*AMSE JOURNALS-AMSE IIETA publication-2017-Series: Modelling A; Vol. 90; N°2; pp 196-208*
*Submitted Mar. 25, 2017; Revised May 08, 2017; Accepted Jun. 08, 2017*

# A Fall Detection Model Based on Asymmetrical Support Vector Machine

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## Abstract

In the existing SVM-based fall detection algorithms, the fall actions and the activities of daily living (ADLs) are similar in sample size. In real life, however, there are far more ADLs than fall actions. Thus, the seemingly accurate detection in experiments often does not apply to real life. To solve the problem, this paper takes acceleration and angle as feature vectors, and introduces the asymmetrical support vector machine (SVM) algorithm. The penalty coefficient was configured by changing the diagonal matrix parameters of the kernel function, and the hyperplane was adjusted to approximate the fall action with the smallest possible sample size, seeking to accurately determine the occurrence of fall actions. Through experimental simulation, it is verified that the proposed model can accurately detect 99.2% of fall actions.

## Key words

Fall detection, Activities of Daily Living (ADLs), Asymmetrical Support Vector Machine (SVM), Acceleration and angle.

## 1. Introduction

Population aging is one of the most significant demographic trends in the modern era. The elderly is very likely to trip and fall due to the decline in physical function. Previous surveys have shown that 30~40% of those aged 65 and older fall down once a year, and 50% at least twice a year [1-3]. In order to reduce the harm the elderly from falls, researchers at home and abroad are competing to make scientific and timely detection of fall actions without disturbing the normal function of the human body.

The existing fall detection methods are mainly grounded on the following bases [4-6]: video images, surrounding environment and wearable devices. The video image-based method [7-8] monitors the body activities with cameras, and detects the fall actions by capturing abnormal body movements. The method achieves high accuracy thanks to the precise information on 2D/3D images captured by cameras. However, the detection results are greatly affected by light ray and other environmental factors, not to mention the heavy computation, high cost and limited scope. The surrounding environment-based method [9-10] discriminates fall actions from other abnormal movements by monitoring the ambient factors of the object, such as pressure, vibration, sound wave, and infrared ray. Under the effect of these factors, this method fails to realize a desirable accuracy. Relying on inertial sensors like accelerometer and gyroscope [11-13], the wearable device-based method is an easy and trendy way to detect fall actions. Free from geographic restrictions, the method fulfills real-time monitoring of body movements without affecting people's normal life [14-16]. Based on acceleration and angular velocity signals, this method usually depicts the object by the support vector machine (SVM) algorithm. As a popular tool of fall detection, the SVM reduces the model complexity and the error resulted from individual differences.

In the existing SVM-based fall detection algorithms, the fall actions and the activities of daily living (ADLs) are similar in sample size. Such algorithms can obtain high detection rates in the experiment. For example, Zhang T. [17] realised the detection accuracy of 96.7% by implementing the machine learning technology of one-class SVM. Doukas C. [18] achieved the SE of 98.2% and SP of 96.7% through the combination of the SVM and the 3-axis accelerometer. Luca Pernini [19] reached the sensitivity of 99.3% and specificity of 96% in a SVM-based experiment on low-cost Android smartphones. In real life, however, there are far more activities of daily living (ADLs) than fall actions. Thus, the seemingly accurate detection in experiments often does not apply to real life. To solve the problem, this paper takes acceleration and angle as feature vectors, and introduces the asymmetrical SVM for detection. The hyperplane was adjusted to approximate the fall action with the smallest possible sample size, seeking to accurately determine the occurrence of fall actions.

