accelerometer	Waist	Mean, SMV, slope of SMV, standard deviation	Gaussian mixture model	Accuracy: 91.15%
[20]	Smartphone camera	Waist	Gradient local binary patterns, edge orientations	Decision tree	Indoor accuracy: 93.78%, outdoor accuracy: 89.8%
[11]	Accelerometer, gyroscope, barometric altimeter	Right anterior iliac spine	SMV, orientation,height, downward vertical velocity	Decision tree	Sensitivity: 80% Specificity:100%
[10]	Accelerometer, gyroscope	Vest	w, SMV	k-NN	Sensitivity: 95% Specificity: 96.67%
[33]	Smartphone compass accelerometer,	Trouser pocket	Tilt angle, wavelet coefficients, SMV	Support vector machine, state machine	Sensitivity: 92% Specificity: 99.75%
[45]	Accelerometer, cardio tachometer	Wrist and waist	SMV, trunk angle, heart rate	Decision tree	Accuracy: 97.5% Sensitivity: 96.8% Specificity:98.1%
[60]	Accelerometer	Waist	Signal magnitude area, tilt angle, SMV	Binary structure classifier	Accuracy: 95.6%
[61]	Accelerometer	Waist	Sum of X and Z axis, total sum of X, Y, and Z axis	One class support vector machine	Accuracy: 96.7%
[62]	Gyroscope	Waist	Pitch, roll, angular velocity	Decision tree	Specificity:100%
[63]	Accelerometer	Jacket collar	Inclination velocity, trunk inclination angle	Decision tree	Sensitivity: 98%
[64]	Accelerometer	Waist, neck, right hand, left hand	Inclination angles of X,Y, Z axis, SMV, activity signal magnitude area	Decision tree	Accuracy: 92.92%
[65]	Accelerometer, barometric pressure	Waist	SMV, signal magnitude area, tilt angle, differential pressure	Decision tree	Accuracy: 96.9% Sensitivity: 97.5% Specificity:96.5%

detect fall based on an observation that normal activities cause measurable vibrations on the floor, which means a when a user falls the down, the impact cause by the body parts with ground will generate vibrations that will be transmitted throughout the floor [70], [71]. An assumption is also made that the vibration signal for falls and ADL are different [71]. Using the events and changes in vibration data make it useful for monitoring, tracking and localization [47]. Vibration signal can be obtained using a piezoelectric sensor or an accelerometer sensor. Floor vibrations are inexpensive, and they can preserve the privacy of the user, but the performance is influenced by the floor type and has a limited detection range [39].

3.2.2 Acoustic detection

The basic idea of acoustic sensor is to make use of a microphone sensor to capture the movements of the users where MFCC features are extracted to detect falls. The MFCC features are extracted by first removing the high frequency component [14]. Segmentation of the audio signals into different frames [14]. A FFT transform is applied to each frame to get the frequency spectral features [14]. After the FFT, mel-scale mapping is performed and finally discrete cosine transform is applied to obtain 12 MFCC [14]. Applying beam-forming technique on the sound signal can enhance the desired signal and reduce the interference from TV, radio, or phone ringing [39]. Acoustic system makes use of a Rescue Randy doll for mimicking human falls, for testing the system [16]. The source of the sound signal, from multiple microphone can be detected using the steered response power with phase transform technique, which can work in any conditions [39]. The sound signal is enhanced using beam-forming technique [39]. Classifier design for acoustic fall design is difficult to design since it is impossible to obtain realistic fall sound signatures for training and testing of the system [72]. Generating fall data is difficult to simulate [72]. When capturing simulating falls, the test subject tries to prevent a painful fall [72]. Most of the acoustic studies make use of Randy Rescue dolls which makes detecting low impact falls difficult, to compensate these different weights of rescue randy dolls is needed to train the system [68]. The studies which make use of Randy Rescue dolls cannot replicate realistic falls sounds due to the hard skin and the lack of bones in the mannequins [72]. The material of the floor and the limited range of the detection of the audio affect the system[16].

3.2.3 Pressure sensor

Pressure sensors are most common method for ambient sensor since its low cost and non-obtrusiveness, a fall is detected based on sensor pressure changes [5]. Pressure senor used to detect the high pressure of the object due to the objects weight for detection and tracking [5]. The pressure changes depending on how close the person is to the sensor [73]. If the person is closer to the sensor, the pressure is high [73]. The disadvantage of pressure sensors is the low detection precision which is below 90% [5]. The disadvantage of only using pressure sensor to detect a fall, it can sense pressure of everything in and around the object, which leads to false positives hence low accuracy is achieved [5], [47]. The distance of impact to where the pressure sensor is located can impact the accuracy of the system [5]. Another problem is that using only pressure sensors it cannot differentiate between lying and falling postures [19]. To solve this problem in [19], the make use of intelligent tiles which consists of pressure sensors and three-axis accelerometers. The accelerometer is used to detect hard human falls, but cannot detect soft falls [19]. The accelerometer is used to enforce the differentiation between the falling and the lying down posture [19]. Each tile has a processing unit and wireless connection and electric power [19]. The disadvantage of the system is [19] is the cost associated with each tile, and it requires power supply for each tile. Pressure sensors can have high false alarms due to the fact the persons weight is not factored in, when detecting a fall; and the system is usually implemented on a small scale e.g. like a mat which makes it costly when implementing it in a home environment. The factors which influence pressure sensors are the placement and sensitivity to pressure.

