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A SVM Algorithm for Investigation of Tri-Accelerometer Based Falling Data

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Abstract Falling in elderly people is one of the main reasons causing serious injuries and increasing the risk of early death. Moreover, it can result in psychological problems from fear of falling. An automatic fall detection system is necessary for elderly people in daily activity alone. In this paper, a fall detection system applying a Support Vector Machine (SVM) algorithm is proposed for fall recognition. Data with different states collected by a trial-axis accelerometer system will be pre-processed using a mean filter for smoothing. In addition, features of the filtered signals will be extracted using a Principal Component Analysis (PCA). Therefore, the SVM will be employed to train feature data and then recognize fall states. Experiments will be performed many trials with eight different states on a subject and results will be processed to detect falling as well as to evaluate the accuracy of the proposed method.

Keywords Tri-accelerometer data, Support Vector Machine, Principal Component Analysis, Fall Recognition

1. Introduction

Falls are common accidents and dangerous in daily activity of people. Unlike young adults, older people are no longer flexibility and reflex, consequently the risk of falls is very high. According to a report by the World Health Organization (WHO) [1] falling increases with age: about 28-35% of people over age 65 fall 2-4 times per year and rising 32-42% people over the age of 70 falling down 5-7 times. Thus the results of falling were injured and more serious as mortality, in which the most common situation is broken bone or another problems such as fractured femur, humorous, traumatic brain injury, and subdural hematoma. Therefore the victim early detection can be the difference between life and death. Indirect impacts on society are health care costs, lost income due to caring relatives of victims. Because of the serious consequences such as a fall should occur, the elderly people need to get medical care immediately.

There have been many research projects with high technical equipment for the purpose of monitoring the activities of the elderly in recent years. Prediction and detection of falls could be required to attend an alarm for the surrounding health workers to timely emergency. In particular, a fall detection system is often one of three types: environmental sensing [2], image sensing, and the wearable sensor [3, 4]. In each way, it has a significant application to each elderly person.

In the case of the environmental sensing method, sensors such as infrared sensors, vibration sensors, pressure sensor are often employed. The event detection using vibration sensors is very effective in the case of surveillance, monitoring and locating. A totally passive and simple system to detect vibrations in the floor was introduced by Alwan [5]. This detection system of falls was evaluated based on the vibration on the floor. It means that the level of the floor vibration generated by the falls is classified from the normal operation, such as walking. In an another study, a vibration sensor of the floor with a sound sensor was employed [6] to analyze spectrum to evaluate the fall. The advantage of using the environmental sensors is that users do not have to wear any devices on their body and this system is only effective in the established space.

Image sensors such as stereo cameras are increasingly used in the system of care and support in families. There are many advantages in comparison with other sensor systems. In particular, an image processing system allows to extract pixels from the background and the contrast of time corresponding to the change in reflectance of light [7]. A motion vector is calculated to indicate the object with fall or normal activity. Moreover, detection of falls is based on the change of body shape in the obtained image. From the motion data, the system space model is obtained automatically by combining a Gaussian Bayesian estimation method and a model describing the minimum length [8]. The system detects the abnormal states through the contextual model, such as a fall compared with normal operations.

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Forough [9] adopted an ellipse approximately around the body to measure the change in shape. Data is analyzed in both horizontal and vertical directions. The feature vector is fed into a neural network to classify the body states. Another research is that an Omni camera was used to detect falls [10]. The system could recognize the falls based on the changes with a threshold. However, the main drawback of this method is the use of camera time and the cost of system [11]. In addition, the use of the camera system affected the privacy of users.

Many researchers have used the wearable sensors, such as accelerometer or gyroscope to determine the location and the orientation of the motion object in recent years. The system can detect falls through wireless communication and allow users to be comfortable in daily activity with a cheaper cost device. Fall detection can be divided into two approaches: data analysis using threshold and identification using machine learning algorithms. The proposed system of Ye [12] combined the threshold and the angle of the wearer. Thereby, the position and status as “go” or “stand” can be determined. A Bourke’s study [13] compared a threshold method with other methods such as amplitude, angle, and vertical velocity to find an optimal performance. An MMA 7260Q accelerometer was worn on the arm of the subject to recognize falls [14]. This module transfers data to a computer for signal processing through the ZigBee standard. Thus, the identification method used a threshold consisting of two levels: the upper limit and lower limit. Acquired data was divided into two categories: the normal operation (activities of Daily Living -ADL) and falling.

