Fall Detection for the Elderly by Accelerometers

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Abstract

Fall detection for the elderly is an ongoing active research topic because of the demanding needs of caring for the elderly. Falls are one of the most vital problems of the elderly. In the meantime, wearable sensors are light-weighted and convenient, and thus can be embedded into clothing, making it possible to promptly detect the falling situation in the daily life. Quick fall detection thus provides necessary help to avoid further harms. This paper gives an overview of the procedures of fall detection, as well as addressing issues in fall detection from wireless accelerometers. Experiments have been conducted on a publicly available data set for fall detection. SVM classifiers and kNN classifiers are implemented in different settings, with extensive analysis.

Keyword: Fall Detection, Classification, Accelerometers.

I. Introduction

Many countries are witnessing growing aged populations, which are exceeding the society's capacity to take good care of the elderly comminity. The rapid growth of the elderly put high demand for corresponding assistive service and technology [1][2]. According to the report, over one in every three elderly people suffer from fall consequences [3]. What's worse, the fall is the most vital risk to the elderly's health among all events, and around fifty percent of the hospitalization of the elderly are directly or indirectly because of falls [4]. Nursing home admission busniss [5] exists due to the fear of falling, and the "long lie" (not being able to get up independently and call for help quickly) may straightly cause death within six months [6]. Hence it is urgent to provide immediate treatment of the injured people [7]. Therefore, the quick detection of falling down of an elderly is really essential for on-time treatment.

There are various types of sensors available, such as cameras [8], GPS, light sensors, accelerometers [9][10], temperature sensors, gyroscope, barometer, etc, even infrared sensors [11]. These sensors can gather a rich data source to measure various aspects of a user's daily life, ranging from health an fitness monitoring, personal biometric signature, healthcare to navigation, localization, etc [12][13]. Body attached accelerometers and gyroscopes have been used to detect human activities, including falls [14]. Roughly the sensors can be grouped into three categories: wearable device, camera-based and ambience device [7][12][15]. The wearable device means the sensors are capable of being attached on human body to record daily activities. The wearable device is convenient, low cost, and stable, making it perfect for fall detection. 3-axis accelerometer is the most powerful sensor for wearable device, and it is normally integrated in mobile phones. Camera-based devices are commonly placed in the living rooms or public places, and they save the data in streams of videos or pictures. Cameras can be placed sideways, on the ceiling, as well as mounted in walls [16]. Ambience device use many installed sensors to collect the data when the elderly is approaching sensors, such as Wi-Fi, Bluetooth, and the sensors attached to objects.

Classification methods are an important part in fall detection as well. After gathering raw data from sensors, preprocessing and feature selection are conducted. Then different classification methods can be applied to detect whether the subjects experience falling situation or not [17][18]. There are mainly two categories of methods for fall detection: one is rule-based method that depends much on domain knowledge, and another method is machine learning based [1][19]. For instance, in [3][20][21], a threshold-based algorithm is proposed. Four different thresholds are set based on domain knowledge of magnitude of falling and other activities, and exceeding any of the limit can cause fall alerts. Similar thresholds are set in [22] as well. But one major drawback of this kind of method is the lack of adaptability and dependence of human experts. The most common approach is machine learning based, since it is more efficient and it costs less expert knowledge [23]. Commonly used methods are Decision trees (Dts) [24], support vector machines (SVM) [25][26], k-nearest neighbours (kNN) [27], hidden Markov models (HMM) [28][29], etc. For applications using these techniques, readers can refer to the following work: [30] builds a software architecture to analyze acceleration data by HMM; [31] builds a tracker based on coarse ellipse model and a particle filter; [32] proposed a novel fall detection approach based on one-class support vector machine.

The rest of this paper is organized as follows. Section II discusses the approaches and steps for fall detection. Section III shows the details of experiments and results, as well as analysis. We conclude the paper and discuss future research directions in section IV.

II. Fall Detection by Classification

Fall detection can be considered as a binary classification problem, i.e., all activities are categorized into 2 classes: falling down (denoted as class +1) and not falling down (class -1). The overall procedure of fall detection is shown in Fig. 1.