3.2.4 Passive infrared sensor

A Passive infrared (PIR) sensors detects falls using infrared signatures [35]. The strength of the received signal from the PIR sensors changes with motion of a hot object within range of the sensors [74]. The PIR sensor cannot be used to differentiate fall since a walking person can produced a signal similar to a PIR fall signal [74]. In [74], a combination of both PIR and floor vibration sensors is used to detect a fall. The PIR sensors is used to reduce the false alarms in the system by detecting whether the vibration signal was caused by a human, and by detecting the presence of the user [74]. A fall alarm is ignored when there is no motion in a room [74]. The biggest problem of using PIR sensors is the line of sight and coverage area.

3.2.5 Doppler sensor

Doppler sensors is a motion sensor that can sense, track, and recognize moving objects and surveillance human activity [41]. Doppler sensors are small and cheap which only detects moving targets by suppressing stationary background cluster, and are noise tolerant systems [75]. A Doppler sensor has different irradiation direction which is less sensitive to the movements orthogonal to the irradiation direction compared to moving in the irradiation direction, it becomes sensitive [75]. A Doppler sends a continuous electrometric wave signal at the carrier frequency and gets back the reflected wave which has the frequency shifted by the moving object [75]. The velocity of the moving object can be determined through the frequency shift within the detection range [75]. The disadvantage of Doppler sensor is sensitive to motion and can penetrate apartment walls [75].

3.2.6 Electric near field

A near-field imaging (NFI) system uses floor sensors to detect falls [76]. The floor sensors detect the locations and patterns of the user by measuring the impedance with a matrix of thin electrodes under the floor [76]. When the NFI is detected, the locations of the electrodes from the matrix is detected [76]. More sensors will be required when the area in the environment increases, hence increase in cost. False positives are generated if there are pets or occlusions available. In table 3, a summary of the different ambient fall detection studies is shown.

3.2.7 Disadvantage of ambient sensors

3.2.7.1 Coverage

The ambient sensors work only indoors or where the device is confined to, dead spaces, suffer from blind spots, has limited recording area, it can only monitor one person and it can be an expensive setup [20], [1], [29], [16]. The limited recording area does not affect electric near field and pressure sensors, but will be expensive to cover a monitoring area. Most of ambient systems, assumes that only one person is present in the monitoring room.

3.2.7.2 Noise

Ambient sensors are affected by the environmental interference, background noise and by ambient noise [3], [7]. Ambiance device can produce many false alarms due to other falls cause by everyday objects [2]. Acoustic and vibration sensors can only work on certain floor type. Movement sensors are affected by obstructions or occlusions which can deteriorate the signal.

3.3 Camera-based methods

The advancement in computer vision and image processing techniques can also be applied in fall detection problems, where a camera sensor is used to monitor the user behaviour and detect fall activities without interfering with the users routines [2], [8]. Camera sensors can record the users position and shape [5]. Using computer vision to detect a fall can be difficult since the human body is composed of several parts which can move freely, which makes the process of identifying and locating people more difficult [21]. To overcome the problem, the current studies uses human parts which can be detected such as the head, waist, or feet [21]. The advantage of camera-based methods is that there is no intrusion on the users since these sensors does not need to be worn or remembered to be worn, due to the fact that the camera system is contactless; and it can be used to monitor one or more people simultaneously; and it can be used to detect falls in public areas [29], [8], [40], [43], [44], [47]. Multiple people can be tracked in a frame through segmentation and marking module [5], [8]. Camera-based methods can be used to serve for two purposes, fall detection and security monitoring. Advantage of camera-based methods compare to the other methods, it is more robust and it can accurately detect falls and different ADLs; and it can verify a fall remotely if a fall has occurred [34], [9], [8], [47], [78]. Camera-based systems is best suited where multiple people need to be monitored e.g. hospital rooms or old age homes etc [32]. Cameras are included in home and care systems which have multiple advantages over sensors based devices such as, multiple events can be detected simultaneously with less intrusion. Figure 3 shows how a camera system detect a fall.

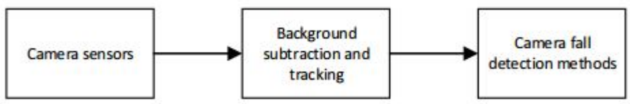

Fig. 3 Operations of the camera system when performing fall detection.

