

Fall Detection by Wearable Sensor and One-Class SVM Algorithm

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Abstract. The fall is a crucial problem in the elderly people's daily life, and the early detection of fall is very important to rescue the subjects and avoid the badly prognosis. In this paper, we use a wearable tri-axial accelerometer to capture the movement data of human body, and propose a novel fall detection method based on one-class support vector machine (SVM). The one-class SVM model is trained by the positive samples from the falls of younger volunteers and a dummy, and the outliers from the non-fall daily activities of younger and the elderly volunteers. The preliminary results show that this method can detect the falls effectively, and reduce the probability of being damaged in the experiments for the elderly people.

1 Introduction

The fall is a common unexpected event in daily life, it usually can only damage the young people slightly, but it is really a crucial problem to the elderly people. About 10% to 15% falls will cause serious injury in the elderly people, and more than 1/3 of the persons aged over 65 will fall at least once per year[1,2]. The early detection of fall is very important to rescue the subjects and avoid the badly prognosis[2,3].

Wearable sensor based fall detection means embedding some micro sensors into clothes, girdle, etc., to monitor the movement parameters of human body in real-time, and determine whether there is a fall occurred based on the analysis about these parameters. Currently, wearable sensor based fall detection systems usually collect acceleration, vibration and tilt signals, and set a few thresholds to these signals respectively, then make decisions by detecting whether there is one or several data over the thresholds[1,2,3]. But there exist many problems about this kind of algorithms, include lacking of adaptability, deficiently in classification precision, etc. For example: Hwang et al[3] use tilt switch to trigger the detection program, when the tilt of the person's upper body over 70°, the program will start to process the acceleration signals to determine whether there is a fall occurred. However, if the person slides fall during going down-stairs, in general he will sit down on the stairs with only a small tilt degree on the upper body, and hence the detection program will not be triggered.

In this paper, we use a tri-axial accelerometer to capture the movement signals of human body, and propose a novel method based on one-class SVM to detect falls. The one-class SVM model is trained by the positive samples from the falls of younger volunteers and a dummy, the outliers from the non-fall daily activities of younger and the elderly volunteers. The preliminary results show that this method can detect the falls effectively, and at the meantime the probability of being damaged in the experiments for the elderly people are reduced.

2 Methods

2.1 Materials

A tri-axial accelerometer, “MMA7260Q”, is selected, it is a low-g micro-machined resistance accelerometer with the volume 4*4*1mm. The chosen measuring range is 4g and the sampling rate is 512 points per second. When in the state of static, it is the acceleration of gravity to the vector sum of the signals from axes x , y and z . The sensor is affixed to a belt and bound to the human body, as shown in Fig.1.

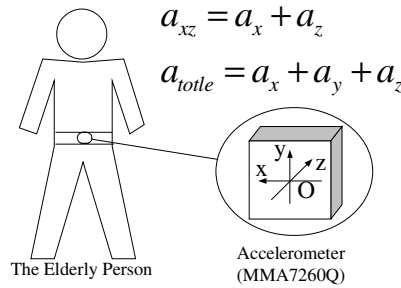


Fig. 1. The accelerometer and its fixed position

2.2 One-Class SVM Algorithm

One-class SVM is an extended algorithm of SVM[4,5], it divides all samples into objective field and non-objective field, mapping all the samples into high dimensional feature space by using of a kernel function. Then, in the feature space, one-class SVM computes the surface of a minimal hypersphere which involves all the objective data inside, and this minimal hypersphere will be the classifier. A group of variables named slack variables are introduced to realize the trade-off between the radius of the hypersphere and the number of the samples which outside the hypersphere. All the samples inside the hypersphere are known as positive samples, the outside samples as outliers.

Let X be a positive sample set, $X = \{x_i, i=1, \dots, l\}$, $x_i \in R^d$, then we use nonlinear mapping to find a minimal hypersphere in high dimensional feature space, let vector a be the centre, R be the radius of the hypersphere, and involves the samples as many as possible. That is an optimal problem as follows:

$$\min_{R \in \square, \xi_i \in \square, a \in F} R^2 + \frac{1}{\nu \ell} \sum_i \xi_i \quad (1)$$

s.t.

$$\|\Phi(x_i) - a\|^2 \leq R^2 + \xi_i, \quad \xi_i \geq 0, \quad i \in [1, \ell]$$

where F is feature space, ξ_i are the slack variables, $1/\nu \ell$ determines the volume of the hypersphere and the number of the samples which will be segmented beyond the hypersphere, $\nu \in (0, 1)$, and ℓ expresses the number of all the samples.

Based on KKT condition, and introduce the kernel function:

$$K(x, y) = \langle \Phi(x), \Phi(y) \rangle \quad (2)$$

the dual expression of the optimal problem (1) is:

$$\min_{\lambda} \sum_{i,j} \lambda_i \lambda_j K(x_i, x_j) - \sum_i \lambda_i K(x_i, x_i) \quad (3)$$

s.t.

$$0 \leq \lambda_i \leq \frac{1}{\nu \ell}, \quad \sum_i \lambda_i = 1$$

The centre of the hypersphere is:

$$a = \sum_i \lambda_i \Phi(x_i) \quad (4)$$

After the training, a group of support vectors will be obtained, and we can calculate the radius R by the following equation:

$$R^2 = \sum_{i,j} \lambda_i \lambda_j K(x_i, x_j) + K(x_s, x_s) - 2 \sum_i \lambda_i K(x_i, x_s) \quad (5)$$

where x_s is any support vector. And then the decision function is:

$$f(x) = \text{sgn}(R^2 - \sum_{i,j} \lambda_i \lambda_j K(x_i, x_j) + 2 \sum_i \lambda_i K(x_i, x) - K(x, x)) \quad (6)$$

