Chameleon: personalised and adaptive fall detection of elderly people in home-based environments

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Abstract: Threshold-based fall detection has been widely adopted in conventional fall detection systems. In this paper, we argue that a fixed threshold is not flexible enough for different people. By exploiting the personalised and adaptive threshold, we propose a novel threshold extraction model, which meets being adaptive to detect a fall, while only taking consideration of data from *activity of daily living* (ADL). We believe this is a solid step toward improving the performance of the threshold-based fall detection solution. Furthermore, we incorporate the proposed idea into Chameleon. To evaluate the performance of this threshold extraction model, we compared Chameleon with advanced magnitude detection (AMD) and fixed and tracking fall detection (FTFD). The results show Chameleon has an accuracy of 96.83% when detecting falls, which is 1.67% higher than FTFD and 2.67% higher than AMD. Meanwhile, the sensitivity and the specificity of Chameleon are also higher than the other two algorithms.

Keywords: accelerometer; fall detection; personalised and adaptive; threshold.

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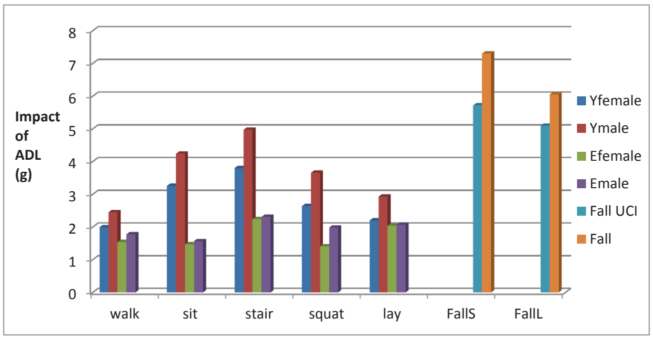
1 Introduction

Due to the increase in life expectancy and decrease in birth rate, the world's population is aging at an accelerated rate. It is reported that the number of elderly people in the world will exceed the number of children under 5 within 10 years (Kinsella and He, 2009). People aged 60 or over will rise to 2 billion by 2050 (10 facts on ageing and the life course, see http://www.who.int/features/factfiles/ageing/en/index.html) from about 506 million in the middle of 2008, while the number of people aged 65 or over will double from 7% of the world's population in the next 30 years. Falling is a high risk and one of the most dangerous accidents for elderly people. It is also the key risk factor affecting the independent living of elderly people in their everyday life. It is estimated that one in every three elderly people, aged 65 or older, will fall at least once every year (Dizziness-Trying to Prevent Falls and Accidents Among the Elderly, see http://www.therubins.com/aging/DIZZI.htm). The risk of falling rises with increasing age. It is reported that people older than 75 who fall are four to five times more likely to fall than those aged 65–74 (Stevens and Dellinger, 2002). Falling also leads to serious consequences, such as fear of falling down, which will limit their activities, body fractures decreasing their mobility, and, most seriously, death. Furthermore, falling also brings out large medical care costs. One research data from a Medicare beneficiary shows that the total medical care costs each year for elderly people who fall once a year is about 29% higher than those who never fall, while the costs for elderly people who fall more than twice will cost about 79% higher than those who do not fall (Shumway-Cook et al., 2009). To respond to these challenges, it is important to propose a high accuracy fall detection method.

Whether the accelerometer-based or the new emerging smartphone-based fall detection system (Igual et al., 2013) is utilised, the focus is on a fixed threshold (Brown, 2005) or multiple fixed thresholds (Li et al., 2009) to detect falls. However, in our research, it is observed that the acceleration impacts of different age groups are different when we analyse a large amount of acceleration impact magnitude of *activities of daily living* (ADLs). Figure 1 gives the acceleration impacts of five ADLs from four different groups of people, including 4 *young females* (Yfemale as shown in Figure 1) aged from 21 to 28 years old, 6 *young males* (Ymale) aged from 19 to 28 years old, as well as 5 *elderly females* (Efemale) aged from 60 to 62, and 4 *elderly males* (Emale) aged from 57 to 62. It also shows the impacts of *fall severe* (FallS as shown in Figure 1) and *fall light* (FallL as shown in Figure 1) activities from 6 young group people aged from 19 to 27, and the impact of 95% *upper confidence interval* (Fall UCI as shown in Figure 1) of FallS and FallL. The data is collected when the volunteers do the ADLs continuously or simulate designed fall action wearing Asgard (Ren et al., 2012). Asgard is a smart sensor, constructed and used to collect the acceleration impacts of various activities at a sampling rate of 62.5 HZ with sensitivity of 200 mV/g. More detail about Asgard is described in Section 3. Obviously, each group has a different acceleration impact, young males have the largest impact among all the groups, young females are in the middle of young males and the elderly, while the elderly group, whether female or male, have the lowest impact. However, most research results show the preset threshold always smaller than the maximum value of the collected ADL data (Jantaraprim et al., 2010; Sorvala et al., 2012). So, from this result and Figure 1, we can see that the fixed threshold in threshold-based solutions is not universal or appropriated for use in all groups of people. For example, a high fixed threshold for a young male is good, and it is simply used to distinguish ADL from falling, but for the remaining groups, some falls will not be detected with the high threshold, especially falls of elderly people. However, if the fixed threshold is set to a small value for the elderly, most falls caused by young people can be detected, but it will bring numerous false alarms. Besides, as mentioned in Lai et al. (2010a), without taking personalised falling detections and body reaction after falling down into account, fall detection still cannot be widely applied. To complement the un-versatile fixed threshold of existing work and meet this, we consider the threshold problem from personalised and adaptive perspectives. We formulate the personalised and adaptive threshold problem as follows: given the impact data of ADL, we find a tunable threshold plan that meets the high performance of fall detection for every person. We take into consideration the group threshold and personal threshold based on probability knowledge, and also the weight method to obtain the final personalised and adaptive threshold. It is expected that the extracted threshold for individual people will improve the accuracy of threshold-based fall detection solutions.

Figure 1 Histogram of the impact of ADLs (see online version for colours)



In this paper, we proposed two tuning strategies: at-group strategy and self-tuning strategy. At-group strategy considers different age partition and different gender to estimate the threshold for each group using ADL data from the pre-collection database. This group threshold is used to tune the threshold for the person to avoid a large deviation from the threshold of the group. Self-tuning strategy commits to extract a personal-based threshold for an individual person. It is a self-adjustment strategy in which further light-tuning is scheduled based on the threshold extracted in the at-group stage, the personal-based threshold for the individual, low probability event criterion defined in our paper, and the weight algorithm whenever a new user starts to use the device. Furthermore, we propose the *Chameleon* fall detection system incorporating the proposed idea of the personalised and adaptive threshold. In general, one distinguishing key advantage of our system is that the proposed novel personalised and adaptive threshold method can be used in other threshold-based fall detection methods to improve the accuracy of fall detection.