3.3.1 Camera sensors

Falls can be detected using a single RGB camera, 3D-based method using multiple cameras, and 3D-based

Table 3 Summary of ambient sensors studies

Study	Sensors	Features	Classifier	Results
[74]	PIR and vibration	Single-tree complex wavelet transform form vibration signal, amplitude from PIR sensor	Support vector machine	Accuracy: 100%
[17]	Vibration and microphone	Shock response spectrum, MFCC	Naive Bayes	Sensitivity: 97.5% Specificity: 98.6%
[39]	Circular microphone array	MFCC	Nearest neighbour	Sensitivity: 100% Specificity: 97%
[41]	Doppler and motion sensors	MFCC	Support vector machine	AUC: 0.98
[68]	Accelerometer and microphone	Shock response spectrum, MFCC,energy of vibration signal, length and energy of sound signal	Gaussian mixture model	Sensitivity: 95% Specificity: 95%
[14]	Microphone	MFCC	One class support vector machine	Accuracy: 90.63%
[70]	Special Piezo transducer	Vibration signal	Pattern matching	Sensitivity: 95% Specificity: 95%
[77]	Far-field microphone	Perceptual linear predictive coefficients and Gaussian mean supervectors	Support vector machine	Recall: 94% Precision: 70%
[71]	Accelerometer	Peak to peak value, average rectified value, weighted average rectified value, duration of the signal, fast Fourier transform	Decision tree	Sensitivity: 87% Specificity: 97.7%
[73]	Piezoresistive pressure sensor	Differential voltage	Decision tree	Sensitivity: 88.8% Specificity: 94.9%
[35]	PIR	Differential voltage	Hidden Markov model	Accuracy: 80%
[75]	Doppler	Power spectral density, MFCC	k-NN	Accuracy: 93.3%
[76]	Electric near-field	Number of electrodes step on, the longest dimension, magnitude	Two-state Markov chain	Sensitivity: 91%

method using depth cameras [34], [5], [78]. The most popular vision-based method is the RGB camera which is the cheapest and easy to setup [5], [32]. Multiple cameras are required to cover a large area which can be solved using omni-directional cameras or a wide-angle camera can be used [21], [43]. The wide-angle cameras have a wide field of view lenses which can be used to monitor large areas [21]. The problem of this type of camera, the images produced are highly-distorted [21]. The camera lens has high radial distortion which needs to be corrected before the calibration process starts [21]. Omni-camera can capture can capture 360 degrees view in a single shot which compensates for the blind spots [79]. The lack of depth information from RGB cameras can lead to a lot of false alarms [34], [43], [34]. The 2D camera methods can cause misjudgements when a there are more than 2 people in the frame [66]. A single camera cannot extract features that characterizes a 3-D objects movement which creates a robust fall detection system, but this can be created from multiple RGB cameras [5], [67]. Multi-camera systems construct a 3-D object from back projecting multiple silhouettes where features such as velocity is extracted for detecting falls [67]. For multi-camera systems installation, calibration, and synchronising of the cameras in the same reference frames is difficult, time-consuming and the cost of the system increases [5], [67]. The 3D techniques which are implemented from RGB cameras are not automatic and requires manual initialization. Appearance deformation can occur as the result of 2D grey or colour images that are the projection of 3D targets [5]. The colour cameras, in a controlled environment achieve high accuracy, but would not work in an uncontrolled environment where the lighting and tracking of user is fully controlled [34], [43].

Depth information alleviates the problems where users or objects do not have consistent colour and texture, but they need to occupy an integrated region in the 3D space [44]. Depth camera allows a person to be extracted from an image at low computational cost [44]. Depth cameras can be used to calculate the distance from the top of the person to the floor [5]. Depth cameras can perverse the privacy of the user, and the light conditions do not have any effect on it [34], [5], [32]. Depth images can be extracted in dark rooms using an infrared light [34]. Depth cameras also can be used to solve occlusion problems and track key joints of the human body [5], [66]. The different depth cameras include stereo vision, Time-of-Flight (TOF), and structured light camera [46]. Stereo vision camera constructs a depth image from two views of a scene [46]. The problem of this camera the systems needs to be calibrated, computationally expensive, and fails when the picture does not contain enough textures [46]. The system cannot work in low light conditions, which can be solved by integrating an infrared light to it, but the loss of colour information can cause segmentation and matching difficulties [46]. The earliest depth camera was the time-of-flight 3D camera, but the cost of setup is expensive, and it is restricted to a low image resolution [5], [46], [66]. Time-of-Flight image can be used to obtain partial volume information which returns precise depth image compared to stereo vision cameras for tackling occlusion problems [46]. The most popular depth sensor is structured light camera which includes the Kinect sensor [46]. The Kinect sensor is a low-cost device which comprises of infrared laser-based IR emitter, an infrared camera and an RGB camera [34]. A Kinect, makes use of infrared light sensors to illuminate the objects in front of it and an infrared camera to observe them in invisible light, the fall detection can be done at any time [44], [43]. A Kinect sensor, can track the body movements in 3D unlike 2D [34]. A Kinect senor, can be used for human behaviour recognition, and detect a fall in 24 day-night cycle [44]. The Kinect sensor is not affected by the external light conditions due to the depth interference is done by making use of an active light source [34]. The Kinect sensor does not require calibration since the automatic extraction of the features [34]. The limitation of the Kinect sensor is that the sunlight interferes with the pattern-projecting laser, which is not suitable for outdoors [34].

