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Adaptive weighted imbalance learning with application to abnormal activity recognition

Xingyu Gao [a,b], Zhenyu Chen [a,*], Sheng Tang [a], Yongdong Zhang [a], Jintao Li [a]

[a] Key Laboratory of Intelligent Information Processing of Chinese Academy of Sciences (CAS), Institute of Computing Technology, CAS, Beijing, China
[b] University of Chinese Academy of Sciences, Beijing, China

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ABSTRACT

Abnormal activity recognition has been paid much attention in the field of healthcare and related applications, especially for the elderly people's physical and mental health, the high risk of the fall accident and its caused injures have gradually attracted more and more concerns. At present, wearable devices based fall detection technology can effectively and timely monitor the occurrence of fall accidents and help the injured person receive the first aid. However, the built classifiers of traditional approaches for fall detecting and monitoring suffer from a high false-alarm rate though they can reach a relatively high detection accuracy, further they have to face with the imbalance problem because sensor data of abnormal activities are usually rare in the realistic application. To address this challenge, we propose two-stage adaptive weighted extreme learning machine (AWELM) method for eyeglass and watch wearables based fall detecting and monitoring. Experimental results validate and illustrate significant efficiency and effectiveness of the proposed method and show that, our approach firstly achieves a good balance between high detection accuracy and low false-alarm rate based on our two-stage recognition scheme; secondly enables our imbalance learning approach for scarce abnormal activity data by two-stage adaptive weighted method; thirdly provides a light-weight classifier solution to resource constrained wearable devices using extreme learning machine with the fast training speed and good generalization capability, which enables large-scale mHealth applications and especially helps the elderly people to greatly reduce the risk of fall accidents finally.

1. Introduction

With the rapid development of sensor technology and the increasing availability of affordable sensor-embedded wearable devices, sensor-based technology is becoming more popular in the fields of artificial intelligence and ubiquitous computing, which has also been widely utilized in a variety of real-world applications, such as security monitoring [1], mobile sensing [2,3], abnormal activity detection [4] and so on. Here, specially for the living-independent elderly people's physical and mental health, a critical demand is personal and pervasive healthcare monitoring [5] for their daily lives. Although monitoring the elderly people's daily behavior is very important and interesting, we pay much attention on the abnormal activity problem, that is, detecting the elderly people's fall accident via wearable sensor based technology, because if the injured person cannot receive the timely aid and missed the first-aid time, the health risk of fall accident will probably lead to various psychological problems like psychological fear of movement, worry about independent living [6], etc.

Unlike detecting normal activities in the daily life, fall detecting in the real-world abnormal activity monitoring, is the computational challenging and imbalance learning problem, because, (1) although it aims to truly detecting the fall as much as possible in order to timely receive first aid, the occurrence of false-alarm will be too many times to let the people use conveniently; (2) in most cases, the abnormal activity such as the fall data is extremely scarce and very difficult to get in the real-world, the built classifier is biased towards such major classes of normal activities with large amount of samples; (3) to some extent, it will significantly trouble the people's regular behaviors if the detecting method is employed as a intrusive way.

Therefore, how to build the classifier for achieving high detection rate and low false-alarm rate simultaneously, has become a key challenging issue for imbalance learning in large-scale wearable computing applications. Accordingly, on one hand, considering the recognition model is trained with high accuracy, the alarm for fall detection should keep low rate, then this way

* Corresponding author.
E-mail address: chenzhenyu@ict.ac.cn (Z. Chen).

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will not trouble the people's normal lives. On the other hand, in terms of extremely rare data of the fall activity and resource-constrained wearable device, there is an imbalance learning problem which even requests a light-weight algorithm running on miniaturized wearable device. In this paper, our main contributions are as follows: (1) The two-stage method is effective to achieve high detection accuracy and low false-alarm rate simultaneously, we recall suspected fall cases as much as possible in the first stage and refine the detection result in the second stage; (2) due to the biased class of fall in both recall stage and refining stage, respectively, we present adaptive weighted method based imbalance learning to adopt different weights in different stages; (3) considering good properties of fast computation speed and generalization ability, we employ two-stage adaptive weighted extreme learning machine (AWELM) method to implement on resource-constrained eyeglass and watch based wearable devices.

The rest of this paper is structured as follows: First, we mainly introduce different types of related work for fall detection in Section 2. Secondly, we detail the design and learning steps of our proposed two-stage adaptive weighted extreme learning machine for imbalance learning in Section 3. Following this, we present the experimental evaluations and analyze the comparison results in Section 4. Finally, we state some concluding remarks in Section 5.

2. Related work

In this section, state-of-the-art fall detection approaches can be categorized into two main paradigms: (i) vision based method, and (ii) wearable sensor based method.

