A Multistage Collaborative Filtering Method for Fall Detection

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***Abstract*— Falls threaten the health and life of the elders heavily because they lead to injuries or even death. Therefore, a reliable monitoring and alarm mechanism is desperately in need to guarantee the quality of elders' life. In this paper, we propose a multistage machine learning method to perform fall detection and solve the false alarm and missing alarm problem in traditional fall detection methods. Our proposed method consists of three stages: 1) threshold filtering, 2) ELM classifier, and 3) orientation-based filtering. Our method utilizes a high-precision triaxial accelerometer to collect the relevant information. After filtered by our three-stage method, the signal can be determined whether it is a fall or not. Experimental results demonstrate that: different from the traditional state-of-art methods with a single machine learning classifier, our method can greatly reduce the missing alarm and false alarm rate on the premise of high accuracy for all detection.**

***Keywords*—Fall Detection; Wearable Device; Multistage; Extreme Learning Machine;**

I. INTRODUCTION

Fall means sudden, involuntary, unintentional position change and falling on the ground or lower plane. According to International Classification of Diseases (ICD - 10) for the fall[1], falling-action consists of the following two categories: (a) from one plane to another plane. (b) fall in the same plane. The U.S. Centers for Disease Control and Prevention(CDC)[2] illustrated that more than 30% living people over the age of 65 happen to fall in their daily life each year and more than 5.6 million of them have fallen down many times. Elders' abnormal muscle tone, decay in muscle atrophy and decline in strength and balance ability with age will make them more vulnerable to fall down. Fall causes serious damage to elders' physical and mental health and even results in disability and death. Fall also leads to physical and psychological problems, which seriously affect elders' daily behavior and bring many physical restrictions in their daily life. Researches showed that the risk of hospitalization could be reduced by 26% and death by over 80% after fall event detection followed by immediate notification to caregivers[3]. Therefore, how to design an ideal and effective method for fall detection is urgently needed and has attracted considerable attention recently.

Currently existing fall detection methods can be divided into two categories, including computer vision-based method[4]and wearable device-based method[5-8]. With the help of video monitors (Cameras[9], Kinect[10], etc.) and the combination with artificial neural network[11] for image processing, this computer vision based method can recognize typical action and subject's behavior change easily. The limitations of this approach are that the change of environment and noise interference can greatly affect the accuracy of the detection result. Besides, the position of the monitor is usually fixed and cannot follow the objects in real time. As a result, computer vision based method can only monitor and detect a certain limited area, which is not applicable for real-life scenario. The wearable device-based method integrates various sensors(such as accelerometer[12], gyroscope[13], etc.) into one[14] or multiple[15] wearable devices and identify falling-action through the signals collected by sensors in real time.

Compared with computer vision based method, wearable device based method has the advantage of low-power, high mobility and real-time. Machine learning techniques, such as support vector machine(SVM)[16], decision tree(C4.5, ID3, CART, etc.)[17] and Hidden Markov Model(HMM)[18], are common adopted to train the detection model and identify fall behaviors in these approaches. The vast majority of methods above usually perform fall detection with conventional one single-phase model[29-31]. Although these kind of single-phase models are capable of generating good recognition results, their detection methods often lack systematic analysis on the characteristics of fall behavior. These defects, as a result, lead to high false alarm rate and sensitivity to noise data. Thus, to solve the high false alarm rate in conventional fall detection methods, we propose a multistage collaborative filtering method in this paper. The general framework of our method is shown in Fig.1. In this method, the whole fall detection process can be divided into three modules: 1) threshold filtering module, 2) extreme learning machine(ELM) classifier and 3) orientation-based filtering module. Our proposed method shows a good performance not only in fall detection but also in reducing the false alarm rates.