3.3.2 Background subtraction and user tracking

Background subtraction is performed to extract the moving object from the image known as foreground segmentation. Simplest background subtraction technique requires an original image with no moving objects. The current frame is subtracted from original image to obtain the moving object. The disadvantage of this technique it does not take into account the lighting changes, shadow changes, and the changes in background due to short-term movements [80]. This can be solved using a Gaussian mixture model background model or using approximate median filter [40], [81], [80]. Morphological operations can be applied to reduce the noise in the background. The extracted object is tracked continuously, until the object is out of the camera view angle.

3.3.3 Camera-based detection methods for fall detection

The camera-based detection can be split into shape change, inactivity, posture, and 3D head motion [2], [5], [45], [47]. In table 4, a summary of the different methods used to detect a fall is shown.
Simple method for detecting a fall using 2D method is to locate the person in the video, and draw bounding box around the person [46], [67], [82]. Most common 2D feature extracted, includes aspect ratio [40], [46]. The aspect ratio is computed as the ratio of the width of the bounding box around the extracted object and the extracted object height [40]. A small aspect ratio means the users posture is upright, whereas a high aspect ratio means the user posture is lying down [40]. Ellipse provides greater information than the bounding box; such as calculating the fall angle [5], [46]. The fall angle of the user is the angle between the long axis of the bounding ellipse and horizontal direction [40]. A small angle represents that person has fallen [40]. The problem of using a bounding box alone, it does not provide enough information regarding the human motion, and the performance of this technique relies on the camera view angles [83]. Analysing aspect ratio can be inaccurate due to the position of the person, camera, and occluding objects. The method of analysing a fall by placing a bounding box around a person can be efficient only by placing the camera sideways and the accuracy of the system depends on the occluding objects. In table 5, a summary of the different camera-based fall detection studies is shown.

3.3.4 Problem of camera-based sensors

Camera-based methods accuracy is dependent on how efficient and accurate the shape modelling methods used are[47]. The problem of camera-based systems is occlusions, light conditions, coverage, privacy, cost, and high processing.

Table 4 The different types of camera-based fall detection methods.

Type	Description	Advantages	Disadvantages
Shape change	When the shape of person will change from an upright position to a falling position, over a certain time period [28].	It can be implemented in real time, simple to model, and easy to compute.	Using 3D shape requires more computation and more cameras which can become unreliable. Most shape-analyse algorithms make use of a few features which is not enough to detect sub-fall actions. The accuracy is also affected by the proximity of the shape attributes [28].
Inactivity	Is when a fall is detected within an inactivity period of how long has the person being in a lying state.	It is fast as it has light computing load, and it can be run on a small computing device.	False alarms are generated since they rely on the context information such as period and threshold and require the person to lie on the ground for long which can cause serious injury. Some users get up from the fall rapidly, hence the static activity after a fall has occurred is not captured [4].
Postures	From the user body, the joints are tracked to determine the posture.	High accuracy is achieved, as it correlates the observed video sequences to the stored ladled video sequence [21].	It is computationally very expensive [21]. This method requires a huge database, to successfully recognise the different postures; and it is hugely affected by occlusions.
Head tracking	Fall is detected if there is an occurrence of large movement is associated with the head. Fall is detected based on the head speed.	This method can help to avoid occlusion problems, since the head is always visible in the scene [84].	The head speed is greater when sitting down fast which generate false alarms, and the head speed is less during slow fall period which results in fall not being detected [85].

3.3.4.1 Occlusions

Occlusions is where a room contains furniture or objects placed between the person and the camera which can create false positives. When elderly people moves to a smaller residence, they tend to take all these items with them resulting in the room being fill with these items, which means the user is partially occluded when moving around the room [40]. Image processing difficulties arises when changes occur in the monitoring area e.g. furniture's being shifted around the room; these changes can also affect the accuracy of the system [14], [40]. To accomplish the bounding box the RGB camera is required to be placed sideways, which can fail due to occlusions [82]. To solve this the camera is required to be placed higher in the room not to suffer occlusions and to have a greater field view [82]. In this case, depending on the relative position of the person, the field of view of the camera, a bounding box will not be sufficient to discriminate a fall from a person sitting down [82]. To avoid occlusions some researchers placed the camera on the celling, where 2D velocity of the person is used to classify the person. The problem of velocity in a 2D method becomes high when the person is near to the camera, which makes the threshold for differentiating falls from sitting down fast difficult to define; and 2D methods also suffer from occlusion problems, this can be easily solved using 3D vision systems [46], [28], [82]. Monitoring the whole body can fail when the elderly people who struggle to walk are assisted with a walking aid such as a rollator or walking frame which causes the lower part of body to be occluded by the system; and when objects are being carried [40], [85]. Head tracking can also be used to solve occlusion problems, where objects cover the user [84].