## 2. Asymmetrical SVM Algorithm

Fall detection is a dichotomic pattern recognition method that discriminates the fall actions from the ADLs. In spite of the rare occurrence, the fall actions may cause fatal harm to the elderly. The SVM algorithm is often adopted for detecting such actions. As one of the most important and mature pattern recognition techniques, the SVM generates the optimal linear detection function in the original feature space based on the optimization theory and linearly/nonlinearly separable training sample set. In this way, the method reflects the conversion feature space implicitly via the kernel, and makes the original pattern linearly separable in the conversion feature space [20]. However, the SVM-based fall detection results are often far from satisfactory, owing to the mixture of the fall sample and normal action data, the limited training time, and the high misclassification rate. In this research, the asymmetrical SVM is employed to adjust the hyperplane to approximate the fall action with the smallest possible sample size, aiming to separate the fall action from the ADLs.

According to the distribution of asymmetrical sample, the few fall actions were put into a category and the many ADLs were allocated to another category. Hence, the penalty coefficient C was also divided into two parts: C+ for the fall actions and C- for the ADLs. If the penalty variable set is denoted as $\{\xi_i\}_{i=1}^{k}$, then the optimal solution is:

$$\begin{cases} \min\limits_{w} \Phi(w) = \frac{1}{2}\|w\|^2 + C^+ (\sum\limits_{\substack{i=1 \\ y_i=1}}^{k} \xi_i) + C^- (\sum\limits_{\substack{i=1 \\ y_i=-1}}^{k} \xi_i) \\ -[y_i(w \cdot x_i + b) - (1-\xi_i)] \le 0_i, i = 1,2,\Lambda\, k \\ -\xi_i \le 0, i = 1,2,\Lambda\, k \end{cases}$$

(1)

Construct the Lagrangian function, find the minimum value, and obtain the Lagrangian constant.

If $y_i$ = -1: $0 \le \lambda_i \le C^-$; if $y_i$ = -1: $0 \le \lambda_i \le C^+$;

Denote C as the vector consisting of C+ and C-, m as the sample size of fall actions, n as the sample size of the ADLs, and d as the total sample size.

Then, the corresponding Hessian matrix is:

$$H = (y_i y_j K(x_i, x_j))_{k\times} \tag{2}$$

Adjust the diagonal so that the diagonal element of the matrix satisfies the following:

$$\begin{aligned} H(i,i) &\leftarrow H(i,i) + \beta \ \frac{m}{d}, \text{if} y_i = \\ H(i,i) &\leftarrow H(i,i) + \beta \ \frac{n}{d}, \text{if} y_i = \ - \end{aligned} \tag{3}$$

where $\beta \ \geq \ ), \beta \ \geq \ )$.

Thus, the decision function is:

$$f(x) = sign(\sum_{x_i \in \ V} y_i K(x, x_i) + \ )) \tag{4}$$

Under the condition of , the hyperplane may shift significantly towards the large ADLs samples in practical training, since *n/d* is much larger than *m/d*. If only *n/d* and *m/d* are taken as parameters or simple fixed parameters , , the hyperplane may mistake many fall action samples as ADLs, pushing up the misclassification rate. Therefore, it is necessary to adjust parameters and through machine learning, so that hyperplane can shift towards and correctly identify the fall action samples.

In the algorithm, C+ and C- are the penalty coefficients to penalize the misclassification of the two kinds of samples. Due to the large sample size of ADLs, the main purpose is to curb the shift towards the ADLs, and ultimately reduce the number of fall actions samples misclassified as ADLs. In view of the small sample size of fall actions, C- should be smaller than C+.

## 3. Asymmetrical SVM Fall Detection Model

The model is constructed mainly through the following steps:

First, collect the acceleration and angle data of the fall actions and ADLs through the detector, and normalize the data.

Second, train the asymmetrical SVM algorithm with the pre-set C+ and C-, weight parameters β+ and β-, and the kernel function for conversion.

Third, judge if the training results have reached the pre-set accuracy; if so, go to the next step; otherwise, return to Step 2, adjust the diagonal parameter of the Hessian matrix, and go on with the training.

Fourth, conduct the SVM classification test.

Fifth, terminate the iteration.