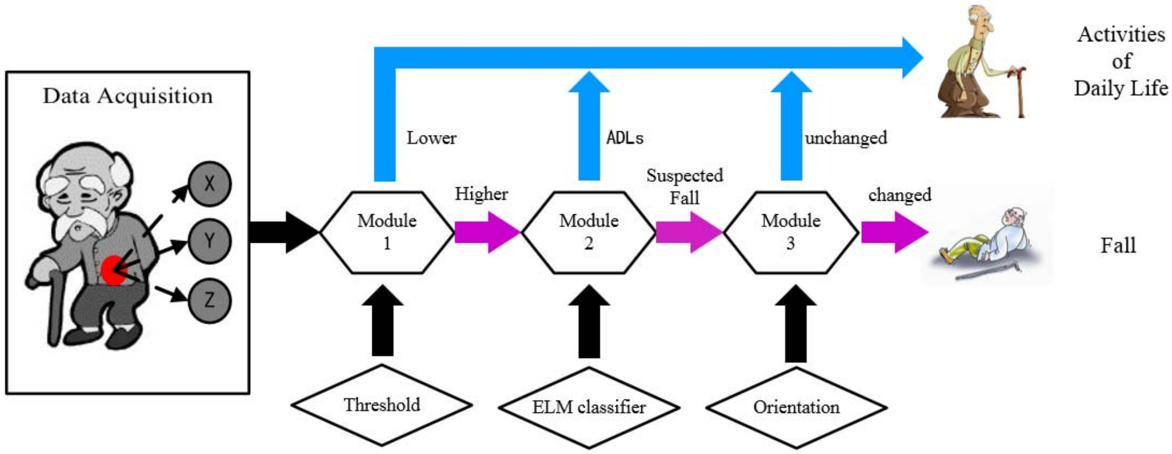

Fig.1 General Framework of Method

The contributions of this paper are as follows: First, we present a Multistage Collaborative Filtering Method to improve the accuracy of fall detection. Furthermore, based on the orientation and posture of human body, without gyroscope, our method can greatly eliminate the false alarm rate. Organizations of the this paper is as following: (1)In section II, the related work and latest methods in fall detection will be introduced. (2) Detailed theoretical analyses of each module will be given in section III. (3) In section IV, we will analyze our datasets and evaluate our method in practical application. (4) In section V, we will draw a conclusion about our method and some further work about fall detection will also be presented.

II. RELATED WORK

Recent advances in computer vision have made various research works looking into the combination of image process techniques and human activity recognition possible. For example, Htike et al.[19] normalized silhouette to 128 × 128 pixels and selected 230 points on the outline of the silhouette. After calculated all pairwise distances, chord distribution is used to present 2-D poses and train 20 probabilistic pose models. Each model produced a probability for the input test image and these probabilities are fed to a fuzzy-state HMM for classification. Auvinet[11] et used a multiple-cameras network to reconstruct the 3-D shape of people. By analyzing the vertical volume distribution ratio and setting the threshold as 40%, the fall behavior can be detected. A common challenge in these fall detection methods is that the elders' daily environment often change from one place to another. It is impossible to detect when the fall behavior occurs outside because the scope of camera is limited.

Compared with the detection methods based on computer vision, wearable device is free from the influence of environment and has advantages of simple configuration, lower cost, greater mobility and practicability. H. Gjoreski et al.[20] created a system consisting of two wearable accelerometers and placed them on abdomen and the right thigh. The detection of falls is performed on a laptop using the raw sensors' data acquired through Bluetooth. If the difference between minimum and maximum acceleration exceeded 1g, a fall behavior is found. He et al.[21] attached two wearable accelerometers to a custom vest. KNN algorithm is introduced to analyze the stream data in a smart phone. When the fall is detected, the smart phone can issue an alarm and provide timely help for the user. Li et al.[22] placed the 3D acceleration and gyroscope on chest and thigh. Their system can recognize four kinds of static postures: standing, bending, sitting, and lying. If the transition before a lying posture is not intentional, a fall event is detected. These wearable device based methods introduced above only used a simple model (one single threshold or simple machine learning model) to identify the fall and often brings false alarms in practical application. Aiming at this problem, we present a multistage collaborative filtering method for fall detection, which can make quick response to fall behavior with almost no false alarm happening.