2.1. Computer vision based method

Nait-Charif and McKenna [7] deploy several panoramic cameras on the roof and determine a fall occurs when the human body lies down in the inappropriate position for too long time, but since the camera is usually installed in fixed locations and the human body is an ambulatory, it is difficult to ensure this method's versatility. Töreyin et al. [8] exploit the wavelet parameters of the ratio of height and width as features, and differentiate walk and fall by exploring HMM (hidden Markov model). In order to improve the detection accuracy, they also employ HMM for analyzing the corresponding audio signals, and recognize the fall by the detection results through fusion of video and audio. Some vision based methods [9–11] are effectively designed for video annotation or video concept detection. However, computer vision based method is often utilized to continuously monitor in an intrusive way, because videos are sensitive to the lighting magnitude and limited to the covering area of the camera capture. Accordingly, the captured images easily introduce the mistake due to confused scene of multiple objects appeared in current view, further the vision way suffers from serious privacy issue additionally.

2.2. Wearable sensor based method

In most cases, wearable sensor based method like accelerometer-based method is suitable for fall detection. Purwar et al. [12] present that the method by calculating the angle between the vertical axes in the triaxial accelerometer sensor can remove error detection for the fall. Anania et al. [13] design a Kalman filter to separate the signal component between the gravity and the acceleration, based on the placed accelerometer over the higher part of the subject's trunk, the proposed approach can detect critical trunk inclination in correspondence of a high trunk rotational velocity. Shi et al. [14] 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. [15] 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 recognize a less number of normal activities but focuses on abnormal activity in the transition section.

Furthermore, fusion method cannot avoid false detection, but can provide more reliable and robust method by fusion with accelerometer and other sensors. Moreover, it cannot guarantee better results by simply adding some sensors. Narayanan et al. [16] invent a waist-mounted rechargeable triaxial accelerometer-based device to detect and prevention the elderly's falling, the system is not only a detector, but also supply the elderly with self-test for risk assessment of the falling. Grassi et al. [17] put forward the high-reliability fall detection framework, which uses three sensors: (i) 3D time-of-flight range camera; (ii) wearable Zigbee MEMS accelerometer; and (iii) microphone. These three sensors are connected with a central PC by the customized interface, and the data is processed in the PC terminal. 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 then. Dinh et al. [18] add a circuit for heart-rate detection, which can detect whether the patient is occupied himself in an anxious manner.

2.3. Comparison and discussion

From the abovementioned fall detection approaches, we can obviously find that, the computer vision based method is easily influenced by environmental situation and also has remarkable shortcomings in terms of privacy issue. In contrast, the wearable sensor based method is a unobtrusive way to monitor the user's behaviors in the daily life, such as Google Glass in the popular application of wearable computing. However, in the field of wearable computing with application to fall detection, existing approaches have to face with several aspects of challenges as follows. The first problem is to balance the high detection rate and low false-alarm rate, because if the recognition model is trained with high accuracy but the alarm for fall detection often happens falsely, which will seriously interrupt the people's regular livings and behaviors. The second one is imbalance learning problem due to extremely rare data of the fall activity, which results from the difficulty of acquiring enough samples. The last is the solution to apply a light-weight learning algorithm on resource-constrained wearable device, which can be non-invasive to conveniently monitor the people's regular behaviors in the daily life.

3. Our methodology

The framework of our proposed method is shown in Fig. 1, which mainly consists of two stages.

(1) *The first stage*: Based on the acceleration magnitude series generated from wearable eyeglass device, we collect accelerometer samples and extract feature data continuously, then the weighted ELM classifier [19] is built to recall suspected fall accidents as much as possible. In the first stage, compared to other normal activities, due to extremely scarce sensor data in the realistic application, the fall activity obviously belongs to the class of a small quantity of samples but the classification result is usually