To any sample, if $f(x) > 0$, the sample will be classified in positive, if $f(x) < 0$, the sample will be an outlier. Here, we use RBF as the kernel function, i.e.:

$$K(x, z) = \exp\left(-\frac{\|x - z\|^2}{\sigma^2}\right) \quad (7)$$

2.3 Fall Detection

By the wearable manner in Fig. 1, a_{xz} and a_y can indicate the accelerations in the transverse section and on the vertical axis of human body respectively. In the course

of falling, either or both of a_{xz} and a_y will take place acute changes and there will be a strongly reverse impact when the subject striking on the ground. Various change patterns of a_{xz} and/or a_y correspond to various fall situations. In order to decrease the dimensions of input space, we just select the one, between a_{xz} and $1.414a_y$, which has stronger reverse impact. Then we use six variables to form the input vectors:

$$\{\Delta t_1, \Delta a_1^{(a)}, \Delta a_1^{(\sigma)}, \Delta t_2, \Delta a_2^{(a)}, \Delta a_2^{(\sigma)}\}$$

the meanings, in sequence, are: the interval between the beginning of falling and the beginning of the reverse impact, the average acceleration during Δt_1 , the variance of acceleration during Δt_1 , the interval of the reverse impact, the average acceleration during Δt_2 , and the variance of acceleration during Δt_2 .

The three pre-processing steps are implemented to acquire the input vectors: 1) low-pass filtering, to get rid of the noise; 2) finding an acute changing section in the sequences of a_{xz} and a_y . In generally, a falling will be completed within 0.4-0.8 second, and follows a period of relative motionless. So, we overlapped intercept 1.5 seconds data section every 0.5 second, then determine whether there is an acute changing in a section based on the non-periodically varieties of the variance of several sequential sections. If both of a_{xz} and a_y changed acutely, we select the stronger; 3) getting input variables, to an acute changing section, we choose the point which has maximal difference value as the beginning of the reverse impact, then determine Δt_1 and Δt_2 from this point, and calculate the other input variables.

The *holdout method* is applied to train and test the one-class SVM model, i.e., the data set divided into two subsets, one for training and one for testing. In order to reduce the affect of noise, for the training set, we select all the positive samples and random choose 1/3 negative samples to train the model, and for the testing set, all samples are used. Such a training-testing course is a basic operation, and it will be repeated 16 times, then we pick the optimal result as classifier. The local optimal pairs $(v, 1/\sigma^2)$ can be found via discretization and global search in each basic operation, and the global optimal pair will be selected among the local optimal pairs.

3 Experiments and Results

The 12 volunteers, 8 males and 4 females aged from 10 to 70 years old with height from 1.36m to 1.80m, are selected to attend the experiments. And the experiments were done on following categories: 1) low-risk fall down, the subjects fell down on the plane with soft cushion; 2) high-risk fall down, the subjects fell down on the hard plane, stairs and slope; 3) critical movement, the subjects did fleet movements that are some alike falling down, e.g. lay prone on the ground quickly, sat down heavily; 4) sub-critical movement, it was similar to category 3, but the movements were slower, including groveling, lying down, etc.; 5) low-intensity daily activities, included daily activities, e.g. walking, jogging; 6) high-intensity daily activities, there were some acute daily activities, e.g. running, jump and gymnastics.

The fall situation is dangerous to human body, especially to the elderly, so the elderly volunteers only attended category 4 and 5, the younger volunteers attended category 1 and 3 to 6, while category 1 and 2 were implemented with a dummy.

We collected about 600 samples, approximately 65 percent of the samples are used to train the one-class SVM model, and the others to test the model, as shown in table 1. Let $v=0.22$, $1/\sigma^2=90$, we obtained the test results shown in table 2. The results show that this model can detect the falls effectively.

Table 1. The samples for each category

category	total samples	samples for training	samples for test	demonstrated by
1	160	100	60	60-younger 100-dummy
2	224	150	74	dummy
3	46	30	16	younger
4	70	44	26	30-younger 40-elderly
5	72	44	28	30-younger 42-elderly
6	30	20	10	younger

Table 2. The test results

category	correct	incorrect	correct ratio(%)
1	59	1	98.3
2	72	2	97.3
3	14	2	87.5
4	26	0	100.0
5	28	0	100.0
6	8	2	80.0
total	207	7	96.7

4 Discussion

For the current fall detection algorithms[1,2,3], there is an implied precondition, i.e., fall is such a course of that the human body posture changed from nearly upright to nearly horizontal rapidly. But in many situations, this precondition is not valid, e.g., the subject slides and sitting down on the ground, stumbled while going upstairs, and falls while bending to pick something on the ground. Hence, the current fall algorithms have many “blind areas”. Our algorithm doesn’t need the precondition, and therefore it has more powerful adaptability to various situations. In the meantime, the experiment results have shown that the algorithm has well classification performance.

The shortage of our algorithm is the complexity in calculation, especially for the pre-processing. So, in the future, we intend to improve the algorithm and test some other intelligent methods. And the fall risk prediction is another subject that we want to study in the next steps. Both the detection and the prediction are important to protect the elderly people, because the high risk means the elder is not suit to live independent at least a short period, and the detection means we can rescue the elder in time when a fall occurred.

5 Conclusion

The wearable sensors system could capture the real-time movement data of human body under the condition of low-cost and less disturbance to daily activities, while one-class SVM could well classify the data of fall and daily movements. Combining wearable sensors with one-class SVM algorithm, we can implement the credible and efficient fall detection for the elderly people.

Acknowledgments

The authors acknowledge the support from National Natural Science Foundation of China, grant 60271025.

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