III. MULTISTAGE COLLABORATIVE FILTERING METHOD FOR FALL DETECTION

Our classification model can be divided into three modules: the first module is responsible for filtering most of activities of daily living(ADL) data at the first stage. Compared with ADLs, fall is a kind of extremely intense behavior and their difference in peak value will certainly be observed directly. In this way, we can filter out most of ADLs. The benefit is that it can reduce the workload of following module (extreme learning machine classifier). More importantly, the fall and no-fall(ADLs) data we collected is very imbalanced and the number of ADL data considerably exceeds the number of fall data. After eliminating most of ADLs, we can greatly lower the negative effects from imbalanced data and improve the accuracy to some extent by this way. After threshold filtering module, we extracted some fall related features from recorded signals and the ELM classifier (module 2) can be used to further identify fall behavior from ADLs. Based on signal-processing technique, we extracted some fall related features from recorded signals and train the ELM model. ELM classifier has very high accuracy in fall detection and its experimental results will be analyzed in detail in section Ⅳ. Although the ELM classifier is an efficient method with high true positive rate in fall detection, only one single classifier is inadequate and it will surely occur misdeclaration due to high false positive rate. To solve this problem, orientation-based filtering module(module 3) is used to decrease the false alarm rate and avoid misdeclaration. Motivated by the fact that: the angle and direction of human body will certainly change when fall is happening. The body posture will vary from standing upright to lying down after fall occur. This kind of change can be easily observed through the signal of both before and after the fall. After filtered by module 3, a detection result with high confidence can be provided and alarm system will be activated based on it. The description of our method in detail is followed.

Algorithm 1 : Multistage Collaborative Filtering Algorithm

▶ **Threshold Filtering Module**
if $RMS_{max} > threshold$
then
    ▶ **Extreme Learning Machine Classifier**
    if $result_{elm} == suspected\_fall$
    then
        ▶ **Orientation-based Filtering Module**
        if $direction == ischanged$
        then $result_{final} == fall$
        else $result_{final} == ADLs$
    else $result_{final} == ADLs$
else $result_{final} == ADLs$

A. Threshold Filtering Module

Fall behavior is usually characterized by rapid acceleration. As the peak value of fall behavior is much higher than the one of ADLs, we can use sum vector magnitude of the acceleration to distinguish most of them. In this module, we use the root mean square(RMS) to calculate the sum vector magnitude as Equation (1):

$$R(i) = \sqrt{(a_x(i))^2 + (a_y(i))^2 + (a_z(i))^2} \qquad (1)$$

where $a_x(i)$, $a_y(i)$ and $a_z(i)$ denote the acceleration of each axis at i. The threshold filtering module is described as Fig.2.

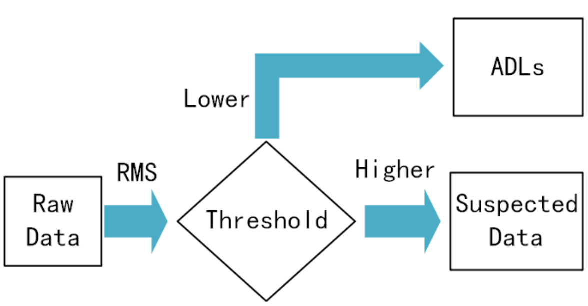

Fig.2 Threshold Filtering Module

After the RMS is computed, we compare the peak RMS with the threshold. If the peak RMS is higher than threshold, it will be classified as "suspected fall", otherwise it will be classified as ADL behavior. If the result is a suspected fall, it needs to be sent into the next module (ELM classifier) for further detection.

B. Extreme Learning Machine Classifier

The signal which is classified as suspected fall by module 1 will be sent into the ELM classifier for further detection. In this module, two results will be given: ADLs and a suspected fall. If the classification result of ELM is still a suspected fall. It will be sent into module 3(orientation-based filtering module) for final detection. The process of this module is described as Fig.3.