3.3.4.2 Light

Camera system should be able to monitor the user in any light conditions [14], [40]. The different light sources at the homes such as sun light, fluorescent light, light bulbs, TV-screen, and the different light intensities that occurs during the day, can result in overexposures in some parts of the image, and the quality of the images is influenced [34], [3], [2], [40], [78]. Overexposure can be slightly compensated through careful placement of the camera in the room [40]. The problem of foreground extraction using traditional cameras it relies on background modelling in colour image space, when in reality it is affected by lighting conditions and shadows [34], [43], [44], [67]. The use of colour-based shadow detection algorithms can be used to improve the output of the background subtraction algorithm; but these algorithms rely on an assumption that if an area is covered by a shadow, only the brightness of the image is

Table 5 Summary of camera-based studies

Study	Sensors	Detection method	Features	Classifier	Results
[78]	Depth sensor	Posture	Joints	Decision tree	Accuracy: 93% Sensitivity: 94% Specificity: 91.3%
[83]	RGB	Shape change	Velocity and motion	Support vector machine	Accuracy: 93.38%
[44]	Kinect and accelerometer	Posture	Human pose and motion	Fuzzy interference and decision tree	Accuracy: 98.6%
[66]	Kinect	Shape change	Vertical motion event and 3D centroid	Decision tree	Precision: 94.31% Recall: 85.57%
[34]	Kinect and accelerometer	Shape change	V-disparity	Support vector machine	Accuracy: 98.33% Precision: 946.77% Sensitivity: 100%
[21]	Wide angle camera	Shape change	Angle, size of the upper body	Support vector machine	Accuracy: 97%
[46]	Kinect	Posture	Height of the user, body velocity	Decision tree	Accuracy: 98.7%
[86]	RGB	Inactivity	Vertical volume distribution ratio	Decision tree	Sensitivity: 99.7% Specificity: 99.7%
[82]	RGB	Inactivity	Coebased on motion history, aspect ration, orientation	Decision tree	Sensitivity: 88% Specificity: 87.5%
[38]	RGB	Posture	Ellipse shape structure, position information of silhouette	One class support vector machine	Accuracy: 100%
[87]	3D	Head tracking	Vertical and horizontal velocity	Decision tree	Accuracy: 78.9%
[85]	RGB	Head tracking	Direction of the body and the ratio of the variances in x and y direction	Gaussian multi-frame	Accuracy: 85%
[84]	RGB	Head tracking, shape change	Ellipse shape, position of the head, vertical and horizontal projection histogram	Multi-class support vector machine	Sensitivity: 90.27% Specificity: 95.16%
[88]	RGB	Posture	Skeltons and centroid context	String matching	Accuracy: 96%
[80]	RGB	Shape change	Movement coe, orientation, aspect ratio	Decision tree	Accuracy: 90%

affected and there is no change in colour information [40]. There is a high risk of falls occurring in low lighting conditions compared to normal illuminated conditions [44]. To solve the problem of lighting conditions for single cameras an active source of infrared (IR) light can be installed along with the camera; but there will no colour available due to the IR illumination for background modelling [67]. Colour information is not available in near-infrared night images, and colour images that are available during daytime are not reliable [40]. Depth cameras can solve the lighting conditions, and can work during both day and night [46].

3.3.4.3 Cost and high Processing

The cost of the infrastructure and installation of sensor equipment's is expensive. Image quality in reality is much lower than the lab experiment setup, this can be accomplished by installing a high-quality camera which can result in high cost [40]. Camera-based systems require considerable computational power running real-time algorithms [44]. One way of minimising the computational power is to integrate the camera based system with an accelerometer [44]. Camera-based system only starts processing when a possible fall is detected from an accelerometer sensor [44]. An accelerometer sensor is used to identify if a possible fall has occurred and the camera system is used to authenticate a fall [43]. The frames are not processed instead there are stored in a circular buffer, and only processed when a fall has occurred [43].

3.3.4.4 Coverage

Camera based systems can only work indoors or where the devices are confined to, which can create blind spots, occlusions cannot be detected, limited field view, and dead spaces are created [34], [3], [1], [2], [9], [47], [78]. Multiples cameras are required to be installed to solve these problems and provide continuous monitoring, which increases the cost of the system [40]. Wide angle camera can be used to provide coverage of the room, but the spatial resolution of the camera system decreases due to the lens of the wide-angle cameras [40].

3.3.4.5 Privacy

The ethical issues that are associated with camera-based methods includes confidentiality and privacy of the monitored person, which makes it difficult to monitor a person in the bedroom and bathroom [34], [2], [47], [78]. The problem of colour camera based systems is that they contain facial characteristics of users which results in privacy concerns, which can be addressed by capturing low quality images, using depth images or image processing technique such as silhouettes [44], [70], [67]. Even though privacy techniques are applied, people still has a feeling of "being-watched" based on their perception of a camera system [43], [70]. Instead of capturing the user, the environment scene can be captured like in [20] and [23].

4 Personalization

Personal information can make the system smarter by adapting the different parameters for different person [79]. If different body postures are not learnt, high false rate could be resulted [29]. Methods that make use of thresholds are most popular and easy to implement, and computationally inexpensive, but does not work on different people, and does not provide a good trade-off between false positives and false negatives [9], [30]. People have different types of body figures; whereas using the same threshold in fall detection algorithm will not work for everyone or would not be optimal [79]. With thresholds is difficult to adapt the threshold to new types of falls and makes it work on different people [2], [9]. Falls of elderly people might last longer than that of young people [28]. The values from the threshold method is determined without using any theoretical and/or experimental basis; and where the fall detection model fail is that it cannot address inter-individual difference [30]. The basic idea behind personalization, is to train the system using the user data, which will result in higher accuracy.