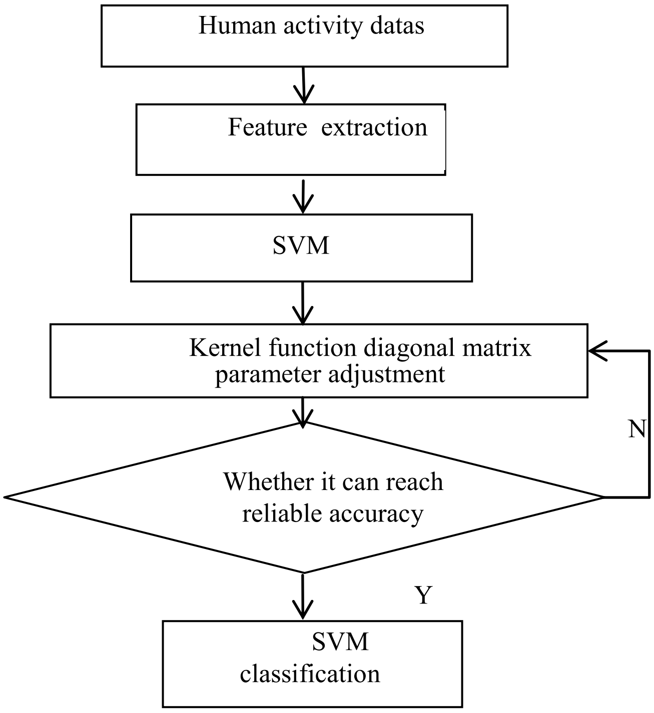


Fig.1. Asymmetrical SVM Detection Model

# 4.Experimental Simulation

## 4.1 Hardware Design

The fall detector is composed of a data collection module, a Bluetooth transmission module and a rechargeable lithium battery module [21]. The 3-axis (gyro + accelerometer) MEMS MotionTracking device was adopted as the sensors. The sensor chip consumes little power and adapts to different voltage modes. The acceleration measurement range covers: $\pm 2g, \pm g, \pm g, \pm 6g$. The collected data are transmitted from the data collection module to the Bluetooth transmission module via the $I^2C$ protocol, and then sent to the upper computer through the Bluetooth adapter.

Due to the frequent activities of the head, the upper arms and the wrists, the wearable detector should not be put on these body parts to prevent misclassification. Neither should it be hung in front of the chest. Otherwise, the detector may affect the subjective feeling of the wearer. The detector should be placed at the waist (56% of the height), the gravitational centre of human body [22].

## 4.2 Feature Selection

In case of a fall action, there will be obvious changes to the acceleration and attitude angle. The acceleration of each axis differs with the direction of the fall. Hence, the resultant acceleration SAM and attitude angle were taken as the features of fall detection.

$$SAM = \sqrt{a_x^{\ 2} + \iota_y^{\ 2} + \iota_z^{\ 2}}$$

(5)

where respectively represent the acceleration in the three directions.

Then, a 3D coordinate system was established for the human body, with the east as the x-axis, the north as the y-axis, and the upward direction as the z-axis. The attitude angles around the x-, y- and z- axes are respectively denoted as roll angle $\gamma$, pitch angle $\theta$ and yaw angle $\psi$.