The rest of this paper is organised as follows: More detailed reasons about why we need a novel threshold-based fall detection system for elder people are introduced in Section 2. Section 3 gives the system architecture and the data collection procedure. We state assumptions and discuss model preliminaries in Section 4. The proposed personalised and adaptive fall detection algorithm is presented in Section 5. In Section 6, details on the evaluation of the proposed threshold approach and fall detection algorithm are revealed. Section 7 summaries the related work of the fall detection algorithm for the elderly. Finally, we draw conclusions in Section 8.

2 Background

In recent years, large amounts of different solutions for automatic fall detection have been proposed. The typical fall detection approach for an elderly person is the threshold-based method, even for the new emerging smartphone-based system (Igual et al., 2013), which is a continuous comparison procedure of raw sensor data with a fixed kinematic threshold to pre-impact a fall or detect a fall. From the perspective of threshold, the simplest fall detection method is based on an acceleration threshold alone (Perry et al., 2009). However, a threshold-only approach would misclassify activities and result in false positives (Bagalà et al., 2012), as some normal daily activities also produce large acceleration impact. To improve the fall detection performance, other parameters are combined by fall detection systems while a single accelerometer is worn. Acceleration magnitude and angle are analysed as two parameters to detect fall in Brown (2005), and Hansen et al. (2005). In Soaz et al. (2012), authors focus on large acceleration produced by the body movement when a fall occurs to determine a possible impact. Once such a large impact is observed, the orientation of the sensor is calculated to differentiate between standing/sitting and lying, while the sum of the windowed standard deviation is cited to further determine the final fall status. Yang and Hsu (2007) investigates acceleration in each axis to determine whether there is any sign of dynamic movement, after which six data series including 3 axes accelerations and their respective tilts are analysed to identify real-time physical activities, while Boyle and Karunanithi (2008) first compares the difference between the mean value of a five-sample sliding window and the mean value of the whole data set to improve fall detection performance, then an accompanied sign change is observed. Other threshold methods combine multiple sensors to detect fall while threshold is a critical parameter in the algorithm. Lai et al. (2010b) uses several triaxial acceleration sensor devices for joint sensing of injured body parts. When a fall occurs, large impact and faster change can be detected, then the angle is analysed using the clustering method. In Baek et al. (2013), a sensor integrated with an accelerometer and gyroscope is used to classify the behaviour and posture of the subject. A pre-fall is detected when the angle of each axis is met, and then large impact and angular velocity are analysed for further determination. Another proposed method is multi-stage thresholds, which uses more than one threshold to trigger the final detection, which is all the predefined thresholds must exceed the pre-defined thresholds over a certain time. Shi et al. (2012) describes the fall action into five-phase, and 16 features are extracted to detect fall, which include maximum and minimum of the magnitudes. There are many other examples of multi-stage thresholds methods as Jia (2008), Luo and Hu (2004), Lindemann et al. (2005) and Bourke et al. (2007). Obviously, the choice of pre-set threshold or thresholds plays an important role in the threshold-based fall detection algorithm, and thus it is critical to extract a proper threshold for a threshold-based fall detection solution: if the value is set too high, the system may miss some real falls but never generate false alarms, which means the sensitivity will be reduced while specificity will be improved. In contrast, if the value is too low, the system can detect all actual falls successfully, but, at the same time, it may generate some false alarms. However, most studies have determined this threshold using empirical data (Bourke et al., 2006; Kangas et al., 2008; Ren et al., 2012) extracted from the impact data of young people. Evidently, this empirical threshold cannot be used directly by the elderly people, so we argue that a fixed threshold is not flexible enough to detect falls for different people. Therefore, we propose a personalised and adaptive threshold extracting model to solve this.

3 System design and methodology

Currently, most threshold-based fall detection solutions use the impact as one parameter to trigger fall detection or detect a fall, as the impact of the body is the main characteristic of a fall, which can be represented by acceleration. Meanwhile, the accelerometer-based approach also has features of low cost, portability, and convenience. Therefore, acceleration is chosen as one of the major parameters in our system to extract a personalised and adaptive threshold and verify the performance of the adaptive fall detection algorithm. Furthermore, to improve the accuracy of the fall detection algorithm, related body angles are also used in our system. All of those parameters are adopted by Chameleon, which is an adaptive fall detection system verified to have high accuracy. More details can be seen in the following subsections.

3.1 Chameleon system architecture

Figure 2 shows the structure of the Chameleon system, which mainly includes two parts: Asgard and home server. Asgard is implemented to detect a fall, the prototype of which is constructed as shown on the top of the figure, while the function components are shown at the bottom. Asgard is a smart accelerometer sensor consisting of a MMA7260Q triaxial accelerometer, a microcontroller (abbreviated as MCU), and CC2520 radio model (a Zigbee module) (Ren et al., 2012). It has been implemented in our former research and is chosen as a data collection and fall detection evaluation platform. MMA7260Q triaxial accelerometer can sense the motion impact of three directions, with which useful parameters on motion can be extracted to detect fall. The microcontroller is the core of Asgard and is used for data collection, pre-processing and implementation of fall detection. The CC2520 radio model is integrated in Asgard for convenient training data collection and emergency message transmission through wireless technology. To identify the suitable position for high accuracy of fall detection, many studies Li et al. (2009), Abbate et al. (2011), Hwang et al. (2004), Kangas et al. (2007) and Zheng et al. (2009) have done experiments of attaching an accelerometer at different parts of the body, such as waist, wrist, chest, thigh, and so on. Fall detection with an accelerometer placed on the waist has been proven to have higher accuracy in threshold-based fall detection methods (Liang et al., 2012). The waist is also considered as the optimal place for fall detection in our paper, as providing reliable information on subject body movements.

Figure 2 The structure of the Chameleon system (see online version for colours)

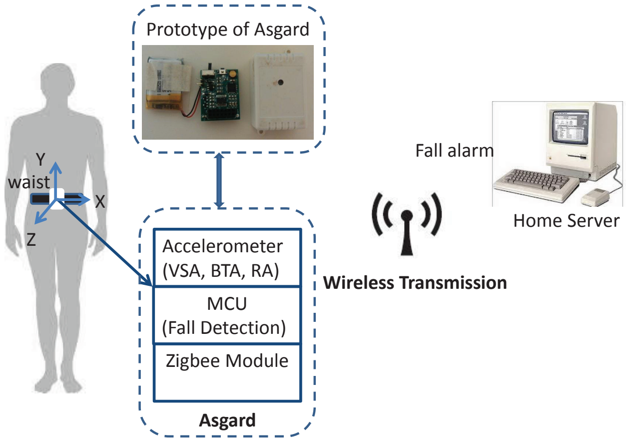


Figure 2 also illustrates the entire data collection and the fall detection procedure. Asgard collects data and transmits alarm information, while the home server receives sensing data or emergency messages. Asgard needs to be calibrated before data collection or fall detection; the operation procedure is described in Ren et al. (2012). After that, Asgard is worn on the waist with an elastic belt, and powered on. For data collection, Asgard processes the acceleration of the body. Processing includes digital, filtering (integrated computing), and then sends the processed data out through the Zigbee transmitter. At the terminal end, there is another Zigbee module as a receiver, through which the home server can receive and store the collected data into the memory for further analysis. For fall detection, Asgard collects and analyses the acceleration locally to determine if there is a fall occurring. Once a fall happens, fall alarm information is sent out to the home server to alert the caregiver for the first-aid in real time.