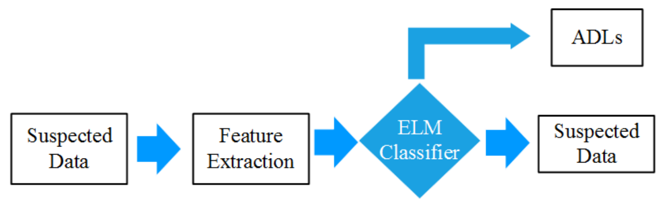

Fig.3 Extreme Learning Machine Classifier Module

We still use RMS to extracted some fall related features for ELM which are described as follow:

- Mean RMS Value (MRV)

Mean is estimate of summation RMS and measure the baseline of the signal. It is given by:

$$Mean = \frac{1}{n}\sum_{i=1}^{n} R_i \qquad (2)$$

Where R_i is the RMS value at i and n is the length of the signal.

- Variance(VAR)

VAR is used to estimate the degree of changes and the diversity of activities. It is given by:

$$VAR = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - mean)^2 \qquad (3)$$

- Maximum (MAX)

MAX can indicate the intensity level of the behavior and the threshold value in module 1 is also determined by it:

$$MAX = \max_i^n R_i \qquad (4)$$

- Minimum (MIN)

MIN is used to measure the base value of standing behavior and often combines with MAX to calculate the variation range of signal.

$$MIN = \min_i^n R_i \qquad (5)$$

- Range

Range indicate the degrees of changes from static to activity. It is given by:

$$Range = MAX - MIN \qquad (6)$$

- Mode

Mode means the value that appears most often in a set of signal data and it is used to represent the aggregate level of the signal.

- Mean Crossing Rate (MCR)

Mean Crossing Rate is the frequency of cross the mean value in a sequence of signal. This feature means the rate at which the signal changes from higher to lower than mean or vice versa. It is given by:

$$MCR = \frac{1}{n-1}\sum_{i=1}^{n-1}\mathrm{sgn}\left[(R_i - mean)(R_{i-1} - mean)\right] \tag{7}$$

Where:

$$\mathrm{sgn}(x) = \begin{cases} 1 & x < 0 \\ 0 & x \ge 0 \end{cases} \tag{8}$$

After feature extraction, we use ELM (extreme learning machine) as the classifier. ELM is a Single-hidden Layer Feedforward Neural Network (SLFN) for classification or regression with a single layer of hidden nodes[23]. Its weights connecting inputs to hidden nodes are randomly assigned and never updated[24]. When the training set is small, compared with other classifier, ELM is more efficient and effective and it is also more time-efficient in offline learning and online prediction[26-27]. The SLFN is shown in Fig.4.

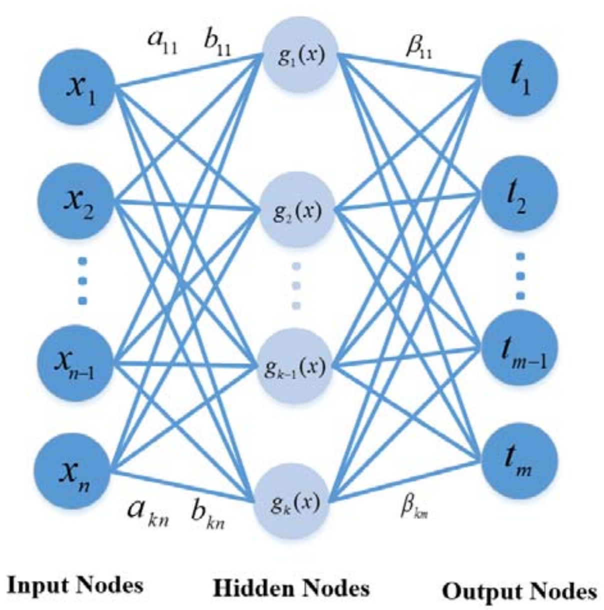

Fig.4 Single-hidden Layer Feedforward Neural Network

Given N samples $(\mathbf{x}_i, o_i) \in R^n \times R^m, i = 1, 2, \cdots, N$

Where the $X = [x_1, x_2, \cdots, x_n]^T$ is an input vector with n features and $T = [t_1, t_2, \cdots, t_m]^T$ is the output vector, the output function can be represented as Equation (9):

$$f(x) = \sum_{i=1}^{k}\beta_i g(a_i x_j + b_i), j = 1, 2, 3, \cdots, n \tag{9}$$