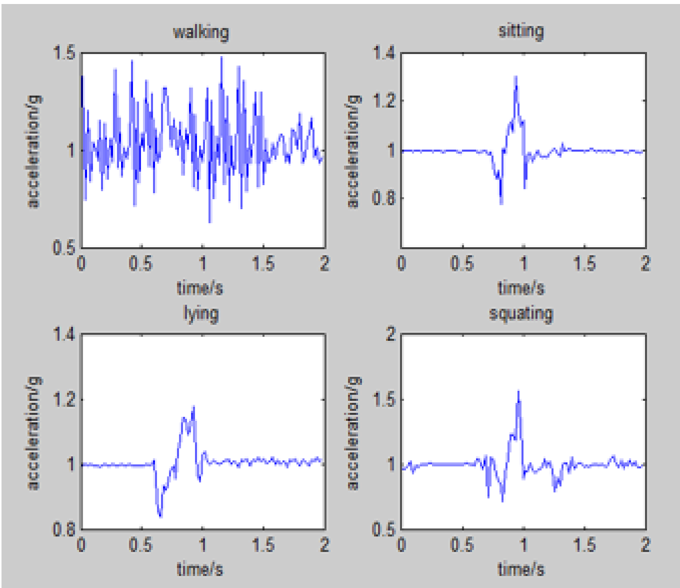


Fig.2. The Acceleration Curves of the Four Kinds of ADLs

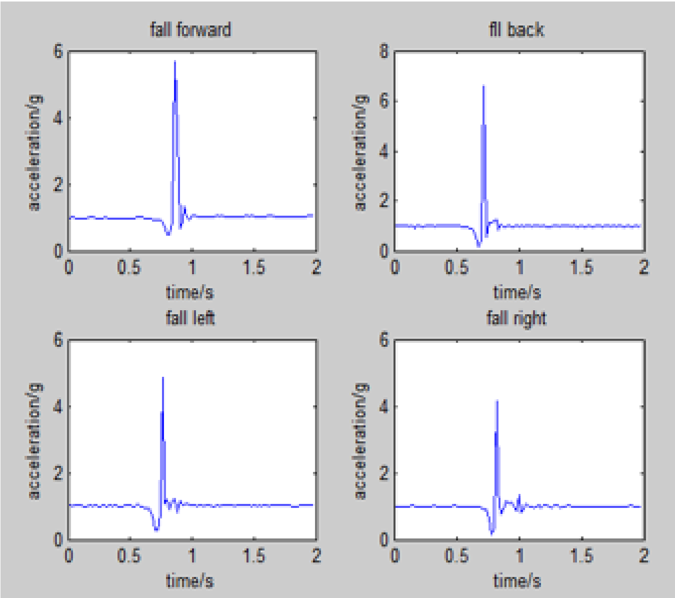

Fig.3. The Acceleration Curves of The Four Kinds of Fall Actions

As shown in Figures 2 and 3, the acceleration varies much more violently during the fall actions than the ADLs. Overall, a fall action usually lasts about 2s. Considering the variation and speed of acceleration, the author took the mean value and variance of acceleration as the acceleration feature vectors of the asymmetrical SVM training.