Machine learning methods are often used for identifying the motion of body [15], in which the experiment simulated six-state activities: “fall”, “lie down”, “sit down”, “stand”, “go”, “sit” and “lie down”. In case of data without noisy, most methods of identification give good results (the accuracy of 95%), except the C4.5, RIPPER method and the Naïve Bayes method. The accuracy of the fall detection system using accelerometer sensors often depends on the position wearing sensor. The authors [16] verified four sensors of tongue strap and four different locations on the body: chest, hip, ankle, on right thigh.The two sensors, one at the chest and one at the chest strap - right thigh have the maximum efficiency.

In this work, a tri-accelerometer sensor which was located on the waist of body was used to collect acceleration data from a subject. A Support Vector Machine (SVM) will be applied to validate the obtained coefficient data for falling recognition. Firstly, data is acquired from daily activities such as “sitting”, “standing”, “walking”, “stooping”, “bending”, and falls from chair. Secondly, features, that describe the person movement during a series of short time periods, were extracted using a Principal Component Analysis (PCA) algorithm. The feature extraction stage allows one to select relevant and more meaningful characteristics that are fed into the next step of a recognition system. The rest of this paper is organized as follows: Section 2 introduces a data acquisition process and a fall detection system with a dataset trained for the recognition process of falling. Section 3 presents the experiment results. Finally, conclusion in the paper is Section 4.

2. Materials and Methods

2.1. System Design

The proposed recognition system consists of two modules: a sensor module and a receiver module of computer interaction. The sensor module has three parts including an ADXL-345 sensor, an Arduino Pro Mini controller module, and an nRF24L transceiver module as described in Figure 1. The receiver module is composed of an Arduino Pro Mini controller module, and an nRF24L transceiver module as described in Figure 2. In particular, the receiver is connected to a personal computer using a UART interface with parameters: Baudrate-115200, DataBits-8, Parity-None, StopBits-1.

Figure 1. Sensor module ADXL 345

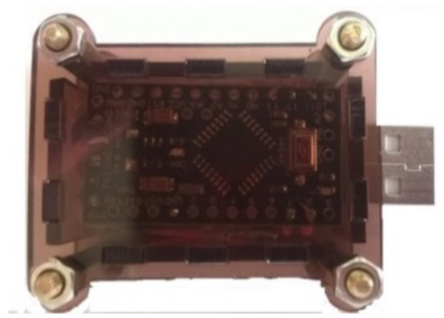


Figure 2. Receiver module plugged in computer

Figure 3. Sensor module is installed with the belt at the body waist

A volunteer (male, 25-year old, weight of 75 kg) is invited to participate in this experiment and he is introduced to the recognition falling experiments. Thus he wears the covered sensor module as illustrated in Figure 3.

In this experiment, the subject showed his activities such as "walking", "stopping", "sitting down", "bending", and "falling" as shown in the APPENDIX.

2.2. Data Pre-Processing

Data obtained from the acceleration sensor have noise from the heart rate and respiration. Therefore, a moving average filter is used for signal conditioning. This filter operates on the principle that each output value is calculated using the average of a number of input values and its formula is expressed as follows:

$$y[i] = \frac{1}{M}\sum_{j=0}^{M-1} x[i+j] \quad (1)$$

in which $x[i+j]$ is the input signal, $y[i]$ is the output signal and M is the number of points. In this research, the value of M is 5. Figure 4 illustrated the value of the effective acceleration in the case of fall from seat state with $M = 5$, in which the blue curve signal is the origin while the signal in red is the output of the average filter.

When the window size is increasingly adjusted, the signal is flattened much more, particularly it is in the range from 1 to 2.5 seconds. However, the choice of the window size must be carefully selected so that the detection system is the higher accuracy. If the size is smaller, noise of the signal could still immerse and this will affect falling recognition.

2.3. Fall Detection Algorithm using Threshold

A falling detection system based on a threshold algorithm is applied to study the data set obtained from the daily routine to find the case of falls. A factor of signal amplitude used to represent all changes in three-axis signals has been suggested in some previous studies [4, 17]. In particular, it is the normalized signal amplitude (*Signal Magnitude Area - SMA*), and calculated as follows:

$$\text{SMA} = \frac{1}{T}\left(\sum_{t=1}^{T}|a_x(t)| + \sum_{t=1}^{T}|a_y(t)| + \sum_{t=1}^{T}|a_z(t)|\right) \quad (2)$$

in which $a_x(t)$, $a_y(t)$, and $a_z(t)$ are accelerations measured in the domain time corresponding to the three axes X, Y, and Z, respectively.

Therefore, the falling detection system based on the comparison of the SMA value and a threshold are shown in Figure 5.