3.2 Procedure for data collection

Bourke et al. (2005) suggested that the acceleration threshold of a triaxial accelerometer is more accurate in fall detection than a single axis threshold. Therefore, a triaxial accelerometer is chosen and used to measure the accelerations of three axes in each direction. Placing the Asgard board as shown in Figure 2, the y-axis will be away from the earth, while x- and z-axes are orthogonal to the y-axis. In a regular scenario, when As grad is static, it would be affected only by gravity. Thus, the acceleration of y-axis will be –1 g in the direction toward the centre of the earth or 1g directed away from the earth, while the other two axes will be 0g. However, the most important feature collected by the accelerometer is the *vector sum of the three axes acceleration*, which is defined as VSA. It is determined by equation (1):

$$\mathrm{VSA} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

where a_x is the sample value of the x-axis representing the acceleration of the x-axis, which is in g units. It is the same for a_y and a_z. VSA can be used to measure the movement intensity, which should be 1g for stationary state. However, when one falls to the ground or hits some object, there will be a large VSA. Therefore, given a *VSA threshold* (denoted as VSA_{th}), we can distinguish a fall from ADL, as VSA caused due to a fall is larger than that of ADL. A personal and adaptive threshold is our objective, while one core idea is only VSA data collected from ADL is used, as a fixed threshold method is not sufficient to detect all falls. However, many studies have mentioned that fall detection with only VSA as a parameter can distinguish a fall from ADL with low accuracy, so improvements need to be performed.

Falling is always accompanied by an angle change in the body. The angle between the body and the ground will change significantly when he or she falls down while it is small when doing ADL. Even falling on something, the accelerometer attached on the waist can also detect a large angle change. Therefore, the final angle of the body is chosen as another parameter for fall detection. As is defined in Ren et al. (2012), the final angle of the body is also expressed as *body tilt angle* (denoted as BTA):

$$\mathrm{BTA} = \arccos \frac{a_y}{\mathrm{VSA}} \tag{2}$$

where a_y is the sample value of y-axis. BTA refers to the tilt of the body in space. Many studies use VSA and BTA at a fixed time to distinguish a simple fall from ADL (Brown, 2005). However, if the person falls slightly and struggles to stand up slowly after a fall which is longer than the set time, this method seems not to work. On the other hand, if he or she falls down seriously and can not move anymore or completely loses consciousness, it takes too long to take the setting time while waiting for the fall detection. To confront this issue, *recovery angle* (denoted as RA) is introduced. RA tracks the real-time status of the body change, which can be obtained by BTA within a time window. RA is defined as equation (3):

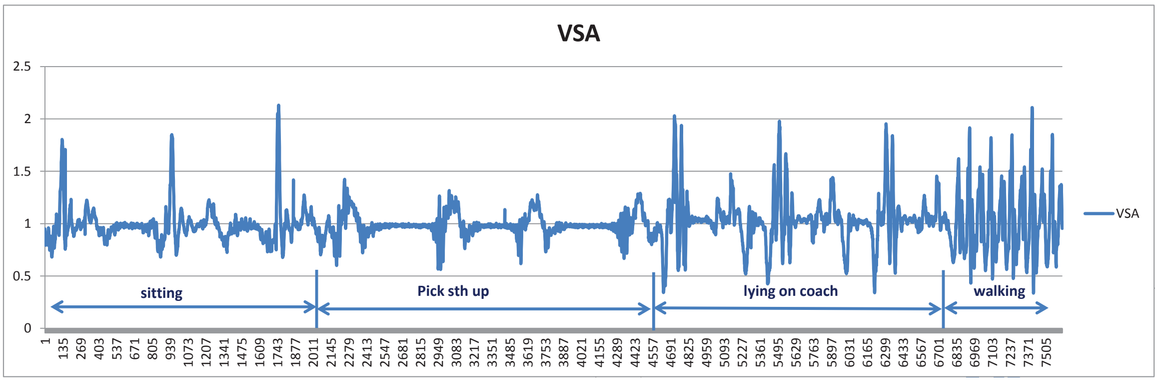
$$\mathrm{RA} = \mathrm{BTA}_{t_2} - \mathrm{BTA}_{t_1}, \quad \text{with} \quad t_2 - t_1 = 0.5 \text{ s} \tag{3}$$

where RA refers to the recovery angle of the body, BTA_{t_1} and BTA_{t_2} are the body tilt angles on t_1 and t_2, while t_1 and t_2 are two time points. The time interval between t_1 and t_2 is set to 0.5 s to detect RA.

4 Personalised and adaptive threshold model

Fall data of the elderly group is difficult to acquire, so previous research on threshold-based algorithms have the limitation of impossible usage of the threshold directly to elderly people, as the threshold which is used to distinguish ADL and fall is extracted using data only from the young. As has been concluded in Section 1, the threshold of the young is supposed to be too high for fall detection of the elderly group. A personalised and adaptive threshold based on only data of ADL can solve the problem of insufficient data from the elderly. In our proposed method, we use group ADL data from the pre-collection database including data collected from different ages and genders, as well as the personal ADL data collected in real time to extract a threshold for each individual person. The pre-collection database is collected as described in Section 6. In the rest of this section, we will state related assumptions

Figure 3 VSA of activities of daily life (see online version for colours)



and discuss the personalised and adaptive threshold extracting method.