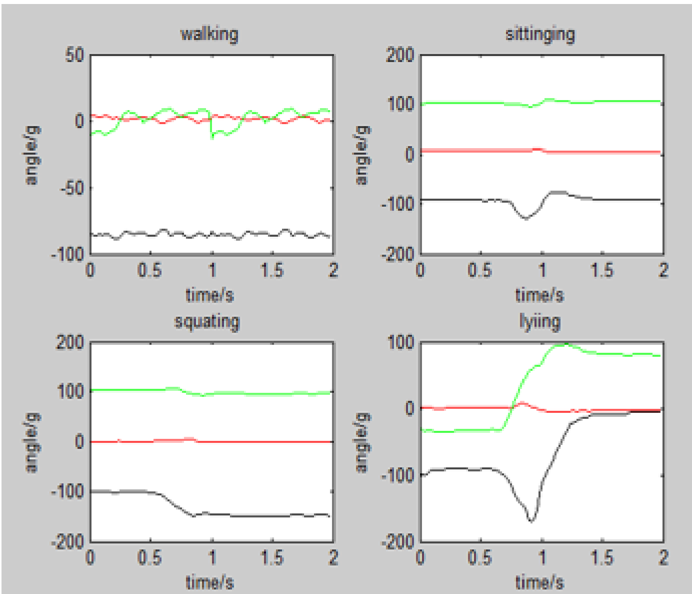

Fig.4. 3-axis Angle Curves of the Four Kinds of ADLs

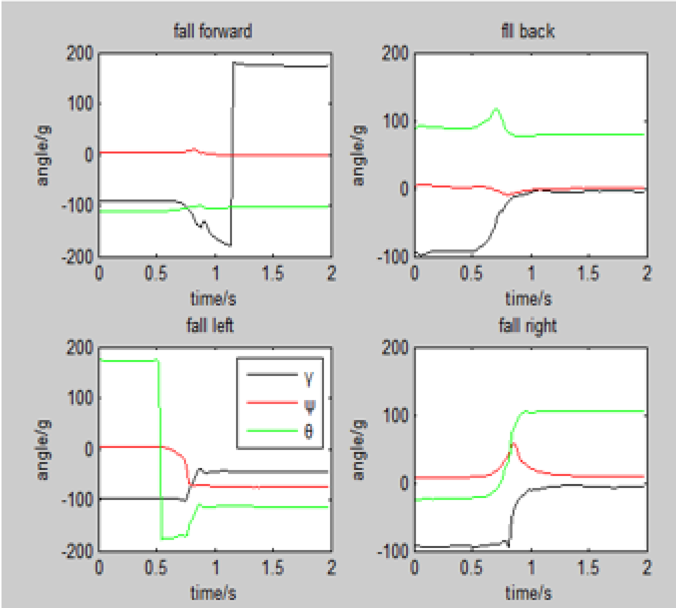

Fig.5. 3-axis Angle Curves of the Four Kinds of Fall Actions

The roll angle γ changes when the body falls from front to back, and the pitch angle θ changes when the body falls from left to right. According to Figures 4 and 5, both the roll angle and the pitch angle vary in the range of 90o. Although the majority of ADLs are of flat angles, it is possible to identify fall actions solely based on the acute change of acceleration and angular variation. Hence, the absolute values of the variations in roll angle and pitch angle before and after fall action were taken as angle feature vectors.

## 5. Experimental Plan

Ten youngsters (age: 20~30; weight: 50~70kg; height: 160~180cm) were selected as measurement objects for the experiment. The objects worn head covers, protective clothes, and sandbags to simulate the slow movements and poor hearing/vision of the elderly. To avoid injuries, they were asked to trip and fall on a 12cm-thick pad.

During the measurement, the objects took the following actions:

(1) Fall down twice respectively from the front, the rear, the left and the right;

(2) Stand for 10 times after each fall action;

(3) Walk for at least 10 times;

(4) Sit down and stand up for at least 10 times, respectively;

(5) Squat for 10 times;

(6) Lie down and get up for 10 times, respectively.

In the final dataset, the training set includes: 32 fall actions, 160 ADLs, and test samples. The number of fall actions and ADLs were calculated by − −, respectively. Given that d=88, m=8 and n=80, the data is nonlinearly separable. Then, the radial basis function was adopted for classification, and the diagonal matrix of the kernel function was adjusted according to Formula 3. The simulated results are displayed in the figure below.