5 Personalization

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5.1 Design of a personalized model

Classification can be trained using the user data or non-user data or the combination of both user and non-user data. The use of supervised machine learning algorithm cannot be used to solve the problem, as the fall data that is used are from simulated falls [9]. Since falls are rare, supervised machine learning algorithms cannot be used [9]. Supervised algorithms can classify known classes which they are trained [9]. Supervised machine learning algorithm requires the data to be label which result in waste of time and effort [9]. Supervised classifiers cannot provide a person-specific solution for individuals [38]. Due to the lack few fall data, supervised classification algorithms may not work as desired, the following classification are needed over/under-sampling, semi-supervised learning, cost-sensitive learning, and outlier/anomaly detection [9].

A large dataset needs to be created for training the supervised classifier which should contain data for different activities; if a person does not fit the dataset e.g. if the person is obese a good performance could not be obtained for the specific individual [38]. Supervised learning algorithms require a balance dataset with has equal misclassification costs for the different classes [9]. When unbalance data is used to train the algorithms, the algorithms fail to distinguish the characteristics of the data, which result in low accuracies; and their prediction tend to favour the majority class [9]. The imbalance class can be handle by performing cost sensitive-classification, where the cost of the classification problem is treated differently [9]. This can be accomplished by adding a cost matrix to a cost-insensitive classifier or by integrating a cost function in the classification algorithm to generate a cost-sensitive classifier [9]. A cost matrix of a fall detection problem is defined, by getting the optimal decision threshold of the classifier [50]. Cost-sensitive analysis can be performed for fall detection using Bayesian minimum risk or the Neyman-Person method [50]. This is calculated by varying the ratio of the cost of a missed fall to a false fall alarm to determine an optimal region of operation using the ROC curve [50]. Generally, the ratios are fixed and should not be dependent on the dataset used [50]. The costs are unknown and are difficult to compute [9]. In [40], the study make use of a weighted SVM to compensate the imbalance of data of the falls and normal activates from the camera. The weights are determined using cross-validation and grid search maximizing the area under curve of ROC [40].

The lack of fall data could also be compensated using sampling techniques to generate fall data [9]. Fall can be oversampled or the normal activity class can be under-sampled to train a supervised classifier [9]. The disadvantage of oversampling it can lead to over-fitting if a lot a lot of artificial data points are generated and do not represent a fall [9]. The disadvantage of under-sampling it can lead to under-fitting it the normal activities class is reduced to match the number of total activities of falls [9].

Another approach is to apply temporal patterns which can be used to describe and provide more information on the events that the user performs[89]. The temporal paths are used to recognize or predict future events that the user may performed [89]. In [89], the system combines the temporal extension of Fuzzy Formal Concept Analysis (data driven) and Fuzzy Cognitive Maps (goal driven) approaches for better decision making [89]. The system recognizes the following events: tiredness, sleeping, having breakfast, and having dinner [89].

Classifiers only require normal activities for training, which eliminates data imbalance between fall and normal activities are known as unsupervised machine learning algorithm [9]. The problem is that if the normal behaviour in not properly learned, the system can result in large number of false positives, as a slight variation from a normal activities can be detected as a fall [9]. The classifier needs to adapt and learn new activities in order to reduce the false alarm rate when detecting falls [72]. The advantage of the unsupervised approach, is that the classifier can easily adapt to new data without worrying about data imbalances [72]. In table 6, below show the summaries of systems which make use of personalized models.

The basic personalization is customizing the threshold based on personal characteristics such as height, weight, etc. [79]. In [79] an Omni-camera is used to record the activities, where a bounding box is placed on the user [79]. The system requires a background image, no user present in the background [79]. To detect a fall the foreground is extracted by performing background subtraction [79]. A fall is detected if the bounding box aspect ratio is greater than pre-defined threshold value [79]. The predefined threshold value is customize based on the following personal information height, weight, and electronic health history [79]. The reason for the personal information is used to adjust the detection sensitivity which reduces false alarms, and provide more attention to the elderly person with specific needs [79]. The use of electronic health history is to increase the detection sensitivity automatically if the person experiences cardiovascular disease or if a fall accident has happened before [79]. In [90] a smartphone system which is based on the user information's such as the ratio of height and weight, sex, age is used to adjust the threshold value and sampling of the acceleration data. From the tri-axis acceleration sensor, the direction of the three-axis was extracted [90]. The system calculates SMV [90]. Based on the BMI, the user age, and sex, the maximum and minimum threshold from the acceleration and the sampling frequency determined through the range of the personal information [90]. Fall is classified based on the thresholds and the system achieves a sensitivity of 92.75% and specificity of 86.75% [90].