where a_i and b_i are the parameters of hidden nodes, and β_i is the weight parameter. $g(a_i x + b_i)$ is the activation function (e.g. sigmoid) so that $f(x)$ can be summarized as

$$T = G\beta \tag{10}$$

where

$$G = \begin{bmatrix} g(a_1 x_1 + b_1) & \cdots & g(a_k x_1 + b_k) \\ \vdots & \ddots & \vdots \\ g(a_1 x_n + b_1) & \cdots & g(a_k x_n + b_k) \end{bmatrix} \tag{11}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_k^T \end{bmatrix}_{k\times m} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_k^T \end{bmatrix}_{n\times m} \tag{12}$$

Once a_i and b_i are assigned to random value, they do not need to be updated during the training process[24-25]. To solve the Equation (3), we can use the Moore–Penrose generalized inverse of G ,which will be:

$$\hat{\boldsymbol{\beta}} = G^{\dagger}O \tag{13}$$

where $G^{\dagger} = (G^T G)^{-1} G^T$ when $G^T G$ is nonsingular and $G^{\dagger} = G^T (GG^T)^{-1}$ when GG^T is nonsingular.

ELM classifier will determine if the signal entered is a ADL or a suspected fall as shown in Fig 3. If the result from ELM is a suspected fall, still, it will be sent into the next module (orientation-based filtering module) for final detection.

C. Orientation-based Filtering Module

As is shown in Fig.5, while fall behavior is happening, the body posture changes from standing to falling down, which will cause the axis along the gravity change from X to Z.

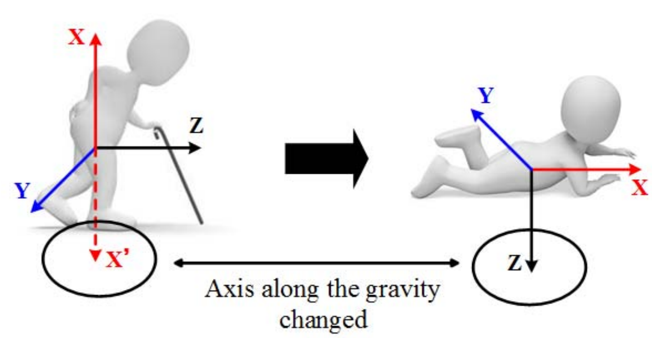

Fig.5 Body Posture and Axis Changed in Falling

Fall always consists of three stages: Start, Impact and Motionless[12] which will also be reflected in signal data. As shown in Fig.6, the characteristic of each stage is has great difference from each other.

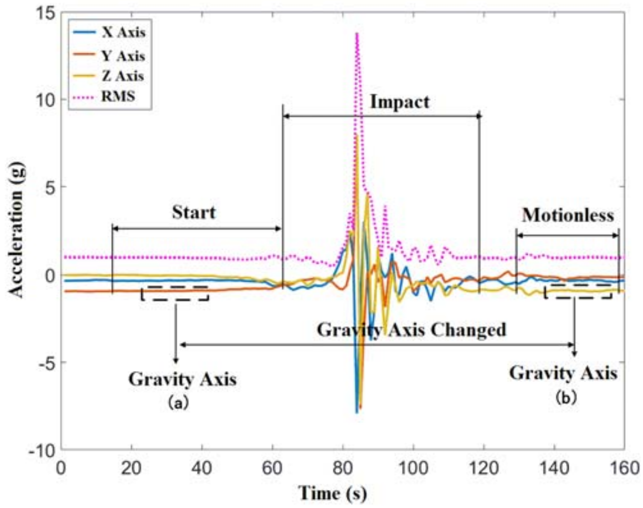

Fig.6 Three Stages of Fall

At the" Start" stage, subject is standing upright and the absolute value of axis along the gravity is the highest (farthest from zero line), which has been shown in Fig 6. As long as the subject falls down to the ground, an extreme impact will happen and the acceleration will increase rapidly to maximum. After the occurrence of falling, subject will lay on the ground for a while and the acceleration will back to normal. At this time, as the posture of body switch from standing to lying down, the axis along the gravity will change from one to another according to Fig 5, Fig 6. In this way, we can easily detect the angle changes of body to identify the fall behavior without any other sensor (Gyroscope, etc.). The process of this module is described as Fig.7.