Table 1. The experimental results of the sensing threshold method with 1.5g and 1.8g

No.	Event	Number of samples	Accuracy (%)	
			Threshold 1.5g	Threshold 1.8g
1	Walk (fast)	10	0	100
2	Stooping	10	100	100
3	Stand	10	100	100
4	Sit down quickly	10	100	70
5	Bending	10	100	100
6	Fall from a chair (backward)	10	100	100
7	Fall from a chair (right side)	10	100	100
8	Fall from a chair (left side)	10	100	100

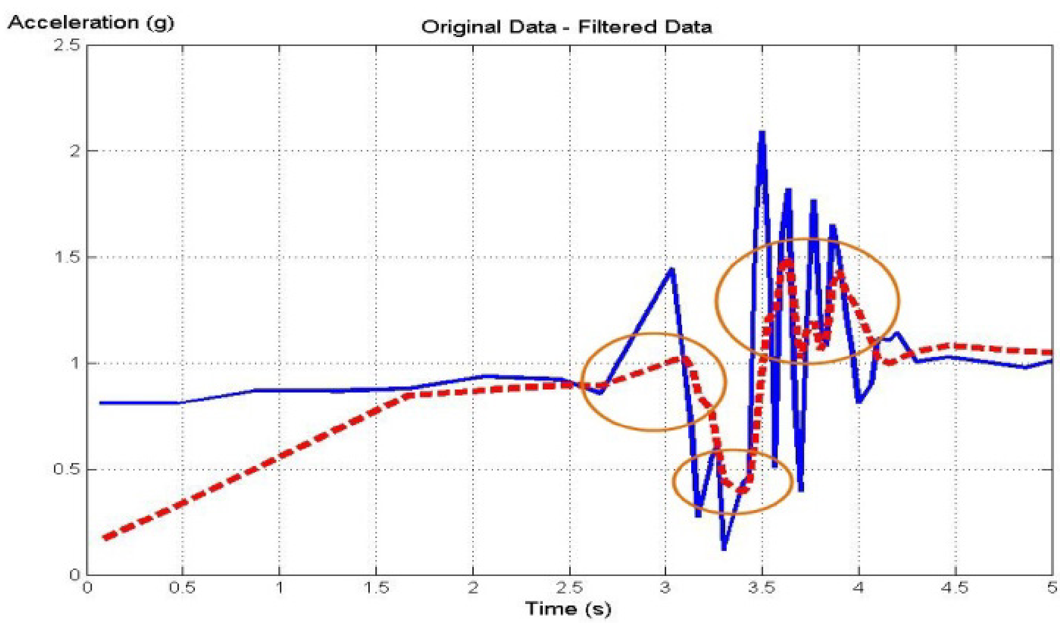


Figure 4. Acceleration signal in the case of the front seat and after falling with $M = 5$

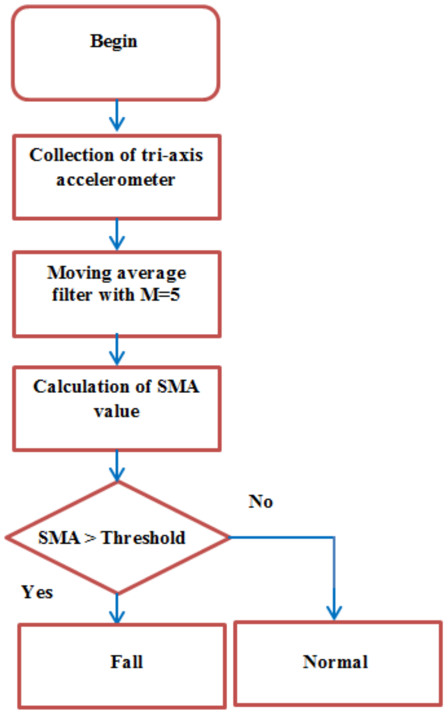


Figure 5. Block diagram of the falling detection using a threshold method

In this paper, both the sensing threshold values of 1.5g [18, 19] and 1.8g [20] were used in the fall system to compare their accuracy. Experimental results of different activities with the 1.8g threshold are presented in Table 1, in which the accuracy of "sit down quickly" is the lowest compared to other events.

In Figure 6, the red, blue, and green lines correspond to the axes X, Y, Z, respectively, and the pink dash line represents the threshold value in the case of the SMA algorithm. When the subject stands, the threshold of the SMA gets the value from -0,7g to 1g which is lower than the sensing thresholds (1.5g and 1.8g).

Assume that the subject stoops (Figure 7a) and bends (Figure 7b) his body, the results are the same to the case of standing and the amplitude value is not exceeded the SMA threshold. In this case, the accuracy of 100% is very high.

In the case of "sit down quickly" as shown in Figure 8, the SMA value is bigger than that of the 1.5 g threshold. Therefore, the system can recognize the falling state of people. In the experiments with ten trials, the threshold of 1.5g allows us to identify falling with the accuracy of 0%. Meanwhile, the 1.8g threshold shows the identification of falling with three times only.

