Leveraging Two-Stage Weighted ELM for Multimodal Wearables Based Fall Detection

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Abstract. For the elderly people, timely detecting the fall accident is very critical to receive the first aid. In order to achieve high detection accuracy and low false-alarm rate at the same time, we propose a multimodal wearables based fall detecting and monitoring method leveraging two-stage weighted extreme learning machine. Experimental results show that our method is able to effectively implement on miniaturized wearable devices, and compared to state-of-the-art ELM classifier, we can also obtain higher detection accuracy and lower false-alarm rate simultaneously, which enables various kinds of mHealth applications in large-scale population, especially for the elderly people's healthcare in the field of fall detection.

Keywords: mHealth, Fall Detection, Wearable Device, Extreme Learning Machine, Weighted ELM.

1 Introduction

With the rapid development of sensor technology and the increasing availability of affordable sensor-embedded wearable devices, commonly massive sensor-based wearables enables various kinds of sensing and communication capabilities in large-scale applications. Especially for the elderly people who always live independently, the fall has become great threat to the public health and seriously diminish the quality of people's lives, accordingly leads to various psychological problems like psychological fear of movement, worry about independent living [1], etc. Therefore, timely detecting and monitoring the occurrence of fall accidents will great help injured elderly people get the valuable first-aid chance. Meanwhile, if the alarm for fall detection often happens wrongly, it probably heavily interrupts the people's regular livings and behaviors.

Noury [1] discusses the psychological consequences after the falling. The worst one is that the elderly cannot call for help after falling with unconscious. Therefore, the aim of their design for the fall detector is to guarantee that the elderly

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can obtain the first aid after the falling, reducing their feared state of mind and encouraging them to more active activity. Narayanan et al. [2] invent a Waist-mounted rechargeable Triaxial Accelerometer-based device to detect and prevention the elderly's falling. The device in [2] is named "Prevent Fall Ambulatory Monitor", which denotes by PFAM for short. The system is not only a detector, but also supply the elderly with self-test for risk assessment of the falling. Grassi et al. [3] put forward the high-reliability fall detection framework, which uses 3D time-of-flight range camera, wearable Zigbee MEMS accelerometer and microphone, where the camera adopts person detection and tracking algorithm to detect the centroid height of the people. When this height is below a threshold, the people is regarded as the falling status. Shi et al. [4] implement an Android application called "uCare" to detect the elderly's falling and seek the first aid. They present the fall detection method by exploring a five-phase model which details the state alternation during the elderly's falling activity. The accelerometer data generated from mobile phones is used for the proposed five-phase model to improve the accuracy of fall detection. Zhou et al. [5] propose an activity transition based fall detection model, this model mainly extracts features from transition data between adjacent activities to recognize various kinds of normal activities and abnormal activities, which is able to reduce a number of normal activities but focuses on abnormal activity in the transition section.

Accordingly, how to build the classifier for achieving high accuracy and low false-alarm rate simultaneously, has become a key challenging issue for imbalance learning in large-scale wearable computing applications. In this paper, running on eyeglass and watch miniaturized wearable devices, our work is to accurately and timely detect and monitor the fall accident using weighted extreme learning machine. The empirical experimental results show that our proposed method is effective and does contribute good impact in the field of fall detecting and monitoring, especially for the elderly people's healthcare.

2 Our Method

The framework of our proposed method is shown in Figure 1, which mainly consists of the initial classification step, the result refining step in the following.

Step (1): the initial classification step. For the accelerometer sampling data from wearable eyeglass device, its related features are extracted accordingly, then the initial classification is trained on the labeled training dataset using weighted extreme learning machine [6], and the optimal parameters of this classifier such as C and number of hidden nodes are generated. Based on the trained classifier, the samples whose classification results are suspected fall will be used as the input of the next stage for result refining. Also, running on wearable watch device with another set of optimal parameters like C and number of hidden nodes, the initial weighted ELM classifier keeps detecting suspected fall activity and is utilized for result refining as the input of next stage as well.

Step (2): the result refining step. If wearable eyeglass device is detected as suspected fall activity, the feature data stored on eyeglass device will be triggered to transmit to the connected mobile phone via bluetooth interface. At the same time, in case when the suspected fall is detected on eyeglass, the feature the feature data stored on wearable watch device will be transmitted as well if suspected fall happened on watch. Accordingly, eyeglass generated features, or eyeglass and watch generated multimodal features will be further refined through another weighted extreme learning machine classifier again. Here, the weight value is different from the first stage, because samples of different classes of all activities are varying between the first stage and the second stage.

