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Research paper

Wearable Device-based Fall Detection System for Elderly Care Using Support Vector Machine (SVM) classifier

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Abstract

Fall is an increasing problem as people ageing. It may happen to anyone, but their incidence does increase with age. Hence, the elderly will be facing catastrophic consequences due to falls. Nevertheless, there are still vulnerable in its accuracy in categorizing and differentiating the Activities Daily Living (ADL) and falls as most of the existing systems cause false alarm. This paper presents the research and simulation of wearable device-based fall detection approach by addressing the building of wearable device-based fall detection system for elderly care by using mobile devices. Two main phases involve in this research: online phase and offline phase. Online phase covers in data acquisition step whereby the raw data of simulated fall by participants is collected via built-in-tri-axial accelerometer in a smartphone, then automatically sent towards the computer via wireless communication. Meanwhile, offline phase covers data pre-processing, feature extraction and selection and data classification where these steps are handled in offline mode. Support Vector Machine (SVM) classifier was employed, and evaluated in the analysis. Overall accuracy rate, sensitivity, specificity as well as False Positive Rate (FPR) and False Negative Rate (FNR) were calculated. The findings suggest that SVM with Polynomial (order 5) method which achieved 68.91% overall accuracy as well as producing only 24.46% FPR is the most precise model for fall detection system in this paper. This approach has the potential to be implemented and deploy in real mobile application in future.

Keywords: *fall detection, elderly, Support Vector Machine, wearable*

1. Introduction

The falls are an increasing problem as people age. They have been identified as one of the most prevalent public health problems facing the elderly as they usually associated with high morbidity and mortality, thus a public health concern. Everyone may experience fall, nevertheless this incidence increased with their age. Furthermore, they can result in serious injuries, enduring disabilities, drastic lifestyle changes, escalating health care expenses, and even death [1]. In addition, Kerdegari *et al.* [2] emphasize more on how falls can affect the quality of life of elderly as
it produce fears, decrease in independency and results in decline in mobility and activity. There are several factors, including due to having slipped, being tripped, and body imbalance, as well as giddiness and weakness of lower limbs. They also highlighted about the environment where most of falls happened, such as in the homes that is highest percentage is recorded, outdoors and occurred while away from their homes and surroundings [3]. The problem of falling becomes more prominent for elderly as more and more elderly are living alone, hence, it is inconvenient for them to call for emergency medical help [4]. However, the innovation and invention of smart technology will possess great potential to improve the quality of life of the elderly.

Fall detection approaches can be categorized into three classes; vision-based, ambient or fusion based, as well as wearable-based [5-6]. Vision-based fall detection approach is increasingly invented in home assistive system [7]. These systems are able to detect multiple events simultaneously by using the camera attached to the wall and the recorded events can be used for monitoring and post verification as well as analysis. However, there is a relatively high cost associated with this technology. In addition, this approach only suitable in an indoor environment as the camera sensors are only stacked in the wall of the specific area. In comparison of vision-based approach, the researchers are starting to familiarize themselves in using ambience or fusion-based. This approach is based on the audio or vibration detection. Ambience/fusion device-based approach uses multiple installed sensors to collect data from a person in close proximity to them. For instance, floor-vibration based fall detection or plantar-pressure based fall detection are the technologies for ambience-based approach that used specialized pressure sensors that embedded in the floor to detect and evaluate vibration pattern when the fall happened [8]. Recent researches explore about using wearable device-based approach as it uses sensors embedded to the garments to detect the posture and motion of the body of the wearer and use a classifier to detect fall. This approach is flexible for any environment. Besides, it is easy to use as the embedded sensor is small and light [9]. In addition, this approach also relatively low cost due to the complexity of the device that's being used [10]. Support Vector Machine (SVM) is a one of the supervised learning methods that available under machine learning which simultaneously minimizes the empirical classification error and maximizes the geometric margin. Based on [2], in this classification method, there is a set of training example, that belong to one of two categories, then SVM will predict that new example fall into which category. In order to classify between fall and an ADL dataset with SVM classifier inside the WEKA software, Sequential Minimal Organization (SMO) algorithm was used. SMO implements the sequential minimal optimization algorithm for training a support vector classifier, using polynomial or Gaussian kernels. By using SMO

all the attributes were normalized by default and categorical attributes were transformed into binary ones.
In this paper, we are going to investigate fall detection system using wearable device-based approach with adequate accuracy to categorize and detect fall in the elderly in diminishing the false alarm events. The investigation will be done on the selected algorithm to determine which approach has the best overall accuracy of the system by evaluating the value of false alarm (false positive) of the proposed system.