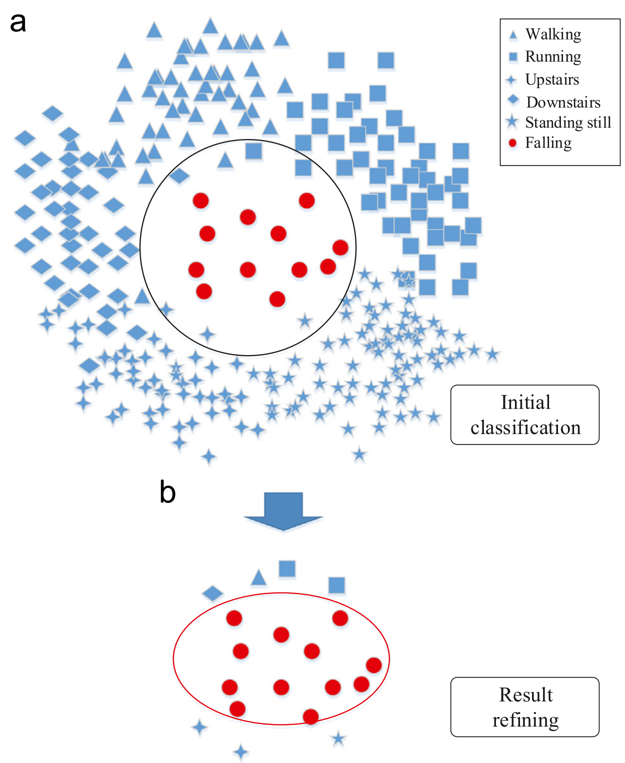

Fig. 1. The two-stage recognition approach for fall detecting and monitoring. (a) Weighted ELM classifier in the first stage. (b) Weighted ELM classifier in the second stage.

biased towards the class of a large number of samples. Thus we need to use the suitable weight imposed on the classification function, and recall suspected fall accidents as much as possible in order to completely include all fall samples. On the other hand, in terms of the arbitrary and false actions from wearable watch device, to some extent, it will make the decision difficulty from the built classifier and make the noisy to the training sensor data, thus in the first stage we adopt the result of suspected fall action from eyeglass sensor to trigger the refining of second stage. While running on wearable watch device, another weighted ELM classifier keeps detecting suspected fall activity, and is utilized for result refining as the input of next stage if the trigger happens from wearable eyeglass device.

(2) *The second stage*: When the suspected fall action occurs, and wearable eyeglass device is detected as the fall activity, the feature data from eyeglass device will be transmitted to the connected smartphone via bluetooth. At the same time, in case when the suspected fall is detected on eyeglass, 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 fusion features will be further refined through another weighted extreme learning machine classifier again. In the second stage, with the weight function in the first stage, the fall activity is considered towards the class with a large amount of sensor data, compared to other normal activities. Therefore, derived from the high recall rate from the first stage, we refine the recognition result with the high precision rate then.

3.1. Brief of ELM

Extreme learning machine (ELM) [20–23] is originally proposed for single hidden layer feedforward network (SLFN) with the purpose of solving both classification and regression problems

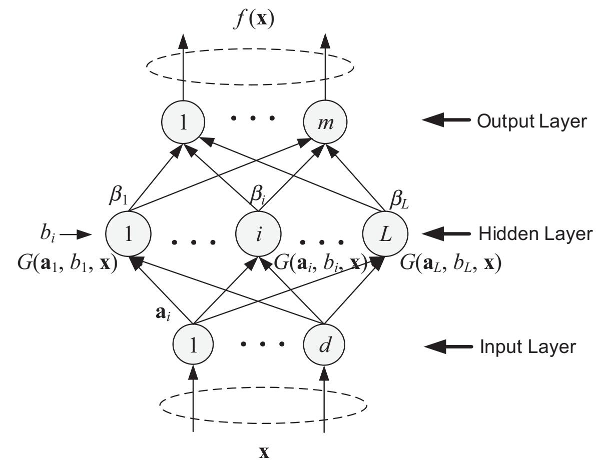

Fig. 2. The network structure of ELM.

[24–27]. Only the classification problem is considered in this paper. We briefly review the structure of SLFN below.

The structure of SLFN (Fig. 2) consists of three layers: the input layer, the hidden layer and the output layer. All the input nodes correspond to instance's d-dimensional features ($\boldsymbol{x} \in \mathbf{R}^d, \boldsymbol{x} = (x_1, \ldots, x_d)^T$). The inputs are weighted and then processed by the activation function $g(\boldsymbol{x})$ in the hidden layer. After that, the d-dimensional vector x is mapped into a L-dimensional vector $(G(\boldsymbol{a}_1, b_1, \boldsymbol{x}), \ldots, G(\boldsymbol{a}_L, b_L, \boldsymbol{x}))^T$. $G(\boldsymbol{a}_i, b_i, \boldsymbol{x})$ is the output of the i-th additive hidden node and is given by Eq. (1). In the end, a m-dimensional vector of outputs $\boldsymbol{f}(\boldsymbol{x})$ is attained by a linear transformation on the L-dimensional vector (Eq. (2)). m output nodes correspond to m classes:

$$G(\boldsymbol{a}_i, b_i, \boldsymbol{x}) = g(\boldsymbol{a}_i \cdot \boldsymbol{x} + b_i), \quad \boldsymbol{a}_i \in \mathbf{R}^d, \ b_i \in \mathbf{R} \tag{1}$$

$$\boldsymbol{f}(\boldsymbol{x}) = \sum_{i=1}^{L} \boldsymbol{\beta}_i G(\boldsymbol{a}_i, b_i, \boldsymbol{x}), \quad \boldsymbol{\beta}_i \in \mathbf{R}^m \tag{2}$$