Sensor selection Firstly, proper types of sensors are selected according to the constraints of cost, subjects, types of activities, place, etc. For instance, if activities are conducted in an indoor environment, then wearable sensors, cameras, as well as ambient sensors attached in the environment are all suitable. If the cost needs to be low, and the sensor should be as light-weighted as possible, then wearable sensors are a good choice.

Data acquisition Sensors are set to be active during the activities. Raw data is recorded continuously, and is synchronized to the processor or a computer.

Data Preprocessing Preprocessing includes de-noising and segmentation. Practically, high frequency noise in acceleration data needs to be removed. Besides, sensors may be dysfunctional during the recording, which may result in incomplete data. If different types of sensors are used simultaneously, then matching of different frequency data from different sensors is needed. Data segmentation is to divide the continuous data streams into small segments, and normally the segmentation can be with overlapping or without overlapping [12]. Top-down algorithms as well as bottom-up methods can also be used to segment the data [33].

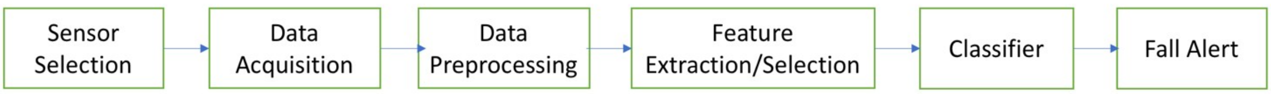
Feature extraction and selection After preprocessing raw data, many kinds of features can be extracted from each segments of data, e.g., time-domain features (e.g., mean, minimum, maximum, variance, correlation, etc), frequency-domain features (energy, entropy, binned distribution, etc) [34][35], heuristic features (which incorporates expert knowledge). The purpose of feature selection is to transform the large input data into a reduced set of most important features. At the same time feature selection helps to limit computational cost.

Classifier The data is split into training and testing data, and a classifier is learnt from training data and therefore can perform prediction on test data. Threshold-based techniques are straightforward, which set thresholds to distinguish activities with various intensities. Machine learning based techniques are widely used as well, such as Decision Trees, k nearest neighbours, Naive Bayes, SVM, HMM and Gaussian Mixture Models. Nowadays neural network based methods are popular as well.

Fall alert Finally, if fall is detected, some warning should be given, then we can provide on-time assistance to the subjects.

Despite the fact that wearable sensors are advantageous for fall detection, there are still many factors that are challenging. One of the major challenges is the variation of falls of different subjects [12]. This is mainly due to the fact that different people have different motion patterns. Even for the same subject, the pattern is not stable at different time or location. Another problem is the insufficiency of available data. It is desirable that the training data contains as many varieties of the subjects as possible. However it's not easy to collect data with many subjects, and the issues of privacy also exists.

Fig. 1. Overall procedure of fall detection.



The Support Vector Machine (SVM) algorithm is one of the most widely used kernel-based learning algorithm [36][37]. Its classification performance is quite robust, and therefore SVM is used in the experiments. SVM aims to choose the separating hyperplane that maximizes the margin between two classes. The optimization primal form is formed to be:

$$\begin{aligned} &min\ \mathcal{P}(w,b,\xi) = \frac{1}{2}w^2 + C\sum_{i=1}^{n}\xi_i \\ &s.t.\ y_i(w^T\phi(x_i)+b) \geq 1-\xi_i, \forall i \\ &\quad\ \xi_i \geq 0, \forall i \end{aligned} \tag{1}$$

where the parameter C controls the tradeoff between large margins and small margin violations [38][39]. The primal form in Eq. (1) of SVM formulation can be transformed into dual form in Eq. (2):

where $K(x_i, x_j)$ can be linear or nonlinear. In the experiments we use RBF kernel, i.e., K(x, z) = exp(- g||x-z||^2).

$$
\begin{aligned}
max\ D(\alpha) &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y_i \alpha_i y_j \alpha_j K(x_i, x_j) \\
s.t.\ 0 &\le \alpha_i \le C \\
\sum_i y_i \alpha_i &= 0
\end{aligned}
\qquad (2)
$$

Besides SVM, kNN is also a very efficient classification algorithm. The main assumption of KNN is that the nearer data points tend to have a higher probability of sharing the same labels. That is to say, for k = 1 case, when predicting the test data's label, we can find the nearest training data and assign training data's labels to the test data. Similarly, for k >= 1 case, the test data's label can be assigned to be the majority of the k nearest training data's labels.