2. Methodology/Materials

The operational design of this research consists of two phases: online and offline stages. The online stages composed of a Data Acquisition phase where the process of recording and collecting data happened. Meanwhile, the offline stages comprised of several phases, including Data pre-processing, Feature extraction and selection, as well as Data classification.

2.1 Data Acquisition

A mobile application called MATLAB Mobile in conjunction with MATLAB Support Package for Android Sensors is used to collect and record all the reading of built-in tri-axial accelerometer data. MATLAB Mobile (version 3.0.0) is a free and open source application is installed in android smartphone. During data collection, the MATLAB (2014b) software will turn on the connector towards the MATLAB Mobile apps in android smartphone. After the configuration of this connection is done, MATLAB (2014b) software will initiate the "mobiledev" object to record the raw sensor data sent by the MATLAB Mobile apps. Then only the tri-axial accelerometer is enabled and logging measurement through MATLAB (2014b) software is started. Five healthy young teenagers and adults have participated in this research. They are ranging in age from 14 to 25 years and will simulate an overall ten type of activities: five types of Activity of Daily Livings (ADLs) including walking, standing, sitting, laying as well as jumping, meanwhile the remaining activities are five types of fall events including fall forward lying, fall forward knee, fall backward lying, fall backward sitting as well as fall sideward. Each participant will simulate each of activities for three repeated trials, resulting in 75 ADLs and 75 falls activities yielding total of 150 activities. Take note that for safety concern, only young teenagers and adults are chosen to be participating in this research and the mattress and cushion have been used when the participants simulate the fall event activities [11].

2.2 Data Pre-processing

In this research, there are three types of data pre-processing techniques will be implemented, including resampling, time series segmentation as well as normalization. Sample rate conversion which is one of resampling technique is used. It is a process of changing the sampling rate of a discrete signal into a new discrete representation of the underlying continuous signal. In this experiment, the sampling rate might change across the period of measurement, due to non-uniformly sample frequency of the Android smartphone. Thus, resampling algorithm is implemented to account for the non-uniformly sampled data to ensure the enhancement of accurate feature identification as well as perform better classification.
In this research, the combination of fixed sliding window and Landmark window is being implemented. All the data width is in the same length. Moreover, the data point of each window starts at the same time when t = 0 and it moves to the right by one data sample per step until the window does not have enough data samples to fill the window length. Min-Max scaling has been chosen to be implemented in this experiment. In this approach, the data is scaled to a fixed range – 0 and 1. This bounded range can make up smaller standard deviations, thus restrain the effect of outliers. The following equation shown is a Min-Max scaling that usually done:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

2.3 Feature Extraction and Selection

There is a total of five features suitable to be used for the classification algorithm to detect the fall. All the features including mean of the magnitude data; magnitude data of zero gravity; Step Count Index (SCI); Maximum Peak Index; and Minimum Valley Index. The magnitude of each axis is obtained, and then Signal Magnitude Vector (SMV) is calculated as follows:

$$SMV = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{2}$$

as *Ax*, *Ay* and *Az* indicates the three axes of the accelerometer. The mean of the magnitude data is calculated by adding up the observed values and divided by the total numbers of values. This feature is conveniently expressed by the following equation:

$$\bar{x} = \frac{(\Sigma x)}{n} \tag{3}$$

The magnitude data of zero gravity are obtained by subtracting the magnitude data with the mean of the magnitude data. This is because by subtracting the mean of the data will remove any constant effects such as gravity. This feature is basically following the equation:

$$magNoG = SMV - \bar{x} \tag{4}$$

Step Count Index (SCI), Maximum Peak Index (MPI) as well as Minimum Valley Index (MVI) are also taken as feature [12]. Walking consists of a regular sequence of steps and jumping consists of a sequence of actions. The typical acceleration pattern is characterized by a sequence of valleys and peaks occurring with quite a regular period. Hence, SCI is taken to be evaluated for each activity.
MPI indicates the highest value of acceleration magnitude. The average values of MPI are 10 m/s^2 for fall events, 6-8 m/s^2 for jumping and walking and below 5 m/s^2 for lying, sitting and standing. In contrast, MVI is the lowest value of acceleration magnitude. The average values of MVI are -4 m/s^2 for fall events, -3 m/s^2 for jumping and walking and 0m/s^2 to -1 m/s^2 for lying, sitting and standing.

2.4. Data Classification

Based on the previous researches, several classification algorithms show high sensitivity as well as the specificity [11]. In order to find the most accurate method for wearable device-based fall detection system in detecting all falls which preventing false negative events (ratio of false negative error) as well as preventing from generating false alarm (rate of false positive), this research is focusing on several types of classification algorithms which are proved to have high acceptance towards the sensitivity, specificity as well as overall accuracy including Artificial Neural Network (ANN) algorithm, K-Nearest Neighbor (KNN) algorithm and Support Vector Machine (SVM) algorithm. These algorithms are chosen to be evaluated more on the rate of false positive as well as false negative errors.
SVM algorithm is used based on the concept of decision planes that define decision boundaries whereby the decision plane separates between a set of objects having different class memberships. The features of this approach are listed as follows:

Algorithm : Support Vector Machine with various kinds of kernel functions
Goal : To find the best decision plane for decision boundaries between classes
Input : The dataset which comprising the features of every activity
Output : Predicted activities with their performance evaluation
Testing : 70% training sets, 30% testing sets
Various kernel function models are used to test the algorithm and the results of these outcomes were compared. The kernel functions implemented such as linear kernel, Gaussian or Radial Basis Function (RBF) kernel as well as polynomial kernel. Polynomial kernel is further divided into several levels of the order, including level 2, 5, 7 and 10.

3. Results and Findings

In this experiment, several types of kernel function methods are selected to be implemented in the SVM algorithm, including the default kernel, Linear, as well as non-linear such as Gaussian/ RBF as well as Polynomial kernel which are further divided into several orders (2, 5, 7, and 10). The overall performance of these kernels is illustrated in Figure 1 and the value of each is presented in Table 1. From the graph, SVM with polynomials (degree 5) kernel shows the highest overall accuracy as well as specificity. Even though the sensitivity of this kernel function is not as high as the others, however, the overall performance, including the accuracy shows that this type of model is the most accurate. Kernel function is used to represent a dot product of input data points that are mapped into high dimensional feature space by transformation, Φ as equation below:

$$K(X_i, X_j) = \phi(X_i) \cdot \phi(X_j) \tag{5}$$

The advantage of kernel function, including the complexity of the optimization problem remains only on the dimensionality of the input space and not of the feature space. Hence, it is possible to operate in a theoretical feature space of infinite height [6]. A linear model kernel function works as a default whereby in the feature space, the linearly separable boundary is created by the following equation:

$$K(X_i, X_j) = X_i \cdot X_j \tag{6}$$

In this experiment, Linear Model shows that it has a 100% of sensitivity whereby this model is capable to fully correctly classify all the fall events. However, there are considered a high amount of ADL's activities that are misclassified into fall events, thus decreasing the TN value and increasing the FP value as it creates a high false alarm. Gaussian or Radial Basis Function (RBF) model works as it uses normal curves around the data points and sums these so that the decision boundary can be defined by a desired topology condition just like shown in the equation below:

$$K(X_i, X_j) = e^{-\frac{|x - x_i|^2}{2\sigma^2}} \tag{7}$$

Gaussian or RBF shows the lowest overall accuracy and specificity compared to the other kernel function model as there is a high amount of ADL's activities are misclassified to be fall events, yielding high FPR. Nevertheless, all the fall events are correctly classified into the fall category which means that this kernel function is able to correctly categorize the fall events towards ADL's activities.