The learning algorithm of ELM utilizes a finite set of labeled instances for training: $\{(\boldsymbol{x}_j, \boldsymbol{t}_j) | \boldsymbol{x}_j \in \mathbf{R}^d, \boldsymbol{t}_j \in \mathbf{R}^m, j = 1, \ldots, N\}$. $\boldsymbol{x}_j$ and $\boldsymbol{t}_j$ are the input and output vectors, respectively (see Fig. 2). For each instance $\boldsymbol{x}_j$, only a single element in the corresponding $\boldsymbol{t}_j$ is "1" representing the label of $\boldsymbol{x}_j$, and all others are "-1". Parameters $(\boldsymbol{a}_i, b_i, i = 1, \ldots, L)$ in the hidden layer are randomly determined, and parameters $(\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_L)$ between the hidden layer and the output layer are calculated by

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{T} \tag{3}$$

where

$$\mathbf{H} = \begin{bmatrix} G(\boldsymbol{a}_1, b_1, \boldsymbol{x}_1) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_1) \\ \vdots & \ddots & \vdots \\ G(\boldsymbol{a}_1, b_1, \boldsymbol{x}_N) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_N) \end{bmatrix}_{N \times L} = [\boldsymbol{h}(\boldsymbol{x}_1), \ldots, \boldsymbol{h}(\boldsymbol{x}_N)]^T_{N \times L},$$

$$\boldsymbol{h}(\boldsymbol{x}) = \begin{bmatrix} G(\boldsymbol{a}_1, b_1, \boldsymbol{x}) \\ \vdots \\ G(\boldsymbol{a}_L, b_L, \boldsymbol{x}) \end{bmatrix}_{L \times 1}, \quad \boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1^T \\ \vdots \\ \boldsymbol{\beta}_L^T \end{bmatrix}_{L \times m}, \quad \mathbf{T} = \begin{bmatrix} \boldsymbol{t}_1^T \\ \vdots \\ \boldsymbol{t}_N^T \end{bmatrix}_{N \times m}.$$

The least square solution with minimal norm $\boldsymbol{\beta}^*$ is analytically determined using Moore–Penrose "generalized" inverse:

$$\boldsymbol{\beta}^* = \mathbf{H}^{\dagger}\mathbf{T} \tag{4}$$

The output function of ELM is $\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{\beta}^{*T}\boldsymbol{h}(\boldsymbol{x})$.

3.2. COELM classifier

Constrained-optimization-based extreme learning machine (COELM) [28] is proposed with the purpose of extending ELM with

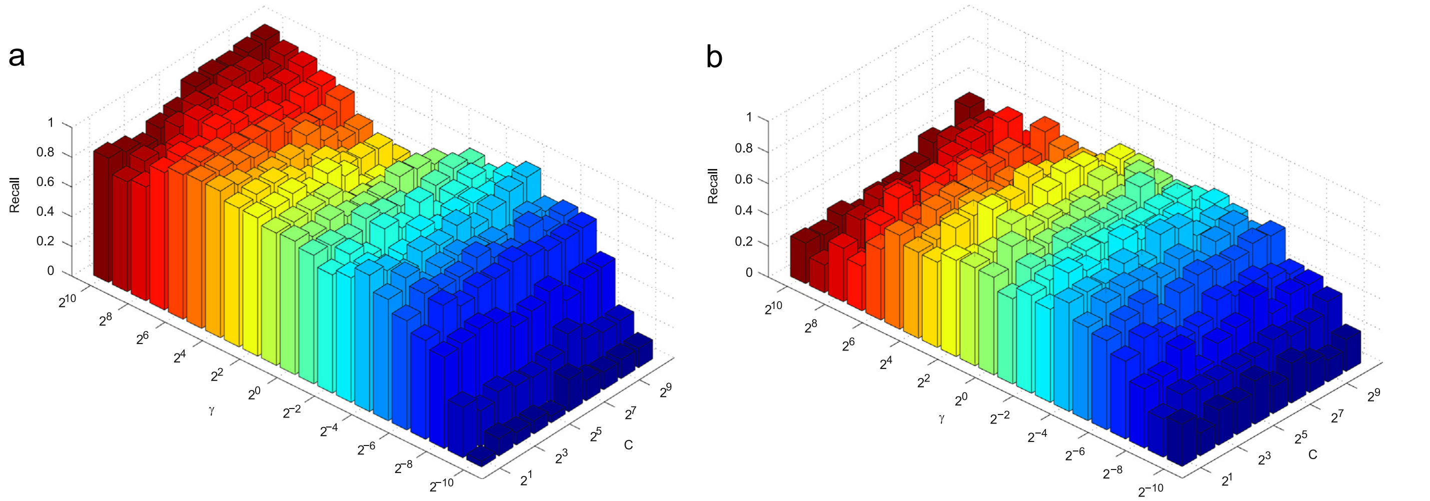

Fig. 3. The optimal parameter selection of ELM classifier in the first stage. (a) Eyeglass. (b) Watch.