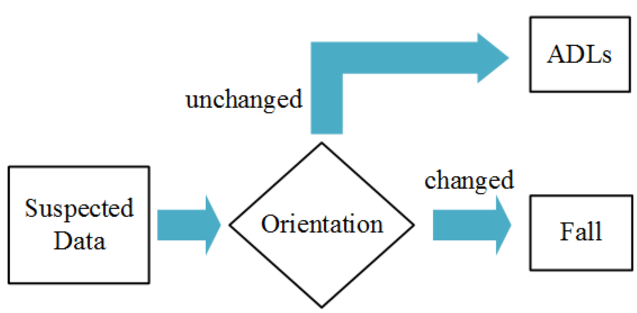

Fig.7 Orientation-Based Filtering Module.

IV. EXPERIMENTAL ANALYSIS

A. Data Acquisition and preprocessing

In this paper, we introduce a wearable device with a accelerometer to collect data and a Bluetooth to transmit data to smart phone. Fig.8(a) shows the architecture of our sensor board. It consists of a high-precision accelerometer and a Bluetooth module with low-power. We use STMicroelectronics LSM6DS0 with 60Hz sample ratio as the 3D accelerometer. Its supply voltage should be 1.71V-3.6V and it has a full scale range of ±8 g. The Bluetooth module is Nordic Semiconductor nRF51822 with 256KB ROM and 32KB RAM, which has a range of 10m.

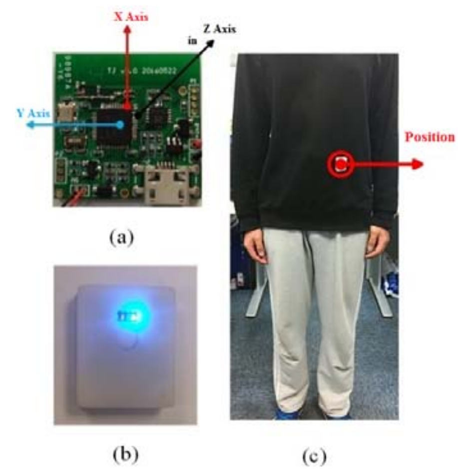

Fig.8 Wearable Device with Accelerometer and Bluetooth

An alarming lamp is installed in our device and it will flicker when the fall behavior occurs. In order to obtain the signal with high quality, we place our device in the waist[8] which is shown in Fig.8 (c).

We collected training and testing data sets from 10 individuals and each person is asked to perform 5 intentional falls in each directions (forward, backward, left and right). Thus, we collected 200 data sets of fall behavior in total. The ADLs consists of five categories: walking, ascending staircase, descending staircase, standing still and running. Also, for each individual (10 persons in total), we collected the data stream for 60 seconds in each category. Finally, in order to evaluate the performance of our method in real life, we collect 3 groups of Real Life Data (RLD) and each group contains 8 hours of continuous data throughout the daytime. The signal we collected is shown in Fig.9.

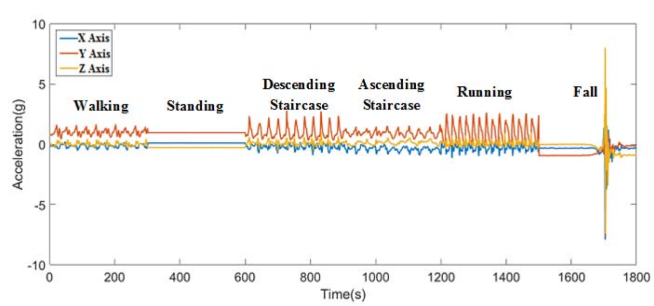

Fig.9 ADLs and Fall Signal

A sliding window is introduced to analyze the data stream and detect fall in real-time. In feature extraction, we set the size of window as 1s and the step as 0.5s so that we can extract one feature from one window data. As a result, we extracted 200 features from fall behavior, 5953 features from ADLs and 71628 features from RLDs. We selected 200 falls and 200 ADLs randomly for cross validation. To evaluate the accuracy and false alarm rate in real life, we use RLDs to test our method in Orientation-based Filtering Module.