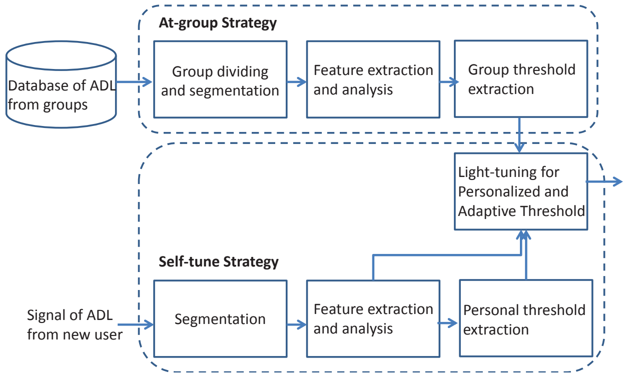
When the person wears Asgard doing ADL, there will be VSA changes with a peak during each action. As shown in Figure 3, the data is VSA with a unit of which is g. It is randomly collected during evaluation experiments. From the figure we can see the first three large impacts are caused by sitting, while the peak is produced when the body makes contact with the seat. Similarly, picking something up, lying down, walking, and so on, also bring out large VSA changes with a peak. Therefore, the VSA peak of each action can be used as the objective parameter to process, which is also used in Bourke et al. (2007) to detect fall. We use x_j to denote the VSA peak of the jth action. It is believed the more frequently x_j occurs, the lower the possibility to be recognised as a fall. In this assumption, running or jumping actions will not be considered, as these actions occur infrequently among the elderly group. Based on this assumption, we can further assume, in real daily usage, x_j occurring frequently will belong to ADL, while x_j with low frequency, which is defined as *low probability event* (denoted as LPE of x_j), is difficult to distinguish from a fall. LPE is used for a later definition of the group threshold and the personal threshold, both of which are computed for light tuning threshold with the weight algorithm for the monitored individual person.

4.1 Threshold extraction model

Figure 4 represents the personalised and adaptive threshold extraction model which contains two strategies: at-group strategy and self-tuning strategy. Both strategies use ADL signals as inputs. In order to position the person's threshold to avoid its deviation due to the complicated environment, ADL data from various groups are used to extract the group threshold for adjusting the personal threshold in the self-tuning strategy for a new user. The self-tuning strategy is similar to the at-group strategy. It consists of segmentation but without the group dividing step, feature extraction and analysis as well as the personal threshold extraction. The self-tuning strategy also contains a further light-tuning procedure based on the group threshold extracted in the at-group stage and the personal threshold acquired in the self-tuning stage.

In summary, the threshold extraction procedure will be concluded as following: the group threshold mentioned above is preset firstly according to the new person's age and gender before Asgard is worn on the body of a new person, and then the new user is required to wear the Asgard and do specified ADLs to extract the personal threshold for him or her. After that, a weight-based light-tuning procedure based on low probability event in the personal threshold feature extraction process is executed to tune the final threshold for the person using the two extracted thresholds of the group and the person.

Figure 4 Personalised and adaptive threshold extraction block diagram (see online version for colours)



4.2 At-group strategy

Now we are in a position to present how to extract a *group threshold for each group*, defined as TH_{group}. This is achieved to locate the person's threshold. This strategy can be divided into three steps as shown in Figure 4: group dividing and segmentation, feature extraction and analysis, and group threshold extraction.

We argue that each age stage, with different gender, has different VSA peaks. Therefore, for the pre-collection database, we divide data into three groups: young female, young male and the elderly in this paper, as the data is only collected from people aged 20–30 and 53–65. These three groups have different levels of VSA peak, which is obviously shown in the former subsections. Here, it is worth mentioning that the group classification of the three classes can be divided into more groups according to the actual application. After groups are divided, segmentation is implemented to divide the VSA peaks into different partitions for further analysis. As seen from Figure 1, the maximum VSA peak is less than 5 g, so here we default the group threshold to lower than 5 g, which is consistent with (Ren et al., 2012). Therefore, in each data group, we segment VSA peaks into 8 partitions, lower than 2 g and higher than 5 g. The partition interval between 2 g and 5 g is 0.5 g, for example, there are two intervals between 2 g and 3 g, 2–2.5 g and 2.5–3 g. We can segment data into more or less partitions according to the application. To extract the useful feature, we map all the VSA peaks into related partitions according to the value of the VSA peak. We use x_{ij} to denote the VSA peak (x_j) of jth action falling into ith partition, while the *ith partition* is denoted as s_i. Therefore, we can get the VSA peak map and compute the number of times that the VSA peak extracted from each action falls into each partition for each group according to ADL data from the pre-collection database. Meanwhile, using the number of times of VSA peak for each group partition, the occurrence probability of the ith partition in each group can also be calculated. Note that all x_j belonging to s_i divided by all x_j of the whole group is the occurrence probability of ith partition for the group, and we can express it as equation (4):

$$p_i = \frac{\sum_{k=i} \sum_{x_j \in s_k} x_{kj}}{\sum_{k=1}^{s} \sum_{x_j \in s_k} x_{kj}} \tag{4}$$

where p_i is the occurrence probability of ith partition, s is the total number of partitions, and x_{kj} is the VSA peak of jth action belonging to kth partition. As is known that a partition with a large boundary value is most likely to be mistaken as a fall, as most ADLs always have small VSA peaks which is visible in Figure 3 and always fall into small boundary partitions. The partition with a large boundary always has a small occurrence probability and a small sum of occurrence probability of partitions. However, most VSA peaks falling into lower than 2 g also have small occurrence probability but with a high sum of occurrence probability of partitions, however, they are from ADLs. Therefore, we can conclude that the smaller sum of the occurrence probability of partitions, the higher the probability to be recognised as a fall. We define cumulative probability of ith partition to determine which s_i has the feature of low probability and can be recognised as fall. In other words, it can be used as a criterion for determining the LPE of s_i for each group. Using the occurrence probability of each partition, we can easily calculate the cumulative probability of each partition by equation (5):

$$F(s_i) = p_{(k \geq i)} = \sum_{k=i}^{s} p_k \tag{5}$$

where $F(s_i)$ is the cumulative probability of ith partition and p_k is the occurrence probability of kth partition. Cumulative probability of the partition is defined as the probability of mistaken recognition as a fall. Low occurrence frequency of partition or partitions shows small cumulative probability of the partition, and vice versa. So the definition of LPE of $s_i$can be visually expressed according to the cumulative probability of the partition, which is a criterion as:

$$\text{If} \quad F(s_i) < F_{\text{LPE}}, \ \text{then} \quad s_i \quad \text{is} \quad \text{LPE}. \tag{6}$$

where F_{LPE} is a threshold that distinguishes if the partition is LPE or not (F_{LPE} in this paper is 0.01). So which partition is LPE can be determined according to the cumulative probability of partition of each group by comparing with a LPE threshold. The next step is extracting the group threshold, a criterion for this threshold determination is proposed as shown in equation (7):

$$\text{If} \quad s_i \in \text{LPE}, \quad \text{then} \quad TH_{\text{group}} = \min(s_i). \tag{7}$$

From this equation, we can see the minimum value of the LPE partition is extracted as the group threshold. By this stage, we have extracted a group threshold for each group. However, VSA peaks exhibit large differences among various people in the same group due to the complicated environment, so the group threshold is not robust enough for everyone's usage. Therefore, a tunable plan is needed to complement this issue. The self-tuning strategy, in which further light tuning is scheduled based on the threshold extracted in at-group stage, personalised threshold in next stage, and low cumulative probability of partition for the person, is a tuning plan for further tuning to extract the final personalised and adaptive threshold.