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

Data source	Optimal parameter	Value	Index
Eyeglass	C	16	4
	γ	128	18
Watch	C	8	3
	γ	4	13

kernel learning. The classification problem of COELM is formulated as

$$\min_{\beta,\xi} \ \frac{1}{2}\|\boldsymbol{\beta}\|^2+\frac{C}{2}\sum_{i=1}^{N}\|\boldsymbol{\xi}_i\|^2$$
$$\text{s.t.} \quad \boldsymbol{h}(\boldsymbol{x}_i)\cdot\boldsymbol{\beta}=\boldsymbol{t}_i-\boldsymbol{\xi}_i, \quad i=1,\dots,N \tag{5}$$

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

$$\boldsymbol{\beta}^*=\begin{cases}\mathbf{H}^T\left(\dfrac{\mathbf{I}}{C}+\mathbf{H}\mathbf{H}^T\right)^{-1}\mathbf{T}, & N<L\\ \left(\dfrac{\mathbf{I}}{C}+\mathbf{H}^T\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{T}, & N>L\end{cases} \tag{6}$$

3.3. Weighted ELM classifier

Based on the COELM in Section 3.2, weighted extreme learning machine (WELM) [19] is proposed with the purpose of extending ELM with imbalance learning. The classification problem of WELM is formulated as

$$\min \quad L_{P_{\mathrm{ELM}}}=\frac{1}{2}\|\boldsymbol{\beta}\|^2+C\mathbf{W}\frac{1}{2}\sum_{i=1}^{N}\|\boldsymbol{\xi}_i\|^2$$
$$\text{s.t.} \quad \boldsymbol{h}(\boldsymbol{x}_i)\cdot\boldsymbol{\beta}=\boldsymbol{t}_i^T-\boldsymbol{\xi}_i^T, \quad i=1,\dots,N \tag{7}$$

Similarly, the solution of problem above is also determined as

$$\boldsymbol{\beta}=\begin{cases}\mathbf{H}^T\left(\dfrac{\mathbf{I}}{C}+\mathbf{W}\mathbf{H}\mathbf{H}^T\right)^{-1}\mathbf{W}\mathbf{T} & \text{when } N \text{ is small}\\ \left(\dfrac{\mathbf{I}}{C}+\mathbf{H}^T\mathbf{W}\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{W}\mathbf{T} & \text{when } N \text{ is large}\end{cases} \tag{8}$$

In [19], they 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:

$$\mathbf{W}1: \mathrm{W}_{\mathrm{ii}}=1/\#(t_i) \tag{9}$$

Then, for our two-stage recognition scheme, we adopt the weighting scheme $\mathbf{W}2$ [19] to learn with different weights for two stages adaptively as

$$\mathbf{W}2: \mathrm{W}_{\mathrm{ii}}=\begin{cases}0.618/\#(t_i), & t_i>AVG(t_i)\\ 1/\#(t_i) & \text{otherwise}\end{cases} \tag{10}$$

4. Evaluation

In the data collection, our study population contains 1 female and 6 males ranging from 23 to 29 years old. All subjects are graduate students and study in computer science. Each participant carries a smartphone and wears an eyeglass device during the data collection, and collects six kinds of activities, including the falling, standing still, walking, running, downstairs and upstairs. Here, the standing still is usually collected about 15 s, other kinds of activities (i.e. walking, running, downstairs and upstairs) are collected for 2–3 min, respectively. Specifically, the falling activity consists of front, back, left and right-toward falls. The duration of fall activity is about 2.6 s on average, and each participant is required to lie immediately before and after the fall activity, also keep still for 5 s.

4.1. Feature extraction

Based on accelerometer readings from wearable eyeglass and watch devices, extracted features are maximum, minimum, mean, standard deviation, energy, zero crossing rate, four amplitude statistics features and four shape statistics features of the power spectral density. Here, the length of windows is 13, and the sampling rate is 10 Hz. For each wearable device, 14 input features are extracted without overlapping between consecutive windows, then totally 28 input features are extracted for the imbalance learning. Moreover, in terms of large ranges of value domain for extracted features, all these features are normalized using the z-score normalization algorithm to eliminate the scaling effects among diverse features [29].