There are several levels of degree of polynomial kernel model that are implemented in this experiment to evaluate which level of degree gives the best performance and it turns out that the polynomial with level of degree = 5 yield the highest overall accuracy. The polynomial kernel model works same just like a linear kernel model; however the boundary set in feature space is defined by the arbitrary order by following the equation below:

$$K(X_i, X_j) = (< x . x_i > +1)^p \tag{8}$$

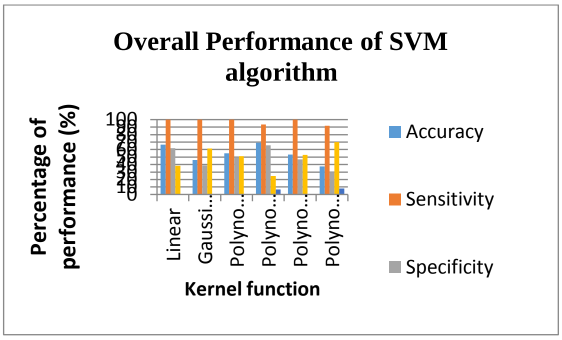

Figure 1. Overall performance of SVM algorithm

Table 1. Performance Analysis of SVM algorithm

Kernel function	Accuracy	Sensitivity	Specificity	False Positive Rate	False Negative Rate
Binary	66.4	100	61.76	38.24	0
Gaussian / RBF	46.19	100	38.77	61.23	0
Polynomial (order 2)	55.13	100	48.94	51.06	0
Polynomial (order 5)	68.91	93.33	65.54	24.46	6.67
Polynomial (order 7)	53.47	100	47.05	52.95	0
Polynomial (order 10)	37.47	91.93	29.96	70.04	8.07

Table 2: Confusion Matrix of SVM algorithm

		Predicted					
		Walking	Standing	Sitting	Lying	Jumping	Fall
Actual	Walking	399	0	0	0	0	81
	Standing	42	0	0	0	19	114
	Sitting	14	0	1	0	0	283
	Lying	160	0	0	0	171	234
	Jumping	0	0	0	0	548	0
	Fall	19	0	0	0	0	266

Table 2 shows the confusion matrix of fall events of the SVM algorithm by using a Polynomial kernel module with level degree of five. This matrix shows the calculation made by the algorithm in predicting the classes of the parameters in identifying the accurate value of fall events as well as ADL's activities. From the table, four out of five ADL categories have caused FP when analyzed by the SVM algorithm, including "Walking", "Standing", "Sitting" as well as "Lying" activities that are misclassified as falls.
Besides, the fall events are misclassified into one ADL categories: "Walking" hence these caused FN situations. Furthermore, there are total of 266 features that are correctly classified as fall events. The other ADLs are correctly classified as ADL activities. The Table 3 is further simplified into Table 3.

Table 3: Simplified Confusion Matrix of SVM algorithm with polynomial kernel function of level degree five

	Predicted	
Actual	**TP**	**FP**
	266	712
	FN	**TN**
	19	1354

4. Conclusion

Wearable device-based fall detection system is mainly the focus of this research by using several algorithm methods. All required information has been successfully documented as planned in this project report. In future, this project can be further developed and implemented in real mobile application for fall detection among the elderly. This research can contribute to the fall detection and activity recognition area as well as give an innovative and better solution in implementing in the community.

The result of each model of algorithms has been summarized and all approaches were compared in this chapter. SVM with polynomials (degree 5) kernel is proven to perform better compared as it shows the highest overall accuracy as well as specificity. SVM is tested by using different types of kernel function models. The SVM with polynomials (degree 5) kernel shows a lower percentage of FPR than the other comparison algorithms whereby it records 24.46%.

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