4.3 *Self-tuning strategy*

The self-tuning strategy is concerned with finding a *personal-based threshold for a person* (denoted as TH_{person}), which also meets the criterions mentioned above. It is a self-adjusting method, in which further light tuning strategy is scheduled based on TH_{person} extracted in this stage and the TH_{group} to get the final personalised and adaptive threshold for the person (to keep consistent with the former definition, here we also denote it as VSA$_{th}$). In the self-tuning strategy, there will be two missions to be fulfilled: 1. Computing the TH_{person} for the next processing step; 2. Light tuning the TH_{person} with the weight method to obtain the final personalised and adaptive threshold.

Finding the TH_{person} utilises almost the same steps as the at-group strategy, but in its segmentation, it is not necessary to divide data into groups. The whole processing for the TH_{person} can be summarised as:

1 Segmenting ADL collected from the person.

2 Computing the probability of ith partition occurrence and the related cumulative probability. In the criterion for the definition of LPE during this strategy, the threshold of F_{LPE} is set to 0.03 to distinguish the partition. This value is bigger than F_{LPE} in the at-group strategy, as the samples of ADL from the person is smaller than that from the group. Even if there is only a one time occurrence of the ith partition, the cumulative probability of it will be larger than F_{LPE} in the at-group step.

3 Extracting a threshold for the person according to the result taken from step 2 and the criterions described in the former subsection. The extracted threshold is the TH_{person} and is obtained for the final VSA$_{th}$ computing. In the remaining parts of this subsection,

we continue with the tunable plan for obtain the final threshold that meets a high performance of fall detection for the right person. The group threshold and the personal threshold are taken into consideration to get the point.

The weight method is used combined with the TH_{person} and the TH_{group}, obtained according to the definition of LPE and the threshold criterion, to get the final VSA$_{th}$ for each person. Note that TH_{person} is more suitable for him or her than TH_{group}, however, it may be very large or small sometimes, which will not keep uniformity with TH_{group} due to unexpected reasons. It can be manifested as TH_{person} strays away from TH_{group}. To avoid such mistakes, a method is needed to solve the deviation problem and improve the performance of the threshold-based fall detection algorithm. The weight method can target this point, as it can achieve a balancing threshold for the person and the related group to get a reasonable threshold for the person. In the weight method, the cumulative occurrence probability of ith partition for ADL data from the person extracted in the TH_{person} computing stage is used to light tune the threshold. The weight-based tuning strategy is shown in equation (8):

$$\text{VSA}_{th} = \alpha \times TH_{\text{group}} + \beta \times TH_{\text{person}} \tag{8}$$

$$\text{Subject to: } \begin{cases} \alpha + \beta = 1, \\ \beta = p_i / F_{\text{LPE}}. \end{cases}$$

where α, β are two coefficients for tuning VSA$_{th}$, and F_{LPE} is 0.03, which is defined to distinguish the partition of LPE for the person.

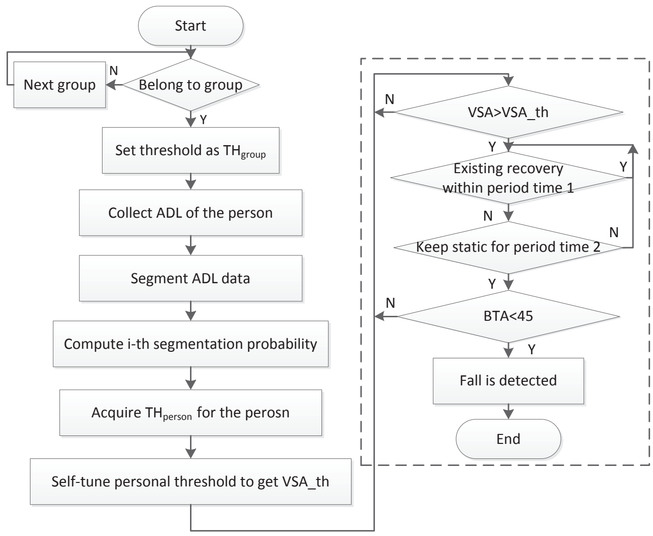
In summary, the personalised and adaptive threshold for the person can be extracted using results from the at-group and self-tuning strategies, while only ADL data is needed. In the proposed two strategies, the group and personal threshold are obtained first, then the weight method is used to light tune the final threshold for individual people.

5 Implementation of personalised and adaptive fall detection

In this section, we are concerned with incorporating the proposed threshold extraction method into Chameleon that can meet appropriate usage for everyone. Solving equation (5) as shown for the cumulative probability of group and personal data, and substituting them into two criterions, allow us to compute three thresholds for each group and a threshold for individual people, which can be used to light tune VSA$_{th}$. Except for the extracted VSA$_{th}$ for the person, we also extract RA to track the real-time status of the body change, and BTA to attain the final angle of the body. With those parameters, we proposed a novel fall detection algorithm.

According to the ADL data from the pre-collection database, which includes data from young females, young males, and the elderly, the group threshold for each group can be extracted and used for later self-tuning. This group threshold, the TH_{group}, is set in advance in Asgard due to the limitation of memory of the device. In other words, when a new user starts to use this fall detection device, he or she needs to choose the group threshold according to his or her age and gender. After that, the personal threshold needs to be obtained based on the new data set of regular ADLs. Therefore the user is required to wear Asgard and do regular ADLs, which are common activities in daily life. Asgard processes the ADL data of the person according to the achievement procedure of the personalised and adaptive threshold strategy. Once the personalised and adaptive threshold is analysed and computed, it will be used as the threshold to trigger pre-alarm for the threshold-based fall detection algorithm. Then Asgard launches angle tracking to determine the recovery action. Until there is no recovery action within the remaining short time, BTA is observed to estimate the final body state. The proposed adaptive fall detection algorithm is illustrated in Figure 5. In this figure, the right part in the dash line is the idea we have proposed in Ren et al. (2012). The basic design of the algorithm for carrying this out is as follows:

Figure 5 Flowchart of personalised and adaptive fall detection algorithm



1 Determine and set the group thresholds of the TH_{group} based on features of age and gender.

2 Collect ADL data of the person and segment them into different partitions.

3 Compute the occurrence probability and the cumulative probability of each partition.

4 Obtain the personal threshold of TH_{person} based on strategies and criterions in Section 3.3.

5 Self-tune to get VSA$_{th}$. The determination of VSA$_{th}$ is explained in the former section while using the results from (1) and (4) to compute.

6 Look for a large VSA, VSA exceeding VSA$_{th}$ is considered as a trigger or pre-alarm condition.

7 Analysis of the recovery action by RA every period time 1 (Period time 1 is set as 0.5 s). If a large RA exists within period time 2 (Period time 2 is set as 6 s), it

means there is a recovery action or the person is trying to recover and stand up. The algorithm will wait for the next recovery determination.