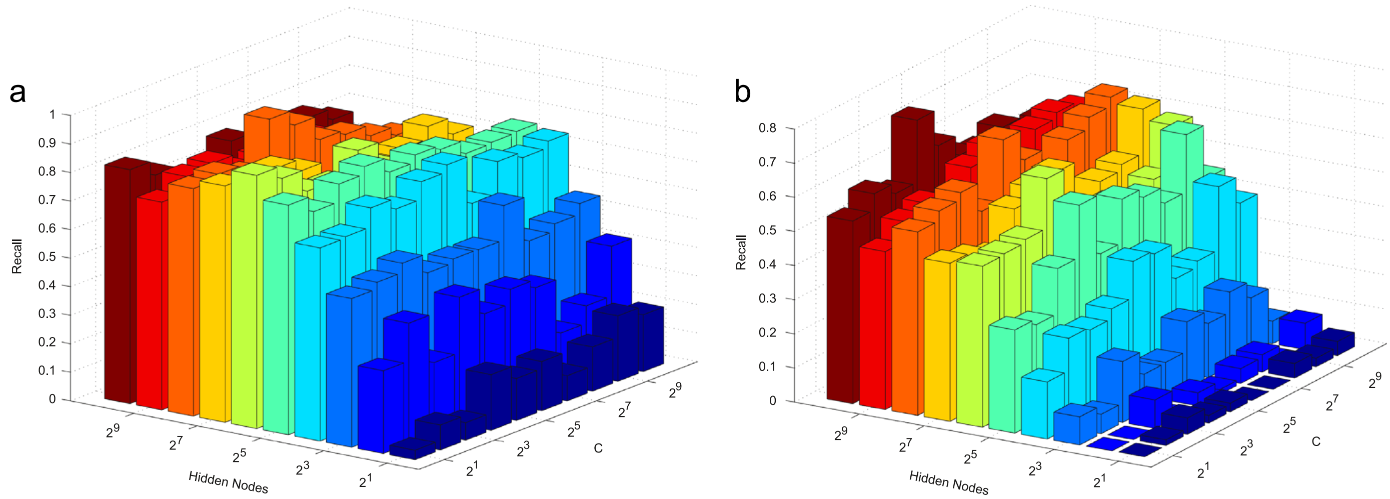

Fig. 4. The optimal parameter selection of weighted ELM classifier in the first stage. (a) Eyeglass. (b) Watch.

4.2. Evaluation metrics

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

$$Precision = \frac{\sharp\ of\ true\ positive}{\sharp\ of\ true\ positive + \sharp\ of\ false\ positive} \tag{11}$$

$$Recall = \frac{\sharp\ of\ true\ positive}{\sharp\ of\ true\ positive + \sharp\ of\ false\ negative} \tag{12}$$

As for the evaluation metrics above, considering our two-stage scheme about the precision and the recall, in the first-stage of suspected fall detection, we adopt the classifier with high recall so as to reduce the number of missing fall detection, meanwhile we can enhance the precision in the second-stage of result refining.

4.3. Performance of first-stage

In this section, first of all, as we know in the field of fall detection, there is a classic problem of imbalance learning, so we naturally intend to improve the performance of ELM classifier by weighted scheme [19]. Then, considering the classifier performance through the precision rate and the recall rate, we firstly select the optimal parameter settings for two classifiers, i.e. ELM classifier and weighted ELM classifier, then evaluate two recognition classifiers' performances for one-stage ELM and one-stage weighted ELM.

Here, our experimental parameters are set by open source codes, and the online source codes of both ELM and weighted ELM classifiers can be downloaded from Professor G.-B. Huang's webpage.[1]

4.3.1. Parameter settings

In the first-stage of classifier training on both wearable eyeglass and watch devices, there are two parameters for ELM classifier, i.e. the regularization coefficient C and the kernel parameter γ, need to be determined on each wearable device. We utilize grid-search method to select the optimal parameter-pair from 210 pairs of parameters in Fig. 3, and this selection process employs 10-fold cross-validation method to determine the optimal parameter-pair in Table 1. We can see that the values of parameters obviously impact the recall of the ELM classifier over eyeglass and watch devices. Specifically, for the optimal parameters of eyeglass, the regularization coefficient C is set as 16 and the kernel parameter γ is set as 128, accordingly the indexes of these two optimal parameters are 4 and 18 in the grid number of Fig. 3(a), respectively. Also, for the optimal parameters of watch, the regularization coefficient C is set as 8 and the kernel parameter γ is set as 4, accordingly the indexes of these two optimal parameters are 3 and 13 in the grid number of Fig. 3(b), respectively.

Table 2
The optimal parameters of weighted ELM classifier for eyeglass and watch in the first stage, respectively.