In [37], a study was conducted to compare personalised systems to non-personalised systems using a smartphone accelerometer. Three unsupervised methods were implemented NN, OCSVM, and (Local Outlier Factor) LOF; and one supervised method SVM [37]. The study was divided into two stages, the first stage is determining which unsupervised method was the best; and the second stage to determine how does personalized perform on both the best unsupervised method and supervised method [37]. The raw data of the three axes of the accelerometers are fed into the classifiers [37]. From the first stage, it was found that NN outperform the rest of the unsupervised methods [37]. For the second stage, the personalized model of the NN is trained with the normal activities of the user; whereas the non-personalized model is trained with the normal activities of other people data [37]. The personalized model of the SVM is trained with the normal activities of the user and fall activities of other people; whereas the non-personalized model is trained with both normal and fall activities of other people [37]. It was found that both the personalized model, NN and SVM outperform the non-personalized model [37]. The personalized SVM model achieved slightly higher geometric mean of 0.9764 compare to the personalized NN model of 0.9688 [37]. The NN model is better compare to SVM model, the reason being it can adapt to new data, and it can recognize more fall types.

Another approach is to adapt the classifier to accept new ADL data and re-train the classifier in order to learn the user movements. In [42] a smartphone tri-accelerometer sensor was used with a NN classifier; where the capture magnitude acceleration data is compared to the store ADL data from the smartphone. A fall is detected when the difference between the stored pattern and incoming pattern is high [42]. The new ADL is added every time the system classifies the incoming data as ADL; where the old ADL record is replaced with new ADL [42]. To reduce processing power and computational time, the system only classifies when magnitude of the acceleration value is greater than 1.5g, and if long lie occurs [42]. The advantage of NN classifier is that it easy to add new data, and it does not require simulated falls for the training the system [42]. The simulated fall data was used only for testing the classifier [42]. The disadvantage of the system is that it cannot detect soft falls and it uses long lie. If a person attempts to get up from a fall but fails each time during the long lie period, the system would not detect a fall event [42].

6 Discussion

High classification accuracy is reported in almost all of the fall detection studies, but it was conducted on limited number of subjects, fall types and activities [4], [12]. The reason for simulated falls, it is extremely hard to collect real-world elderly person fall data; since 30% of elderly population over age of 65 years old fall at least once per year [12]. Current fall detection studies are only tested in controlled experiments where they achieve high accuracy, but when placed in the real world the accuracy of these systems decreases [20]. Studies test the specificity of ADL through laboratory experiments by the same subjects who generate fall data [12] These data could be biased, since subjects are forced to perform activities, which are typically spontaneous [12]. The choice of the mattress to reduce the impact of the falls to protect the volunteers from injuries, can reduce the accuracy of the system when applied to the real world [12].

It is difficult to compare the different fall detection studies in a fair play since each study made use of they own dataset from different conditions [15]. The problem comes in when comparing a system since each study validated they research on different data collection protocols, subject groups, and environment settings, hence they cannot be directly compared to previous studies [4]. The factor which influence the performance is the number of training samples are used for training the system [15]. The main problem of acceleration based studies is that it is difficult to compare the different studies; since that each research study make uses its own dataset composed of simulated falls and ADL [15]. It is difficult to judge whether the results obtained from these studies are influence by the dataset complied, and it is impossible to make a comparison since the dataset used in each study are different [15]. Since these devices are required to be worn for long-periods or the whole day a complete dataset is required compared to fall detection studies where the dataset is limited [20].

Table 6 Summary of personalized fall detection systems

Study	Sensor	Method of personalization	Features	Algoirthm	Results before personalization	Results after personalization
[79]	Omni-camera	Changing the pre-defined threshold value based on user height, weight and electronic health history	Aspect ratio	Threshold tree	Accuracy: 78%	Accuracy: 90%
[37]	Smartphone accelerometer	Training the system with only personalized data	X, Y, Z axis from the accelerometer	Nearest-neighbour	Sensitivity:94.15% Specificity:93.84%	Sensitivity:96.65% Specificity:97.15%
[37]	Smartphone accelerometer	Training the system with only personalized data	X, Y, Z axis from the accelerometer	Support vector machine	Sensitivity:96.48% Specificity:95.73%	Sensitivity:97.97% Specificity:97.34%
[69]	Smartphone accelerometer	Changing the pre-defined threshold value based on user height, weight, and level of the activity	Signal magnitude vector, time, period, angle	Threshold tree	NA	NA
[31]	Accelerometer	Adding new records to the system randomly, and adapting the system based on user weight and mobility	Filtered acceleration value, energy of acceleration	Threshold tree	NA	Sensitivity:100% Specificity:95.68%
[42]	Smartphone accelerometer	Adding new records to the system	Signal magnitude vector	Nearest-neighbour	Area under curve: 0.969	Area under curve: 0.978
[91]	Magnetometer ,accelerometer , gyroscope	Self-adaptive, update the threshold for the user	Signal magnitude vector	Threshold tree	Accuracy: 90.7% Sensitivity:97.7% Specificity:79.8%	Accuracy: 92.1% Sensitivity:98.7% Specificity:81.7%
[90]	Smartphone accelerometer	Changing the pre-defined threshold value and sampling frequency based on user BMI, age and sex.	Signal magnitude vector	Threshold tree	NA	Sensitivity:92.75% Specificity:86.75%