When the subject falls from a chair, the SMA signal decreases to zero (point 1) and gets the highest value at about 2.0g (point 2) as shown in Figure 9. As the result, the SMA values are greater than that of 1.8g, so two threshold values give the accuracy of 100%.

2.4. Recognition Algorithm using the SVM

A PCA method is proposed to be the best technique in multivariate analysis [21]. The main purpose of this method is to reduce the dimensionality of a data set with many variables that retains the inherent variability in the data set. The dimensionality reduction is performed by transforming data into a new set of variables containing the main components.

Assumed that we have the data set as the matrix X (size of $m \times n$), with n is the number of experiments, m describes the number of samples in an experiment. The first step of the PCA algorithm is to standardize data and expressed as follows:

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \overline{X})}{(n-1)}} \tag{3}$$

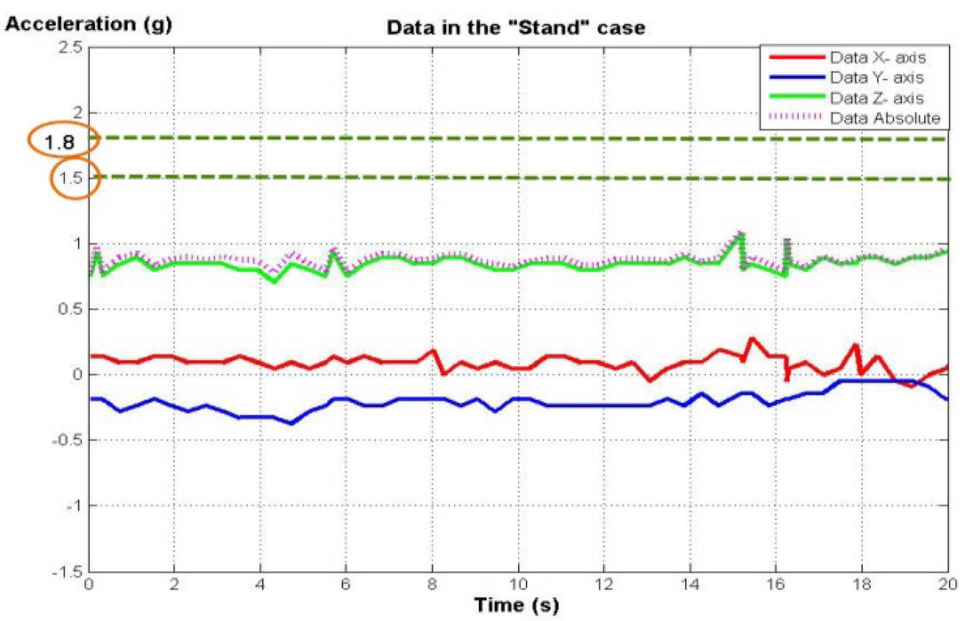
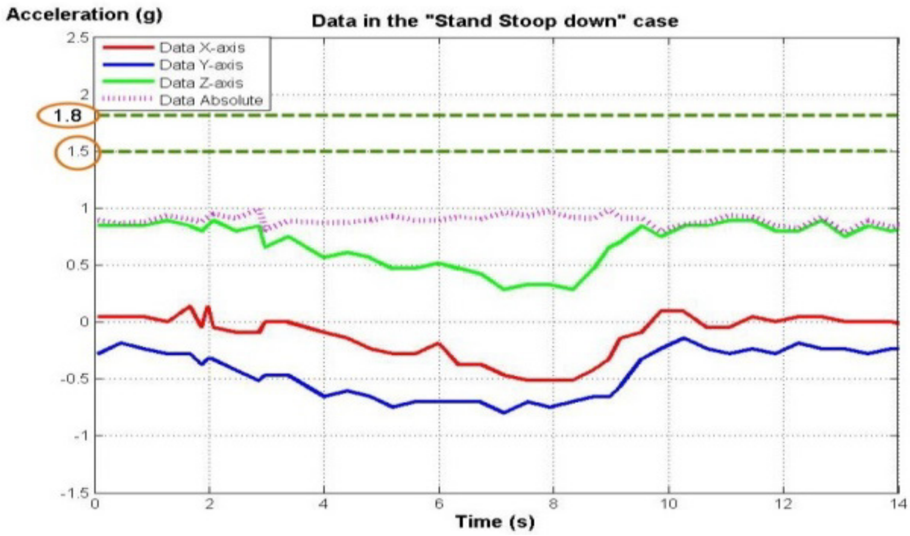
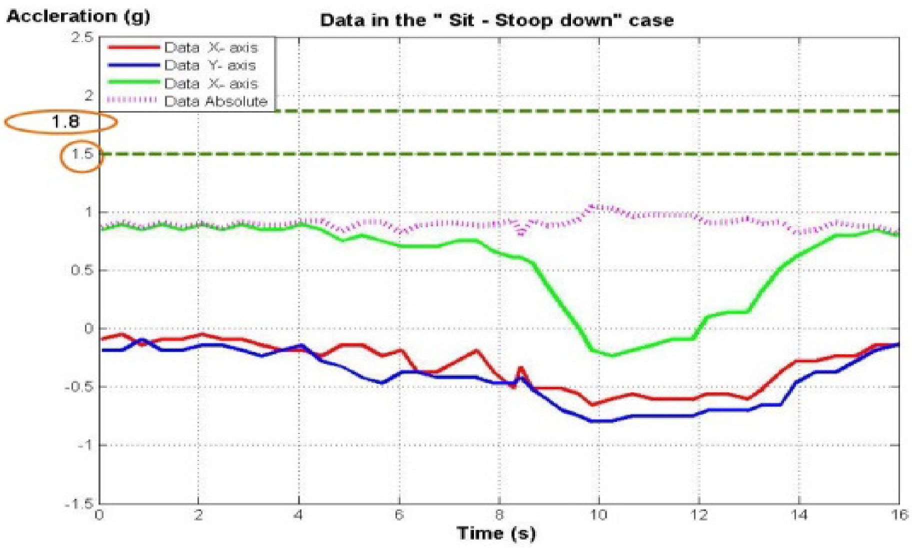