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

Similarly, there are two parameters, i.e. the regularization coefficient C and the kernel parameter γ, which need to be determined for weighted ELM classifier. we employ grid-search method to select the optimal parameter-pair from 100 pairs of parameters in Fig. 4, and determine the optimal parameter-pair in Table 2. For the optimal parameters of eyeglass, the regularization coefficient C is set as 16 and the number of hidden nodes is set as 256, accordingly the indexes of these two optimal parameters are 4 and 8 in the grid number of Fig. 4(a), respectively. Also, for the optimal parameters of watch, the regularization coefficient C is set as 16 and the number of hidden nodes is set as 1024, accordingly the indexes of these two optimal parameters are 4 and 10 in the grid number of Fig. 4(b), respectively.

Obviously, for both ELM classifier and weighted ELM classifier, Figs. 3 and 4 show the recall changes according to varying parameters, we can see that the values of parameters greatly impact the recall of both eyeglass and watch devices. Compared with subfigures (a) and (b) in both Figs. 3 and 4, we can draw the observation that the eyeglass-based device is able to outperform the watch-based one on the recall rate.

4.3.2. Performance comparison

For the comparison of classifier performance, as shown in Fig. 5 we can find that, weighted ELM classifier has better classification performance than ELM classifier, accordingly weighted ELM classifier's recall rate is greater than ELM classifier. As aforementioned in Section 4.2, our two stage scheme needs to select a better

[1] http://www.extreme-learning-machines.org

classifier with higher recall than the other, because we aim to recall all suspected fall actions as much as possible. Thus, we can see from Fig. 5, we adopt weighted ELM classifier with better recall performance in the first stage.

On the other hand, in terms of performance of eyeglass and watch in Figs. 3 and 4, the recall of watch is significantly lower than eyeglass, because the activities of user wrist are more arbitrary and diverse in people's daily life and even some activities of wrist are vast scale and the feature possibly approximates to the activities of wrist for the fall action. Therefore, we choose the eyeglass as the monitoring device in the first stage and trigger to fuse the data of eyeglass and watch in the second stage.

4.4. Performance of second-stage

In this section, followed by the first stage, we recall all suspected fall activities as much as possible, so that the class of fall becomes towards the major class of a relative large number of samples as shown in Fig. 1 of Section 3. Accordingly, there is also an imbalance learning problem so that we utilize the ELM classifier with weighted scheme [19] again. Then, considering the classifier performance through the recall rate in the first stage, we improve the precision rate of recognition classifiers in the second stage. Firstly, we select the optimal parameter settings for two classifiers (ELM and weighted ELM classifiers), then we evaluate and comapre two recognition classifiers' performances for one-stage scheme and two-stage scheme of weighted ELM, and two-stage scheme of ELM and weighted ELM, respectively.

4.4.1. Parameter settings

Similar as optimal parameter selection in the first stage, accordingly there are two parameters, i.e. the regularization coefficient C and the kernel parameter γ for ELM classifier, and the regularization coefficient C and the number of hidden nodes for weighted ELM classifier, which need to be optimized and determined in the second stage as well. We utilize grid-search method to select optimal parameter-pairs (see Tables 3 and 4) from 210 pairs and 100 pairs of parameters for ELM classifier and weighted ELM classifier, respectively, and this selection process employs 10-fold cross-validation method to get the optimal parameters shown in Figs. 6 and 7 for both ELM classifier and weighted ELM classifier. We can see that the values of parameters obviously impact the precision of two classifiers, and the optimal parameters, the regularization coefficient C, the kernel parameter γ, the number of hidden nodes and the indexes of these two optimal parameters are illustrated in Tables 3 and 4 for both eyeglass and eyeglass–watch devices.

4.4.2. Performance comparison

On one hand, in order to evaluate the effectiveness of two-stage scheme in the field of wearable device based fall detection, we compare the recognition performance between one-stage WELM method and two-stage WELM method together. Fig. 8 demonstrates the performances of two-stage detection method, including the precision rate and the recall rate for the first stage about initial fall detection and the second stage for result refining. The initial fall detection indicates the suspected fall activities are detected through the WELM classifier over eyeglass device. Then, when the initial detection result is truly determined via WELM, and the detecting result by the classifier in the first stage is utilized as the input to the second-stage detection. From the results of Fig. 8, we can conclude that our proposed two-stage adaptive weighted ELM (AWELM) approach enhances the high detection accuracy (recall rate is slightly improved from 93.23% to 93.67%) from the first-stage of initial fall detection, and also increasingly improves the precision from 87.50% to 95.74% in the second-stage of result refining, which shows that the false-alarm rate is lower than 5%. Thus, our proposed method can achieve high detection accuracy and low false-alarm rate simultaneously.