III. Experiments and Results

A. *Fall Detection data set*

Experiments are conducted based on one publicly available data set: UR Fall Detection Data Set (URFD) [40]. The data set consists of 5 subjects' actions of 70 activities, of which 30 are falls and other 40 are activities of daily living, such as walking, running, etc. Besides the labelling of falling down/not falling down, the data set also contains class 0, which represents temporary pose when the person "is falling down". Two Microsoft Kinect cameras together with an accelerometer (256 Hz) are utilized to record the data. In our experiments we merely use wireless sensor data other than camera-based data. Accelerometer data includes four features: three accelerations A_x, A_y, A_z on three axis x, y ,z and a total sum by $\sqrt{Ax2+Ay2+Az2}$.

B. *Experiments setup*

We randomly split the data into training and testing data by the ratio of 0.7 and 0.3. All experiments are repeated 6 times and the average results are shown in below. SVM classifiers and kNN classifiers are applied to learn the classification models, and to predict the labels. The parameter range of SVM is {0.001, 0.01, 0.1, 1, 10, 100} for g, {0.1, 1, 10, 100, 1000} for c, and for kNN, k is chosen among {1, 2, ..., 10}. We perform two kinds of classification: binary classification (ignore the temporary class 0) and 3-class classification (take into account all 3 classes).

The macroF1 and microF1 are utilized as performance measurement since F1 measure can combine both precision and recall [29]. The definitions are as follows:

$$
\begin{aligned}
macroF1 &= \frac{2 * macroP * macroR}{macroP + macroR} \\
macroP &= \frac{1}{n}\sum_{i=1}^{n} P_i \\
macroR &= \frac{1}{n}\sum_{i=1}^{n} R_i
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
microF1 &= \frac{2 * microP * microR}{microP + microR} \\
microP &= \frac{\bar{TP}}{\bar{TP} + \bar{FP}} \\
microR &= \frac{\bar{TP}}{\bar{TP} + \bar{FN}}
\end{aligned}
\tag{4}
$$

where n is the number of classes, TP is true positive, FN is false negative, FP is false positive and TN is true negative (refer to Table I).

Table I Definition of TP, FN, FP, TN for precision and recall

		Predicted positive	Predicted negative
true	positive	TP	FN
true	negative	FP	TN

C. *Results and analysis*

The overall results and optimal parameters are listed in Table. II. From the results, it is clear that classification performance is higher when the number of classes is fewer. The results of SVM and kNN are comparable for miF and maF. Table. III and Table. IV are confusion matrix of SVM for each problem. In SVM's binary case, only 2 actions are misclassified. But in 3-class case, misclassification cases are more frequent. It shows there are (129+23 =) 152 actions of class +1 and -1's data that are misclassified as class 0. Yet the misclassification case is rarer between class {-1, +1} (8+0=8) compared to case of {+1, 0} or {-1, 0}. This makes sense since class 0 is a transit state between not falling and falling, which is less discriminative.

Table II

Experiments Results and Best Parameters of SVM and kNN for binary and 3-class classification problem.

problem	method	Best parameters	microF1	macroF1
binary	SVM	g 1, c 100	99.932	99.932
binary	kNN	K 1	99.661	99.661
3-class	SVM	g 1, c 10	93.474	93.238
3-class	kNN	K 3	93.763	86.633

Table III

Confusion matrix of binary classification problem by SVM

	-1	1
-1	2252	1
1	1	694

Table IV

Confusion matrix of 3-class classification problem by SVM

	-1	0	1
-1	2172	129	8
0	36	370	30
1	0	23	695

IV. Conclusion

Fall detection of the elderly is crucial in order to provide assistive service for the growing number of aged population nowadays. In this paper, we give an overview of fall detection, by treating it as a classification problem. Two efficient and stable classifiers, i.e., SVM and kNN classification methods are implemented to perform fall detection on the URFD data set. Results show the effective effects of SVM and kNN classifiers on fall detection. Binary classification problem achieves better performance than 3-class classification problem. Thus, future research can focus on how to improve detection accuracy when there exist many other confusing classes.

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