Figure 6. The acceleration signals in case of "stand" are compared with the two thresholds



(a)



(b)

Figure 7. The acceleration signals in two cases: (a) Stooping, (b) Bending

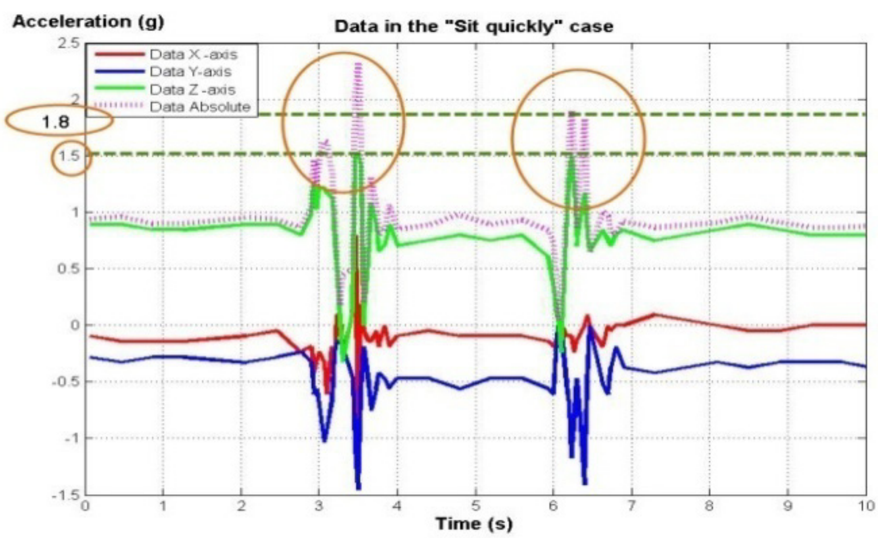


Figure 8. The acceleration signals in the case of moving foster versus the sitting threshold

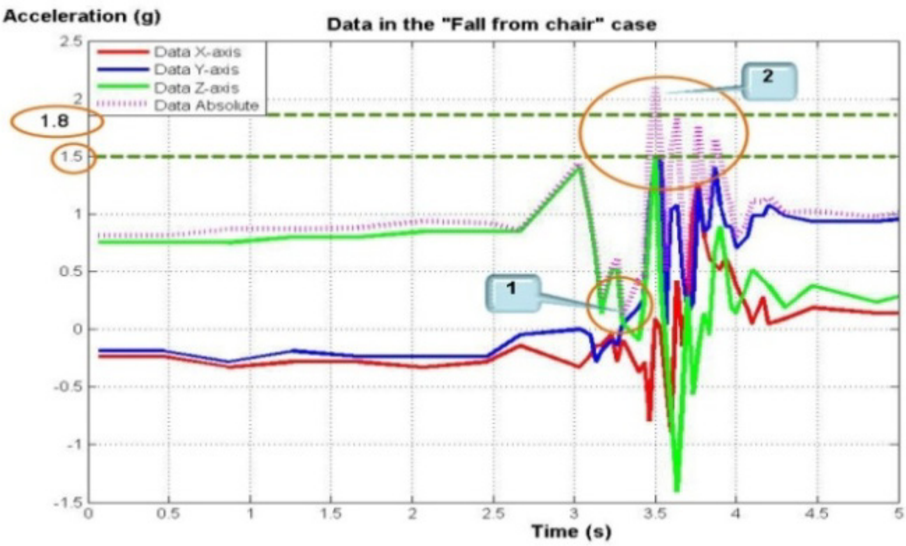


Figure 9. The acceleration signals in case of falling from a chair

Secondly, calculating the covariance matrix from adjusted data is as follows:

$$C^{m\times n} = \left(c_{i,j}, c_{i,j} = cov(Dim_i, Dim_i)\right) \quad (4)$$

where $C^{m\times n}$ is a matrix with m rows and n columns, and Dim_i is the i^{th} dimension.