8 Else, it is considered as falling too seriously to struggle to stand up or there is no fall appearing, BTA is acquired for further determination. Using this angle to designate the body is deviating from the uprightness or not. Only if the angle is less than 45 degrees do we classify it as a fall.

6 Evaluation

6.0.1 Training phase trails

In this subsection, the experimental environment and the requirements of evaluation for the training phase and the testing phase are described. Experiments for these two phases have been performed in the same environment and situation, but with more numbers of young volunteers and no elderly volunteers participating in the testing phase. Besides, more activities were also taken in this phase. The detailed information is presented as follows.

In the training phase, the pre-collection database was collected for group threshold extraction, which was used in the testing experiments. In this phase, 1180 ADLs were taken by the 20 volunteers participating in the training experiments, including 5 young males, 4 young females, and 11 elderly people. Volunteers were healthy people with average ages, weight, and height as seen in Table 1. All the volunteers performed ADLs with an Asgard on their waist. In the experiments, volunteers were asked to do tasks as described in Table 2, which only includes the most common activities, such as walking, sitting down, picking up, squatting to standing, lying down, and going up and down stairs. All those ADLs were done as they normally do without any restriction. During the testing, Asgard recorded VSA at the frequency of 62.5 Hz.

Table 1 Characteristics of the experiments performed in threshold extracting phase

Total volunteers		*20*	
Group	*YMale*	*YFemale*	*Elderly*
Numbers of volunteer	5	4	11
Male/Female		9/11	
Age	25 ± 3	23 ± 1	58.6 ± 6
Weight(Kg)	69.4 ± 5	56.27 ± 7	58.6 ± 10
Height(cm)	180 ± 1	164.5 ± 1.5	157 ± 8
Total numbers of experiments		1180	

Two sets of experiments were performed to acquire the threshold for individual people and study the performances of the personalised and adaptive threshold strategy, as well as the Chameleon system based on this threshold. First, personalised and adaptation threshold for fall detection are studied. In this experiment, ADL data from people of three groups for pre-collection database are collected and analysed. These help us to understand thresholds for different groups and also allow us to propose a personalised and adaptive threshold for the person, this is called the training phase. Second, we evaluated the performance of the proposed personalised and adaptive threshold extraction method, as well as Chameleon based on this threshold, which is important to see how this self-tuning threshold strategy behaves. We compared Chameleon with the algorithm of *the advanced magnitude detection* (AMD) proposed in Brown (2005) and the algorithm we proposed in Ren et al. (2012) (denoted as *fixed and tracking fall detection* (FTFD)), this is the testing phase.

Table 2 Experiment of ADLs in threshold extracting phase

Action	*Times*	*Description*
Walking	5	The subject walks at normal speed for 20s
Sitting down	10	The subject stands still first, and then sits down on chair respectively
Picking up	5	The subject walks to a dropped thing on the ground and picks it up with knee bent down a bit or more as usual
Squatting to standing	5	The subject stands still first, and then bends down completely, after that standing up again
Lying down	10	From standing status, the subject lays down on a bed and sofa, respectively, and stays there for 20 s
Climbing stairs	24	The subject walks to stairs, then climbs stairs until the top stair, he or she turns back to walk down stairs, total of 12 steps each time

6.1 Experiment setup

6.1.1 Testing phase trails

To evaluate the proposed personalised and adaptive threshold model, as well as the performance of Chameleon, the other two algorithms, AMD and FTFD, have been re-implemented in our study as comparison algorithms. We implement the three algorithms on the Asgards as threshold-based comparison solutions while all the volunteers performed experiments wearing them on their waist, simultaneously. In this phase, there are activities related to falls, which are dangerous for the volunteers, especially for the elderly person to perform. Ideally, evaluating the Chameleon system with the aging population is the best; however, we decided not to do the experiments with elderly because of the following two reasons. First, asking the elderly participants to do the experiments has high risk and should be the last resort; second, the novelty of the proposed Chameleon system lies in the adaptiveness and personalisation; we think the young participants should be good enough to validate the advantages of the proposed approach. Therefore, only the young people were recruited in this phase, 15 young volunteers were asked to do the test, including 10 young males and 5 young females. The average age and weight are listed in Table 3. Furthermore, the entire evaluation experiments were implemented in a controlled lab environment. Especially, for related fall activities, volunteers were asked to mimic those dangerous activities on a mattress.

Table 3 Characteristics of the experiments performed in testing phase

Total volunteers	*15*	
Group	*YMale*	*YFemale*
Male/female	10/5	
Age	24 ± 5	24 ± 3
Weight (Kg)	68 ± 6	54 ± 7
Height(cm)	178 ± 3	163 ± 2.5
Total numbers of experiments	1200	

There are two steps based on the proposed model in this phase. The first step is extracting a personalised threshold to light tune thresholds for the volunteer himself or herself. Therefore, each volunteer was required to do ADLs as listed in Table 2, which is similar to the training phase, while more young volunteers participate in this step. In contrast with the training phase, this step test is not done by all the volunteers together, but one volunteer each time is used to collect the data of the individual and analyse the personalised threshold for him or her. Once the personalised threshold is extracted, the other step is performed to evaluate the performance of Chameleon based on the results from the training phase and the first step of this phase. The second evaluation step is the main objective of our experiments. In this step, each volunteer was asked to carry out several actions, including five ADLs, five transform activities, and six different types of falls as shown in Table 4. Each activity was performed 5 times by each volunteer. In all tests, three Asgards were fixed on the waist of the subject during the whole evaluation phase. As presented in this table, more ADLs and falls were required to be taken for verification of the personalised and adaptive threshold strategy, as well as the performance of the Chameleon system. Once a fall is detected by Asgard or Asgards, when the subject does the experiments, the label of the three different algorithms will be sent out to the Homeserver.

6.1.2 Performance evaluation criteria

A high quality fall detection system is preferred to garner public acceptance. To evaluate the proposed personalised and adaptive threshold model, as well as the performance of Chameleon, three well-established criteria are widely used in fall detection systems, which are defined by four possible cases for fall detection:

- *True positive* (TP): A fall occurs while the system detects it as a fall.
- *True negative* (TN): An ADL activity is carried out while the system detects it as an ADL.
- *False positive* (FP): An ADL activity is carried out but the system detects it as a fall action.
- *False negative* (FN): A fall occurs but the system detects it as an ADL.

Based on the four result values, three widely used criteria of sensitivity, specificity, and accuracy can be computed. Sensitivity is the capability to detect a fall, and it can be expressed as equation (9).

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{9}$$

Specificity is the capability to detect ADL, and it is given as equation (10).