In [12] evaluation was conducted on real falls based on accelerometer fall detection algorithms where 29 real world falls were tested on. The result from the evaluation show a reduce sensitivity and specificity values compare to when conducted in an experiment environment to evaluate the effectiveness of the algorithms to detect falls in real-life events [12]. The study achieved average specificity of the algorithms is 83.0% and average sensitivity of the algorithms is 57.0% which are much lower compared to the simulated environment [12]. There is a huge number of false alarms generated from the algorithms in a one-day monitoring period which ranged from 3 to 85 [12]. The results obtained from the study is to encourage researchers to take reality activities into consideration [12]. The problem with these studies is that they cannot work in the real world since no training data for falls were used, and low accuracy will be achieved since classifier cannot predict a fall that it has never observed before [9]. Collecting fall data is futile as it requires a person to perform a real fall which can result in serious injuries [9]. About 94% of fall detection studies used simulated falls from laboratory experiments for training the classifiers [92]. This shows that the difficulty in obtaining real fall data [92]. Instead of real falls, artificial falls are collected in a controlled laboratory environment, which does not represent an actual fall [9]. The advantage of artificial fall it provides information of how falls is occurring, but does not make it easier for detecting falls [9]. Classifiers which use artificial falls as training data can result in over-fitting, which can cause poor decisions on the actual fall [9]. The fall data are limited quantity and suffer from ethic clearance [9]. To get accurate fall data, a long-term experiments needs be conducted in nursing homes using wearable sensors, ambient sensors, or camera based methods [9].

The main problem of vision based the absence of flexibility, as these systems are case specific where they are designed and optimized for a certain situations or scenarios [2]. Camera-based studies algorithms are evaluated from data collected from controlled environment, optimal conditions such as perfect illumination, simple scenarios or scenes, and falls are simulated by actors [40]. The challenges found from real life data compare to the simulated data is that the image quality is low and falls are rare and vary a lot in terms of speed and the nature of fall [40]. Most studies make use of simulated data, where the falls been recorded in artificial environments and the person performing are young people [40].

Each individual has different characteristics and motion patterns compare to people used in the training data [30]. Another problem is difficult to detect all the ADL since the classifier is required to be trained with each type of ADL [72]. The classifier needs to adapt and learn new activities in order to reduce the false alarm rate when detecting falls [72]. It is difficult to detect the different types of falls for the different people; since a fall has different acceleration characteristics and magnitude of acceleration has high variation among various body types [23]. The phone placement differs from person to person [23]. The limitations of current fall detection studies are the difference in the shape or strength of measured signals if healthy adults or elderly people wear the fall detector and if the falls are simulated or real, with possibly relevant effects on the design and the performance of the fall detection algorithm [11]. ADLs such as lying down and sitting down can generate high impacts which can be misclassified as a fall, for overweight users [4]. Falls with recovery and backward collapses, where users end up in a sitting position result in a misclassification [4]. An actual free fall is not created due to the cautiousness of subjects, which results in not a proper fall detection [20]. Even when safety precautions are there, subjects are still too afraid to fall [20]. The occurrence of fall rate is low, which results in insufficient or no data [9]. Different types of fall can occur, which makes it very difficult to model [9].

The solution, is to create a personalized system; which adapts and learns the users movements. By learning the users movements, the system will be available to recognize a wide range of ADLs and not force the user to perform certain activities. One way to achieve a personalized system, is by using unsupervised machine learning algorithm; which can easily adapt new data without worrying about data imbalances [72]. Unsupervised algorithm, would only be required to trained with ADLs which are easier to capture compare to fall activities. The biggest advantage of personalized system, it will work on anybody, regardless of their weight and height.

7 Conclusion

In this paper, the different fall detection systems that exist were discussed and analysed, where each one has their own advantages and disadvantages. The accuracy of the system depends on the sensors used and the type of classifications. The wearable and camera-based sensors are the most popular ones compared to ambience sensors. Ambiance sensors are highly influence by the environment. The wearable sensor can include a device of MEMS sensors or the use of a smartphones and the system can include a false alarm button. Camera-based sensors, main disadvantage is that the limited coverage and the performance being affect by objects in the environment. The wearable devices main disadvantage is that it intrusive and the placing of the device on the human body is uncomfortable. Wearable sensors are preferred method as it is practical and allows for continuous monitoring and is not influence by the environment. The wearable sensor also provides outdoor monitoring, and can be used to collect real data in a cost-effective approach. A smartphone can be used as a wearable device since a lot of people have them, and it is not intrusive. Wearable device can be placed in the user pocket, which would not interfere when the user is performing ADLs. Experimental systems are limited to the laboratory setting, which would not work in reality and is limited to certain ADLs. Personalization is key, in fall detection system; since it does not only increase the accuracy of the system, but can also be adapted to learn new activities. Adapting new activities can be done by implementing an unsupervised machine learning algorithm, since data balance would not be an issue.

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