Thirdly, the eigenvectors and eigenvalues of the covariance matrix are calculated to collect the following characteristic polynomial:

$$|C - \lambda I| = 0 \quad (5)$$

where C is a square matrix, λ is called the eigenvalue of C. Thus, we can find eigenvalues which satisfy the following equation:

$$\det(C - \lambda I) = 0 \quad (6)$$

Therefore, x is the eigenvector associated with the eigenvalue λ. The final step of the PCA is to choose components and to form a feature vector. The eigenvector with the highest eigenvalue is the principle component of the data set. The eigenvectors are ordered by their eigenvalues from highest to lowest deriving the new data set. We can choose the components that to be kept in new data set and form a feature vector as follows:

$$FinalData = RowFeatureVector \times RowDataAdjusted \quad (8)$$

where

RowFeatureVector is the matrix with the eigenvectors in the columns transposed so that the eigenvectors are now in the rows with the most significant are in the top.

RowDataAdjusted is the mean-adjusted data transposed so that the data items are in each column, with each row holding a separate dimension.

FinalData is the final data set, with data items in columns, and dimensions along rows.

In this study, the data set, which was obtained from the experiments, are arranged into a matrix. This matrix has the size of 160 x 450 as shown in Table 2.

In practice, there are many methods of identification and classification such as: Artificial Neural Network, Bayesian network, Network C4.5 or SVM. The previous studies [3, 15, 22] have performed many falling identifications by using a SVM algorithm with the success of 95.5%. In this study, the identification method based on the SVM algorithm has been applied to analyze the accelerometer data.

Table 2. The states with the matrix sampling arrangement

No.	Posture	Column
1	Walking (fast)	1 – 20
2	Stooping	21 - 40
3	Standing	41 - 60
4	Sit down quickly	61 – 80
5	Bending	81 - 100
6	Falling from a chair(backward)	101 - 120
7	Falling from a chair (right side)	121 - 140
8	Falling from a chair (left side)	141 - 160

The coefficients obtained from extracting features of using the PCA of different data sets in the daily activities are considered. In this research, a linear Support Vector Machine (SVM) algorithm was applied to split the feature into two parts with two sets of bound and support vector. In the linear SVM algorithm, assume that the training data $\{x_i, y_i\}$, $i = 1, \ldots, l$, $y_i \in \{-1, +1\}$, $x_i \in R^d$. The points x which lie on the hyper plane satisfy $w.x + b = 0$, in which $|b| / \|w\|$ is the distance from the hyper plane to the origin and $\|w\|$ is the Euclidean norm of w. Let $d(+) + d(-)$ is the shortest distance from the separation hyper plane to the closest positive (negative) samples corresponding to the coefficients of fall events and daily activity, respectively.

Assume that the margin of the hyper plane is $d(+) + d(-)$ in the linear case, the support vector looks for the separating hyper plane with the largest margin using the primal Lagrangian. Suppose that all training data satisfy the following constraints:

$$x_i \cdot w + b \geq +1, for\ y_i = +1 \quad (9)$$

$$x_i \cdot w + b \le -1, \text{for } y_i = -1 \quad (10)$$

The optimization problem is considered to transform Eq. (9) and Eq. (10) using the primal Lagrangian as follows:

$$L_p(w,b,\alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i . w + b) + \sum_{i=1}^{l} \alpha_i \quad (11)$$

where $\alpha_i \ge 0$ are the Lagrange multipliers.

Differentiating $L_p(w,b,\alpha)$ with respect to w, b, and then getting the results to zeros, we have the following equation:

$$\frac{\partial L_p(w,b,\alpha)}{\partial w} = w - \sum_{i=1}^{l} y_i \alpha_i x_i = 0 \quad (12a)$$

$$\frac{\partial L_p(w,b,\alpha)}{\partial b} = \sum_{i=1}^{l} y_i \alpha_i = 0 \quad (12b)$$

One can re-write to calculate the support vector as follows:

$$w = \sum_{i=1}^{l} y_i \alpha_i x_i \quad (13)$$

The regressed data will be trained using the SVM method, in which the hyper plane is a linear function and divided into two planes: D+ contains the coefficients and $y = +1$ is of the falls; similarly D− has the coefficients and $y = -1$ is of daily activities. Based on these theories, as well as the observations are made in the proposed identification algorithm of falls using the PCA-SVM. First, the acquired data must be pre-processed by the moving average filter to reduce noise. Then, accelerated features will be extracted using the PCA to find specific coefficients. Finally, with these coefficients, one can base on a SVM classification system to identify the subject falls or not as illustrated in Figure 10.