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{10}$$

And accuracy is the proportion of true results (both true positives and true negatives) in the fall detection, which shows the correct detection result. The computed method of accuracy is shown as equation (11).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

6.2 Results and analysis

6.2.1 Group threshold in at-group stage

In a threshold-based fall detection system, the value of acceleration exceeding a fixed threshold can trigger the condition of detecting fall. However, a personalised and adaptive threshold for the individual can achieve better distinguishing ADLs from falls while improving the accuracy of fall detection. According to the proposed threshold extracting model, firstly, a group threshold for the individual needs to be extracted in light of his or her age and gender. To extract the group threshold for light tuning the personalised and adaptive threshold for an individual person, we processed and analysed trial data collected in the training phase from 3 groups of people. In this stage, VSA peak of each ADL activity from all the sample values are extracted for further processing. After that, the extracted VSA peaks are segmented into 8 partitions per group. Table 5 provides all the occurrence probability of each partition. Since there is no data larger than 5 during the training data collection, the last partition is not listed. As shown in this table, the partitions are drawn on the top row, while the occurrence probability of the ith partition for each group is listed above. In this table, G is defined as a group and P stands for partition. The grids in the table with a star are marked as the chosen group threshold partition according to the criterion of LPE, while the minimum values of these partitions are the group threshold values. The results of three groups shown in Table 1 target 3.5 g as the threshold for the young female group, 4.5 g for the young male group and 3 g for the elderly group. As a general observation in this table, the threshold for young males is the highest one among the three groups, young females are in the middle position, while the elderly group has the lowest threshold, which are consistent with the observation mentioned in the introduction section.

6.2.2 Accuracy of fall detection algorithms

Fall detection performance is an important factor affecting its feasibility in reality. In this subsection, we mainly study the

Table 4 Evaluation tasks in testing phase

Category	*Task*	*Description*
ADL	Walking	The subject walks at normal speed for 20 s at least
	Sitting	The subject stands still firstly, then sits down and remains seated
	Running	The subject runs at normal speed for 20 s at least
	Jumping	The subject jumps up or forward, and then stands still
	Lying down	From a standing position, the subject lays down and keeps there for 20 s at least
Posture transitions	Walking to sitting	The subject walks at normal speed and then sits on the chair
	Running to sitting	The subject runs at normal speed and then sits on the chair
	Jumping to sitting	The subject jumps up or forward and sits on the chair
	Squatting to standing	Initially in a standing position, the subject squats down and then stands up
	Fall but recovery	From standing position, the subject falls on the ground, but tries to recover to stand up
Fall	Fall forward	The subject stands still and falls on the ground with face toward the ground
	Fall backward	The subject stands still and falls on the ground with back touching first
	Fall lateral	The subject stands still and falls on the ground with lateral first touching
	Fall on something	The subject stands still and falls down on something
	Fall with recovery	From standing position, the subject falls to the ground and tries to recover, but fails to stand up
	Fall from stair	The subject stands on stairs and falls to the ground

Table 5 Occurrence probability of ith partition

P(g) / *G*	*<2*	*2–2.5*	*2.5–3*	*3–3.5*	*3.5–4*	*4–4.5*	*4.5–5*
YFemale	0.7289	0.2214	0.0299	0.0174	0.0025*	–	–
YMale	0.6572	0.2008	0.0568	0.0325	0.0243	0.0223	0.0061*
Elderly	0.9051	0.0678	0.0196	0.0045*	0.0030	–	–

*The grid with a star is marked as the chosen group threshold partition.

performance of Chameleon with contrastive experiments for evaluating the performance of Chameleon with the threshold extracted from the two strategies discussed in this paper. As comparative experiments, AMD and FTFD were re-implemented. The three algorithms are all threshold-based fall detection solutions, but with different parameter settings. Table 6 presents the difference among the three algorithms. In this table, we can see Chameleon is similar with FTFD which we have proposed in our previous works, but with a personalised and adaptive threshold in Chameleon as a trigger condition, while a fixed threshold is used in FTFD. AMD is another algorithm with a fixed threshold for pre-alarm and a fixed time to detect body angle, but real-time body tracking is done in Chameleon and FTFD.

According to the proposed personalised and adaptive threshold extracting model, we need to analyse the data of the individual to acquire the personalised threshold for him or her after we acquire the threshold for the group. The whole procedure is the same as the at-group phase. Asgard is worn at the waist to collect ADL data of the person. Then the data is analysed based on the occurrence probability, the cumulative probability of the partition, and the weight method as the proposed model to extract the personalised threshold. According to the personalised threshold result and group threshold, Asgard light tunes the threshold for the person, which is used in his or her testing experiments. Here the thresholds for eight volunteers are listed due to the limitation of space as shown in Table 7. According to the group threshold, young females have 3.5 g as the group threshold. However, from the table we can see some volunteers have thresholds larger than the group threshold, while the thresholds for others are lower. This is reasonable, as the personalised threshold will light tune the final threshold for each volunteer according to the real time data collected by Asgard. That means the threshold for each individual will distribute around the group threshold. The same situation happens for the young male group volunteers.

Table 6 Differences of three algorithms

Algorithm	*VSA threshold*	*Final angle* (°)	*Detection time* (s)
Chameleon	Adaptive	45	$6 + 0.5\times$ times
FTFD	Fixed	45	of recovery
AMD	Fixed	60	16

Table 7 Personalised and adaptive threshold for each volunteer

	YFemale				*YMale*			
Volunteer	1	2	3	4	5	6	7	8
Threshold	3.3	3.52	3.38	3.43	4.2	4.53	4.45	4.1

Table 8 shows the performance of Chameleon. In this table, SA is simple activity of daily life (ADL as shown in Table 4), while TA is transition activity of daily life (Transform as shown in Table 4). From the data presented, we found the correct detection ratio for SA is 100%; 98.13% of TAs are correctly detected, and less than 6% of falls fail to alarm. Obviously, Chameleon can correctly detect simple activities of daily life without any false alarms. Transition activity is complex human behaviour, each person acts different when doing TA. However, only a small amount of false alarms happen during transition activity in daily usage using the proposed fall detection system while it retains a high correctness ratio of fall detection. During this test, it is observed that running to sitting and jumping to sitting are similar to fall. The VSAs of running and jumping are easier to exceed the preset threshold than other activities, which is the pre-fall trigger condition. Meanwhile, there will be a large angle if the person sits with his or her back lying on the backrest, so the ending postures of those two TAs are similar to the fall's ending status. Therefore, some of the two TAs are detected as falls during the evaluation experiment. In total, among 7 ADL false detection cases, 5 of them are caused by running to sitting and jumping to sitting. However, these two activities rarely happen among the elderly people. Here, we only want to test the robustness of Chameleon. In the fall tests, less than 6% of falls fail to alarm. Most of them are caused by the small VSA. Some of the volunteers dare not do fall imitations in fall trials but just lie down, which show small VSA and cannot trigger the fall detection. This is the main reason for fall missing.