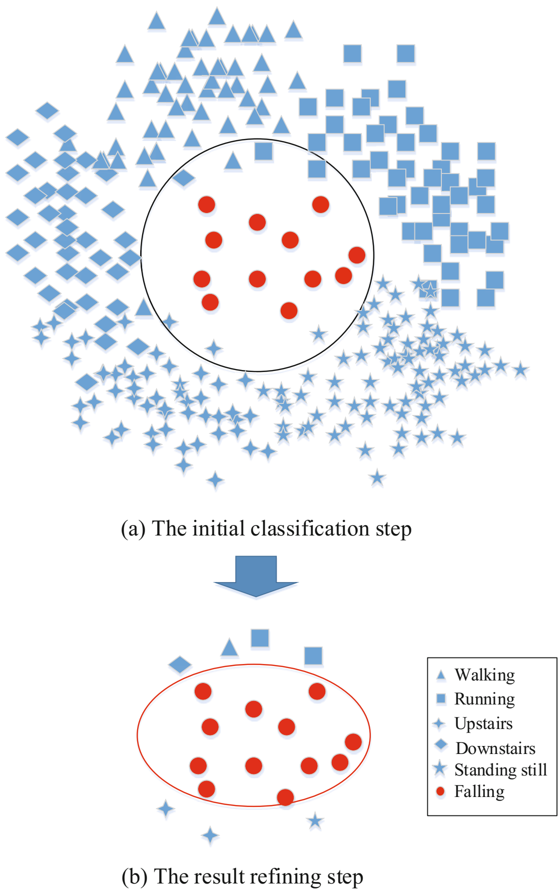

Fig. 1. Our proposed method for fall detecting and monitoring

2.1 Feature Extraction

For the collected accelerometer magnitude series from eyeglass and watch devices, the sampling rate is 10Hz and the length of windows is 13, totally 14 acceleration features [7] are extracted without overlapping between consecutive windows. They are maximum, minimum, mean, standard deviation, energy, zero crossing rate, four amplitude statistics features and four shape statistics features of the power spectral density (PSD) [8].

Extracting these features from accelerometer data on eyeglass, there are 14 features as the input feature vector, and when features come from accelerometer data on both eyeglass and watch, there are 28 input features in total. Meanwhile, due to these extracted features have large ranges of value domain, all these features are normalized using the z-score normalization approach to eliminate the scaling effects among diverse features.

2.2 COELM Classifier

Extreme Learning Machine (ELM) [12,13,14] is originally proposed for single hidden layer feedforward network (SLFN), solving both classification and regression problems [9,10,11,16,17] in various fields of applications [18,19,20,21,22,23,24,25]. Constrained-optimization-based extreme learning machine (COELM) [15] is proposed with the purpose of extending ELM with kernel learning. The classification problem of COELM is formulated as:

$$\begin{aligned} &\min_{\boldsymbol{\beta},\boldsymbol{\xi}} \frac{1}{2}\|\boldsymbol{\beta}\|^2 + \frac{C}{2}\sum_{i=1}^{N}\|\boldsymbol{\xi}_i\|^2 \\ &\text{s.t. } \boldsymbol{h}(\boldsymbol{x}_i)\cdot\boldsymbol{\beta} = \boldsymbol{t}_i - \boldsymbol{\xi}_i,\ \ i = 1,\cdots,N \end{aligned} \tag{1}$$

The meaning of all the notations is the same as in the last subsection. C is the trade-off parameter between training error minimization and generalization ability maximization principles, and needs to be tuned appropriately. $\mathbf{I}$ represents the identity matrix. The solution of problem above is also analytical determined as:

$$\boldsymbol{\beta}^* = \begin{cases} \mathbf{H}^T(\frac{\mathbf{I}}{C} + \mathbf{H}\mathbf{H}^T)^{-1}\mathbf{T},\ N < L \\ (\frac{\mathbf{I}}{C} + \mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{T},\ N > L \end{cases} \tag{2}$$

2.3 Weighted ELM Classifier

Weighted extreme learning machine (Weighted ELM) [6] is proposed based on constrained-optimization-based extreme learning machine (COELM) recently, with the purpose of extending ELM for imbalance learning. The classification problem of Weighted ELM is formulated as:

$$\begin{aligned}&\text{minimize} \quad \mathrm{L_{P_{ELM}}} = \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\mathbf{W}\frac{1}{2}\sum_{i=1}^{N}\|\boldsymbol{\xi}_i\|^2 \\ &\text{s.t.} \quad \boldsymbol{h}(\boldsymbol{x}_i)\cdot\boldsymbol{\beta} = \boldsymbol{t}_i^T - \boldsymbol{\xi}_i^T, \; i = 1,\cdots,N\end{aligned} \tag{3}$$