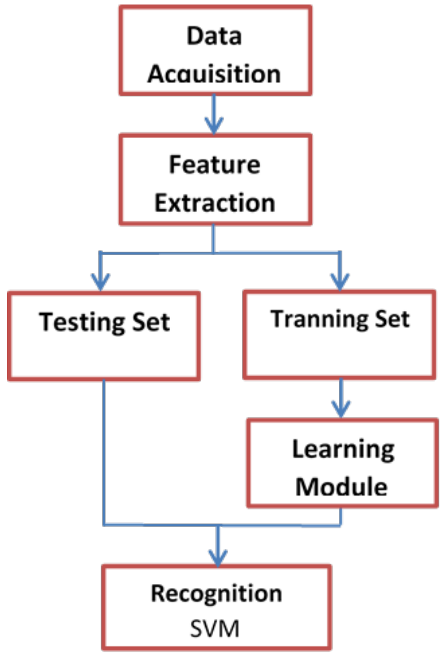


Figure 10. Block diagram of fall recognition using the SVM

Data arrangement is shown in Table 3, including 100 trials of daily activity and 60 trials of falling. Eight activities form a data set from h_1 to h_{160}.

Table 3. Arrangement of features

Normal activities status					**Fall status**		
Walk (fast)	Stooping	Stand	Sit down quickly	Bending	Fall from chair (backward)	Fall from chair (right)	Fall from chair (left)
$h_1 \ldots h_{20}$	$h_{21} \ldots h_{40}$	$h_{41} \ldots h_{60}$	$h_{61} \ldots h_{80}$	$h_{81} \ldots h_{100}$	$h_{101} \ldots h_{120}$	$h_{121} \ldots h_{140}$	$h_{141} \ldots h_{160}$

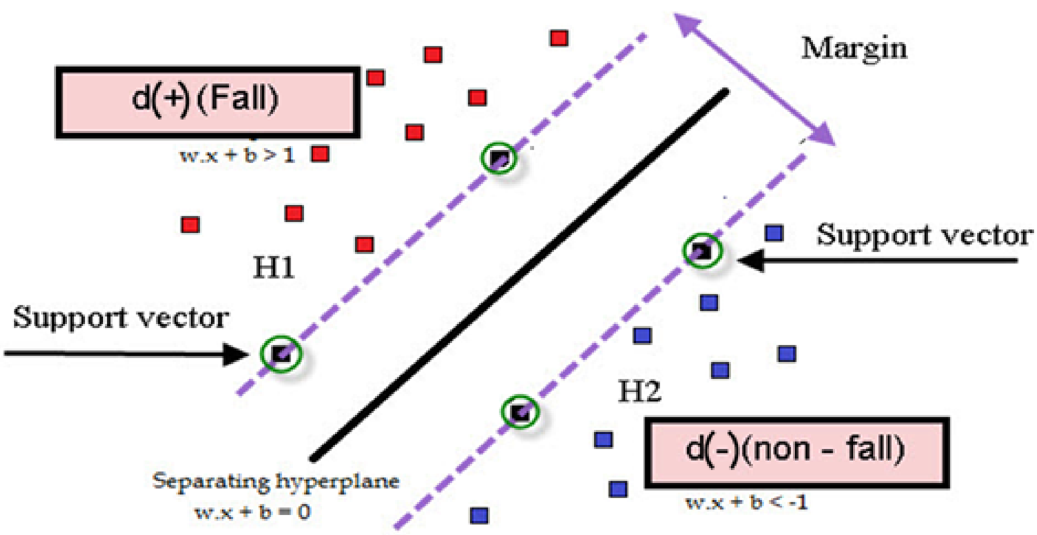


Figure 11. Labeled characteristics based on hyper plane in the SVM algorithm

These coefficients are distinguished using the SVM, including D (+) domain contains the fall coefficient, labeled y = +1 and D (-) domain contains the coefficients of non-fall states, labeled y = -1, as shown in Figure 11.