Table 8 Performance of Chameleon

Item	*Total times*	*Correct*	*Incorrect*	*Correct ratio (%)*
SA	375	375	0	100
TA	375	368	7	98.13
Fall	450	419	31	93.11

Table 9 illustrates the performance of three algorithms. Viewing Table 9 as a whole, we find that the accuracy of Chameleon is 96.83%, while 95.16% for FTFD, and 94.16% for AMD. The sensitivity of Chameleon at 93.11% is 2.44% higher than FTFD and 3.11% higher than AMD. Meanwhile, the specificity of it is 99.07%, 1.2% higher than FTFD, and 2.4% higher than AMD. Therefore, Chameleon has higher accuracy, sensitivity, and specificity than both FTFD and AMD. According to the testing procedure, while viewing Tables 6 and 9 together, we found that the most important difference among these algorithms is a higher false positive rate of AMD. The reason for the higher false positive of AMD is that the final angle is set a bit higher than the other two, which is the direct cause of many fall-like activity alarms. False negatives of AMD and FTFD are also higher than Chameleon. It is a reasonable result. As some volunteers are quiet most of the time and not active enough, he or she will have a small movement threshold, some may be less than 4 g, which is lower than that of AMD and FTFD but consistent with Chameleon. With even a small impact caused by a fall, the VSA of Chameleon can easily trigger fall detection and alarm. In summary, the performance of Chameleon is better than the other two comparison algorithms.

7 Related work

Numerous commercial and academic fall detection approaches aiming at detecting fall with high performance have been proposed and achieved in recent years. Those fall detection methods can be classified into four classes: environmental-based solutions, camera-based solutions, classification-based solutions as well as threshold-based solutions:

- *Environmental-based solutions*. This type of solution always installs multiple sensors in the places that the elderly are monitored to acquire and analyse related information when the people are in the monitoring space of them. Those sensors or sensor arrays can sense the change of environment which can be used to distinguish ADL from fall. Litvak et al. (2008) achieves fall detection based on floor vibration and acoustic sensing, and uses a pattern recognition algorithm to discriminate between human or inanimate object fall events. Popescu et al. (2008) achieves fall detection using an acoustic fall detector equipped with two microphones. When a sound is detected, the features are extracted from this sound for pattern recognition. If those features match with the fall's features, it is recognised as a fall. In Popescu et al. (2012), authors present a fall detection system using multiple infrared sensors while Ariani et al. (2010) investigates fall detection system based on the pressure mats and infrared sensors. These approaches use cheap devices which are non-intrusive for comfortable usage. However, the detecting range and coverage area equipped with sensors are restricted, meanwhile, the installation of the sensors or sensor array is a complex job for users.
- *Camera-based solutions*. Cameras are installed in the rooms for fall detection. It is based on extracting data from still image or live video using various processing technologies. The images or video can be collected through one or more cameras. Nghiem et al. (2012) uses one camera to detect the possible head positions, based on which the speed of the head and the body centroid and distance to the ground can be extracted to detect a fall. Many studies Huang et al. (2008), Willams et al. (2007) and Auvinet et al. (2011) propose distributed cameras to detect falling. The cameras work together in a single room to complete the fall detection. The camera-based approach can simultaneously detect many events which cannot be achieved by other methods. It is also a non-intrusive method. However, the system has high cost, is difficult to install and is limited to the coverage area. Moreover, the privacy of the individual is another concern issue.
- *Classification-based solutions*. There are also many classification-based approaches using machine learning to detect falls with recorded data. For example, Gatton and Lee (2010) proposes a fuzzy logic based decision making system, which integrates the current health condition, the expected activities and behaviour of the patients to make the decisions. Tong et al. (2013) presents a hidden Markov model (HMM)-based method to detect and predict a fall. Luštrek and Kaluža (2009) tries various machine learning algorithms to train

Table 9 Accuracy comparison of three algorithms

Algorithm	*TP*	*TN*	*FP*	*FN*	*Sensitivity* (%)	*Specificity* (%)	*Accuracy* (%)
Chameleon	419	743	7	31	93.11	99.07	96.83
FTFD	408	734	16	42	90.67	97.87	95.16
AMD	405	725	25	45	90	96.67	94.16

classifiers for classifying the behaviour into the six activities. C4.5 decision trees, Naive Bayes, 3-nearest neighbours, support vector machine (SVM), random forest, bagging and Adaboost M1 boosting are implemented to compare the classification accuracy. Multilayer perceptron, Naive Bayes, decision tree, SVM, ZeroR and OneR are implemented in Kerdegari et al. (2012) to investigate the performance of different classification algorithms for a set of recorded acceleration data. The methods of this type can improve the accuracy of fall detection. However, due to the large calculating overhead, most of them are off-line processing procedures, which limit the usage in real daily life.

- *Threshold-based fall detection*. Threshold-based fall detection is the most common and basic method that has been widely adopted in conventional fall detection systems. It uses accelerometers to extract various parameters to detect falls. For example, many studies use the impact of activities as a threshold to determine a possible fall (Brown, 2005) while combining with other parameters to determine the final fall event, which include the angle of the body (Brown, 2005; Chen et al., 2005; Purwar et al., 2007), the time interval (Abbate et al., 2011) and so on. These solutions achieve fall detection with low cost and in a real time way. However, they face energy hungry and accuracy issues.

The proposed Chameleon system is a threshold-based system, which has significant improvements and advantages compared to the four classifications. First, Chameleon is a novel threshold-based fall detection system, which has advantages of being easier to distribute and operate than environmental-based and camera-based fall detection solutions. Environmental-based approaches always need to install multiple sensors or a sensor array in a specified monitoring range while a camera-based solution will need at least one camera with a complex installation procedure for the user. Second, Chameleon is more robust compared with other threshold-based solutions. For this type of fall detection, we know the threshold determination is important for the accuracy of a fall detection algorithm. It will bring out many false positives or false negatives if the threshold is set too low or too high, however, most studies have determined this threshold using empirical data (Ren et al., 2012; Bourke et al., 2006; Kangas et al., 2008) extracted from the impact data of young people. Evidently, this empirical threshold is too high for elderly usage. However, we argue that a fixed threshold is not flexible enough to detect falls for different people, and propose a personalised and adaptive threshold for different individuals to improve the performance of the fall detection system. Besides, the proposed threshold extracting model can also be used in most threshold-based fall detection algorithms.

8 Conclusion

In this paper, we have developed an adaptive fall detection system called Chameleon, with the personalised and adaptive threshold extracted by two proposed strategies combined with the weight method, while only ADL data is collected using Asgard. The algorithm solves the problem of the low accuracy caused by fixed threshold usage in a fall detection algorithm for every person. Comprehensive evaluations are implemented by comparing it with two other threshold-based fall detection solutions. Our experiment results show the proposed personalised and adaptive threshold method improves the performance of threshold-based solutions.

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