Similarly, the solution of problem above is also determined as:

$$\boldsymbol{\beta} = \begin{cases}\mathbf{H}^T(\frac{\mathbf{I}}{C} + \mathbf{WHH}^T)^{-1}\mathbf{WT}, \text{ when N is small} \\ (\frac{\mathbf{I}}{C} + \mathbf{H}^T\mathbf{WH})^{-1}\mathbf{H}^T\mathbf{WT}, \text{ when N is large}\end{cases} \tag{4}$$

They [6] firstly use a weighting scheme $\mathbf{W}1$ automatically generated from the class information, which is in fact a special case of the cost sensitive learning:

$$\mathbf{W}1: \quad \mathrm{W_{ii}} = 1/\#(t_i) \tag{5}$$

Accordingly, for our fall detection problem, we adopt different weights for the initial classification step and the result refining step as the weighting scheme $\mathbf{W}2$ [6]:

$$\mathbf{W}2: \quad \mathrm{W_{ii}} = \begin{cases}0.618/\#(t_i), \; t_i > AVG(t_i) \\ 1/\#(t_i), \qquad \text{otherwise}\end{cases} \tag{6}$$

3 Experiment

In the data collection, our study population contains 1 female and 6 males ranging from 23 to 29 years old, each participant carries a smartphone and wears an eyeglass device during the data collection and collects six kinds of activities, including the fall, standing still, walking, running, downstairs and upstairs, where the fall consists of front, back, left and right-toward falls. The duration of standing still is about 15 seconds each time, and other activities except the fall are collected for 2-3 minutes. The duration of fall activity is about 2.6 seconds on average, and each participant is required to lie immediately before and after the fall activity, also keep still for 5 seconds.

In the experimental evaluation, the precision and recall are used to measure the accuracy, which are defined in the following:

$$Precision = \frac{\sharp \textit{ of true positive}}{\sharp \textit{ of true positive} + \sharp \textit{ of false positive}} \tag{7}$$

$$Recall = \frac{\sharp \textit{ of true positive}}{\sharp \textit{ of true positive} + \sharp \textit{ of false negative}} \tag{8}$$

In the classifier training on wearable eyeglass and watch devices, there are two parameters, i.e. the regularization coefficient C and the number of hidden nodes, need to be determined. We utilize grid-search method to select the optimal parameters from 100 pairs of parameters and employ 10-fold cross-validation

Table 1. The optimal parameters of Weighted ELM classifier for eyeglass and watch features in the first stage

	Optimal parameter	Value	Index
Eyeglass	C	16	4
	Hidden nodes	256	8
Watch	C	16	4
	Hidden nodes	1024	10

Table 2. The optimal parameters of Weighted ELM classifier for eyeglass and eyeglass-watch features in the second stage

	Optimal parameter	Value	Index
Eyeglass	C	2	1
	Hidden nodes	512	9
Eyeglass-Watch	C	4	2
	Hidden nodes	64	6

Table 3. The performance comparison of precision and recall between the original method of ELM and two-stage method of weighted ELM

	Original ELM	Two-stage weighted ELM
Precision	73.68%	95.74%
Recall	90.74%	93.67%

method, then we obtain optimal parameters of the regularization coefficient C and the number of hidden nodes in Table 1 and Table 2 for different two stages, respectively.

Accordingly, in the first classification step, the initial fall detection indicates the suspected fall detection through the weighted ELM classifier over wearable eyeglass device. Then, the initial detection result is further recognized for determining the final fall activity, this detecting result by weighted ELM classifier is utilized as the input to the next step. Next, in the second result fining step, based on the feature data generated from wearable eyeglass device or eyeglass-watch devices, the suspected fall is further refined through another weighted ELM classifier again, through adopting different weights from the first step. At last, we can see from Table 3, our proposed two-stage weighted ELM classifier can obtain higher recall rate (the recall rate increases from 90.74% to 93.67%) than original ELM classifier, and significantly improve the precision rate from 73.68%

to 95.74%, which shows that the false-alarm rate is lower than 5%. Accordingly, compared to the result of original ELM classifier, our method can achieve the high detection accuracy and low false-alarm rate simultaneously, also verify the effectiveness of imbalance learning for the weighted ELM classifier.

4 Conclusion

In this paper, we propose a multimodal wearable devices (i.e. eyeglass and watch) based fall detection method using two-stage weighted ELM. In particular, we explore the initial classification to detect the suspected fall firstly, then another weighted ELM classifier is employed again to refine the detection result. Compared to the original ELM classifier, our proposed method is able to detect the fall activity with high detection accuracy and low false-alarm rate simultaneously. Our encouraging results contribute towards the on-going development of mHealth technology which is effective to track the key fall activity in the field of healthcare, especially for the elderly people in the real-world.

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