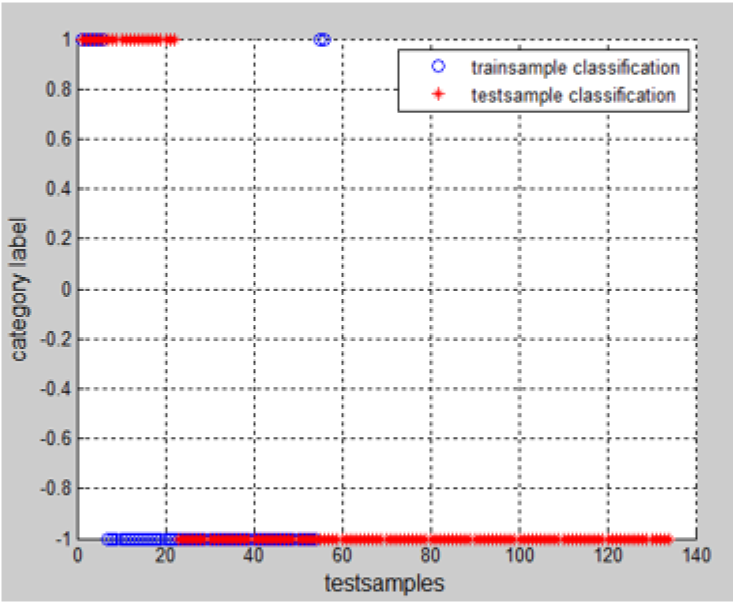


Fig.6. Simulated Results of the Proposed Algorithm in Fall Detection

## 6.Comparison of the Proposed Algorithm and Standard SVM

To verify the effectiveness of the proposed fall detection algorithm, the author introduced one detection criterion, and divided the experimental results into four independent categories:

(1) True positive (TP): the fall action is detected as fall;

(2) False positive (FP): the ADL is detected as fall;

(3) True negative (TN): the ADL is detected as non-fall;

(4) False negative (FN): the fall action is detected as non-fall.

The experimental results were judged by the following three performance indices:

The sensitivity SE: the detection accuracy of all fall actions.

$$SE = \frac{TP}{TP + \surd P}$$

(6)

The specificity SP: the proportion of correct detection of all ADLs.

$$SP = \frac{TN}{TN + FP}$$

(7)

The accuracy AC: the proportion of correct detection of all the movements.

$$AC = \frac{TP + TN}{TP + TN + FN + FP}$$

(8)

In the experiment, the two feature vectors of acceleration and angle were used separately for judgement. As shown in Table 1, the sensitivity and specificity are lower than those judged based on both acceleration and angle.

Tab.1. Comparison of Different Indices of the Proposed Algorithm

| index | acceleration | angle | acceleration+angle |
|---|---|---|---|
| SE% | 97.63 | 89.58 | 99.31 |
| SP% | 97.38 | 86.24 | 99.16 |

According to Table 2, the asymmetrical SVM achieved better accuracy than the standard SVM in the case of only a few fall action samples, making the experimental results closer to the actual condition.

Tab.2. Comparison of the Proposed Algorithm and Standard SVM

| classes | sample size | accuracy | | | | | |
|---|---|---|---|---|---|---|---|
| | | MISVM | | | SVM | | |
| | | Acceler-ation | angle | Accele-ration+ angle | Accele-ration | angle | Accele-ration+ angle |
| Fall | 32 | 97.32 | 88.14 | 99.21 | 96.9 | 82.31 | 97.24 |
| ADL | 160 | 96.96 | 85.87 | 99.01 | 97.4 | 83.22 | 98.66 |

As can be seen from Table 2, the asymmetrical SVM is less accurate on detecting ADLs with a large sample size than the standard SVM, but more precise on detecting fall actions than the latter, provided that acceleration and angular are the only feature vectors. This is because the misclassified ADLs samples only account for a small portion of all ADLs. The propose algorithm can separate the objects with a small sample size mixed in those with a large sample size, but not vice versa. With the aid of acceleration and angle, the asymmetrical SVM manages to identify the often miscalculated fast squatting and sitting down of ADL, and thereby enhances the detection accuracy of ADLs.

## Conclusion

This research bridges the gap between the experimental fall detection and the fall actions in real life, where there are many more ADLs than fall actions. In order to enhance the detection rate of fall actions among the elderly, the author took acceleration and angle as feature vectors, and introduced the asymmetrical SVM algorithm to change the position of hyperplane by modifying the parameters of kernel function diagonal matrix. The penalty coefficient was altered so that the hyperplane can approximate the small sample data or the large sample data. Meanwhile, the weight coefficient could be any real number larger than 0 and be adjusted according to the sample size. After making the fall action penalty coefficient smaller than the ADL penalty coefficient, the author managed to separate the small sample data from the large sample data, and thereby enhanced the accuracy of fall detection.

## Acknowledgments

This work was supported by the science and technology fund of hebei agricultural university (NO.LG20150202).

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