B. Determination of The Optimal Threshold

Firstly, we calculate RMS of sliding window data according to Equation (1), which is shown in Fig.10.

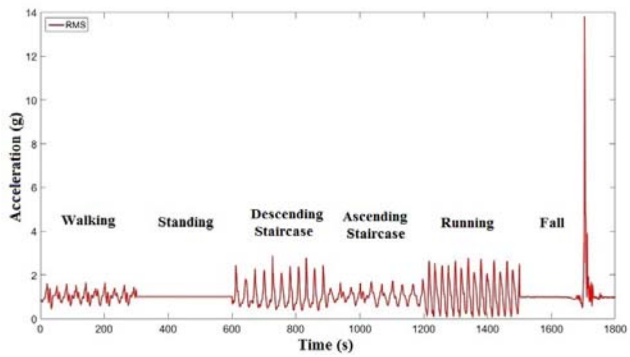

Fig.10 RMS of Sliding Window Data

The peak value of RMS differs greatly between the data of falls and ADLs. Fig. 10 shows that by statistical method, we can filter most of ADL data if we find the minimum value of falling data. Considerable number of existing methods have demonstrated: when the impact is happening, although the data acquisition equipment is different, the gravitational acceleration is roughly similar to each other (e.g. 2.0g [35], 2.76g [36], 2.39g [37]). In our dataset, in order to make sure no fall action is missed, according to statistics, the minimum peak of falling data is set to **2.1176**. This threshold is similar to the existing methods with high confidence and only **703** ADL data exceeds this threshold. We can conclude that the threshold 2.1176 can filter **88.2%** of ADL data on the premise that all the fall data can be detected. The ADL data is marked with blue and the falling data is marked with red in Fig.11.

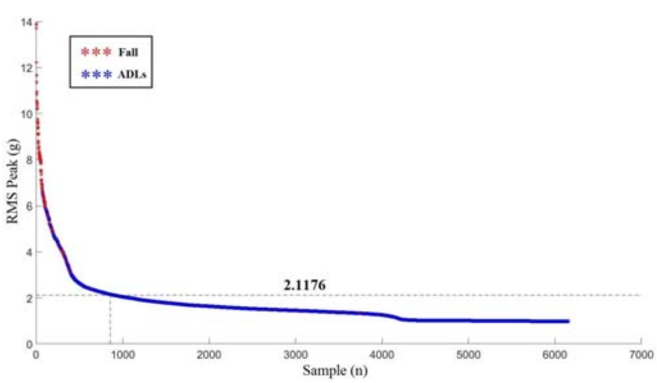

Fig.11 RMS Distribution of Fall and ADLs

C. Evaluation of The Extreme Learning Machine Classifier

After the Threshold Filtering Module, the suspected fall is sent into the ELM classifier and the performance of ELM is shown in TABLE. I and Fig. 12.

TABLE I. THE ACCURACY OF ELM CLASSIFIER

	J48	NavieBayes	SVM	ELM
Training	0.9554	0.9455	0.9628	**0.9967**
Testing	0.9554	0.9381	0.9455	**0.9654**

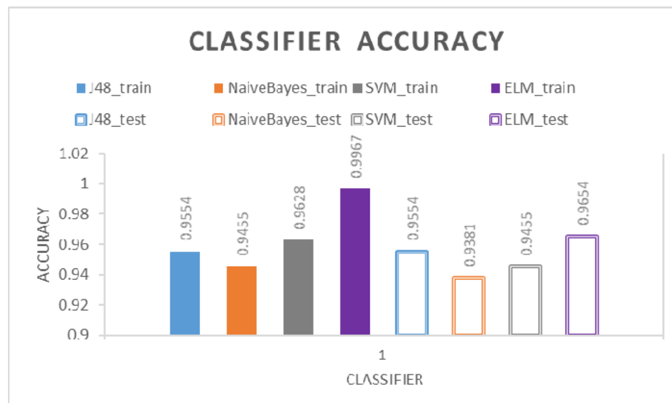

Fig.12 Accuracy of Classifier

According to the classification result of Fig.12, ELM is more precise than other classifier in both training and testing. However, although the classification accuracy has achieved **96.54**% after the ELM classification, in actual use, high rate of false alarms may affect user's experience. So we use RLDs (71628 window data) to evaluate its performance in actual use. The testing result of RLDs is showed in Fig.13.