3. Results and Discussion

In this paper, the experimental results with different states in real time were performed. Features of fall states were then extracted using the PCA algorithm and the SVM method was applied to recognize the fall state based on these features. Eight experiments were performed to analyze the difference between fall and non-fall states, in which every fall state is compared and recognized with a non-fall using the SVM. The accuracy of the PCA-SVM method is shown in Table 4, in which the accuracy of all identified cases is from 80 to 100%. In this table, there are many fall pairs with the accuracy of 100% such as "Fall-Stand to sit", "Fall-Bent" and "Fall-Stand". This means that the proposed method for recognition of these experimental activities produces the very high performance.

Table 4. Results of identity falls from normal case with cross-examination

No.	Events	Test Sample	Accuracy (%)
1	Fall – Normal	Fall	95
		Normal	96
2	Stand to sit (quickly) - Fall	Fall	100
		Stand to sit (quickly)	100
3	Walk (fast) – Fall	Fall	93.33
		Walk (fast)	80
4	Bend – Fall (forward)	Fall (forward)	100
		Bent	100
5	Stand - Fall	Fall	100
		Stand	100

In addition, the recognition algorithm of falls was employed with the online model of the recognition system in real time and the results are shown in Table 5. This table shows that the recognition of four types of the online sample sets is the high accuracy, except the Falling (forward) set is 70%.

Table 5. Results of identity fall from normal case with online samples

No	Test Sample	Numbers	Recognition		Accuracy (%)
			Fall	Normal	
1	Walking	10	0	10	100
2	Standing	10	0	10	100
3	Standing to Sitting (quickly)	10	0	10	100
4	Falling (forward)	10	7	3	70

In this paper, the fall signals were obtained from the tri-acceleration sensor system mounted on the body of a subject. The signals are passed through the moving average filter with the size of the M=5 sliding window for smoothing. Moreover, the recognition system is designed to be able to use two methods, including the two-threshold algorithm and the SVM for evaluation and comparison.

Results showed that the selection of the threshold values affects the accuracy of recognition. In particular, two thresholds used in this research are 1.5 g and 1.8 g, in which the 1.8 g threshold conducted the higher accuracy than that of the 1.5 g as presented in Table 6. Thus, this table shows the average accuracy and standard deviations to illustrate the effectiveness of the proposed method.

Table 6. Average accuracy and its standard deviation of the threshold

Threshold	Average accuracy (%)	Standard deviation (%)
1.8 g	96.25	10.6

Whereas, the accuracy in the fall recognition based on the SVM is shown in Table 7 with two states of fall and normal, in which the case of "Normal" produces the average accuracy of 98.4% higher than a little that of "Fall". In similar, the standard deviation of case t of "Normal" is smaller than that of "Fall".

Table 7. Average accuracy and its standard deviation of the PCA – SVM

State	Average accuracy (%)	Standard deviation (%)
Fall	82.55	9.9
Normal	98.4	1.95

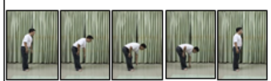
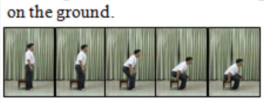
In research of Wen-Chang Cheng [23], a Triaxial Accelerometer sensor was installed at different positions such as chest, waist, left ankle and right ankle on body to illustrate the effectiveness of the proposed method. Moreover, the paper applied cascade-AdaBoost-SVM classifier for fall detection and obtained optimal performance. In this research, the sensor to collect data on body is the same. However, it is different from events of fall detection, particularly the events in this research are *Fall-Normal, Stand to Sit-Fall, Walk-Fall, Bend-Fall, Stand-Fall*. Therefore, a PCA-SVM algorithm was employed to detect fall state by comparing the fall state with other ones. Experimental results showed that the PCA-SVM algorithm is a good choice for fall recognition.

4. Conclusions

Data was collected from a tri-accelerometer sensor system mounted on body of a male subject with eight daily activities such as "Fall-Normal", "Stand to sit-Fall", "Walk (fast)-Fall", "Bend-Fall (forward)" and "Stand-Fall". For filtering noisy signals, a moving average filter was applied. In addition, a PCA algorithm was employed to extract features of the filtered falling data. For evaluation of falling states, the threshold and SVM methods were utilized and compared to find the higher identified performance. Therefore, the threshold approach with the calculation of low cost produced the higher average accuracy of 96.25% compared to the SVM.

Appendix

Description of the protocol for data acquisition is presented as follows:

No.	Posture	Description	Sampling time (s)	Number of samples
1	Walking (fast)		5	20
2	Stopping	Bending forward and free handling at the mid-thigh height. 	5	20
3	Standing		5	20
4	Sitting down quickly		5	20
5	Bending	Bending forward and free handling on the ground. 	5	20
6	Falling from a chair (backward)		5	20
7	Falling from a chair (right side)		5	20
8	Falling from a chair (left side)		5	20
Total of samples				160

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