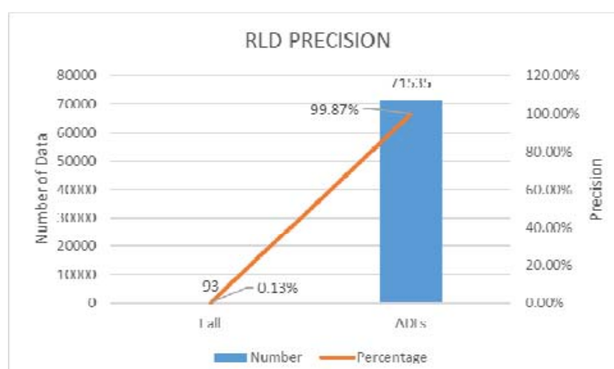

Fig.13 Performance of ELM in RLDs

D. Evaluation of Orientation-based Filtering Module

From Fig 13, among the 71628 RLD data with no fall behavior, it happens **93** times false alarms. Although the accuracy of **99.87%** and false alarm rate with **0.13%** is satisfied, it means 93 false alarms will happen in 24 hours and this is unacceptable to the user. In order to further decrease the rate of false alarm, we introduced Orientation-based method in module 3 which has been described in detail above. After filtered by module 3, the final accuracy is shown in Fig.14.

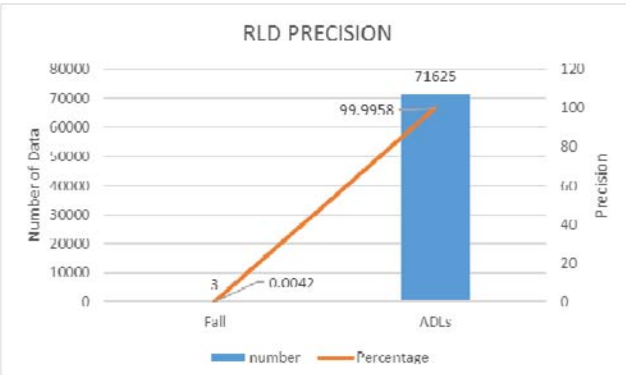

Fig.14 Performance of Module 3 in RLDs

Comparing of Fig.13 and Fig.14, after filtered by module 3, the rate of false alarm reduces from **0.13%** to **0.0042%** and the number of false alarm drops from **93** to **3** in 24 hours. This means that orientation-based method is effective in reducing the false alarm rate. According to the experiment result, our multistage collaborative filtering method can greatly reduce the false alarm rate on the premise of not decreasing the accuracy of fall detection. At the same time, compared with traditional methods using both accelerometer and gyroscope, our method only uses accelerometer sensor which can greatly reduce power consumption. Thus, we can draw a conclusion that our method is more convenient and effective than traditional methods.

V. Conclusion and Future Work

Fall detection is an important part of daily monitoring of the elderly, which is greatly related to the physical and mental health of elder people. Thus, the research of falling detection is not only meaningful but also practicable. With the development of the microminiaturization in hardware, wearable device is adopted in fall detection due to its convenience, non-invasion, low power consumption and cost. To solve the problem of high false alarm rate in traditional wearable devices-based falling detection methods, this paper proposes a multistage model to detect falling behavior precisely with accelerator sensor. Compared with conventional methods only using single classifier, our method using multistage filtering modules has more advantages in precision and low false alarm rate.

Our wearable device has been produced for public medical institution, hospital and famous rehabilitation center. Its performance in practical application is quite satisfactory. The next step of our work is to provide predictive function and we are looking forward to forecast the fall according to the body posture and walking speed of user.

VI. Acknowledgement

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