On the other hand, to evaluate the effectiveness of imbalance learning, we present classifier performance of one-stage ELM and WELM in Section 4.3, further considering two-stage scheme and imbalance learning together, we illustrate the comparison of different two-stage recognition methods, i.e. two-stage ELM and two-stage weighted ELM. As can be seen from Fig. 9, based on the function of imbalance learning, two-stage weighted ELM outperforms two-stage ELM for both the precision and the recall. Furthermore, as for one-stage method of Fig. 5 and two-stage method of Fig. 9, compared with both precision and recall, we can see that not only ELM classifier but also weighted ELM classifier, the two-stage method has better recognition accuracy than the one-stage method, respectively. Especially for weighted ELM classifier, the recall rate keeps the same performance from the first stage to the second stage, and the precision rate enhances obviously, which shows the advantage of two-stage method and also balances the goal of high detection accuracy and low false-alarm rate at the same time.

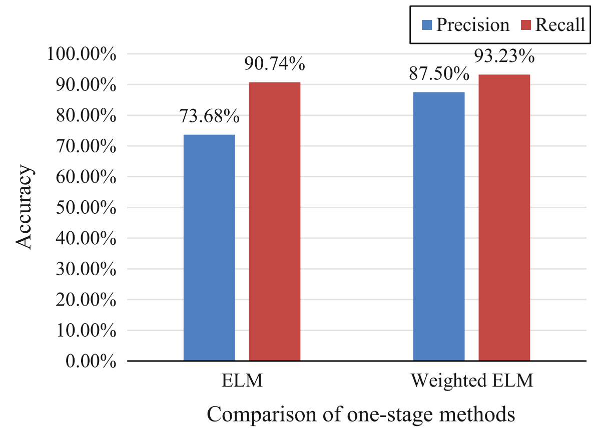

Fig. 5. The one-stage comparison of precision and recall for ELM and weighted ELM running on wearable eyeglass device.

Table 3
The optimal parameters of ELM classifier for eyeglass and eyeglass–watch features in the second stage.

Data source	Optimal parameter	Value	Index
Eyeglass	C	32	5
	γ	0.0078	4
Eyeglass-watch	C	8	3
	γ	0.002	2

Table 4
The optimal parameters of weighted ELM classifier for eyeglass and eyeglass–watch features in the second stage.

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

5. Conclusion

In this paper, we propose a two-stage adaptive weighted ELM (AWELM) approach for eyeglass and watch wearables based fall

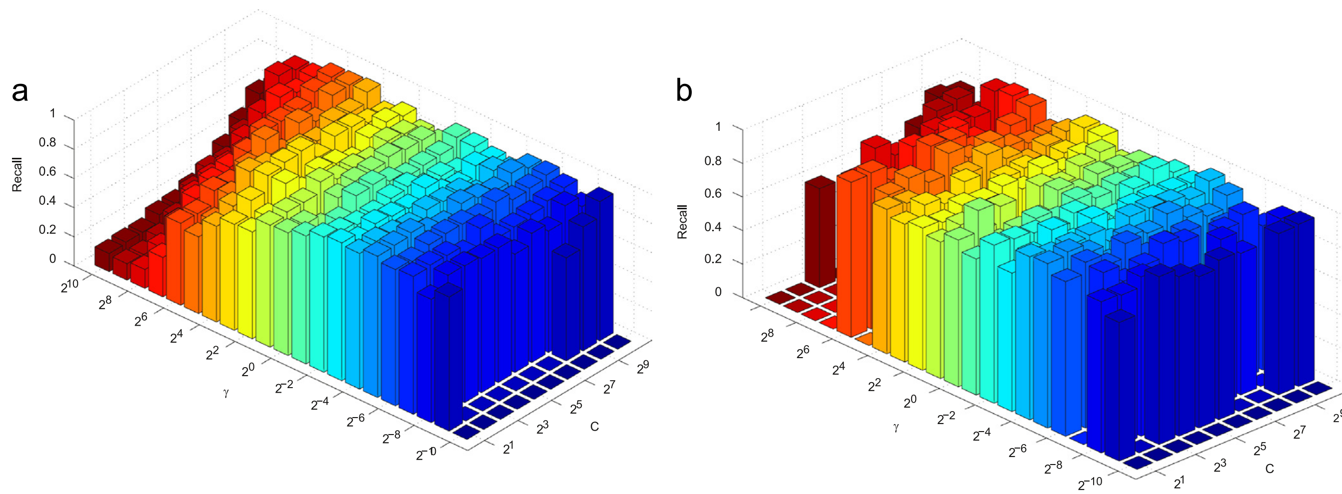

Fig. 6. The optimal parameter selection of ELM classifier in the second stage. (a) Eyeglass. (b) Eyeglass–watch.

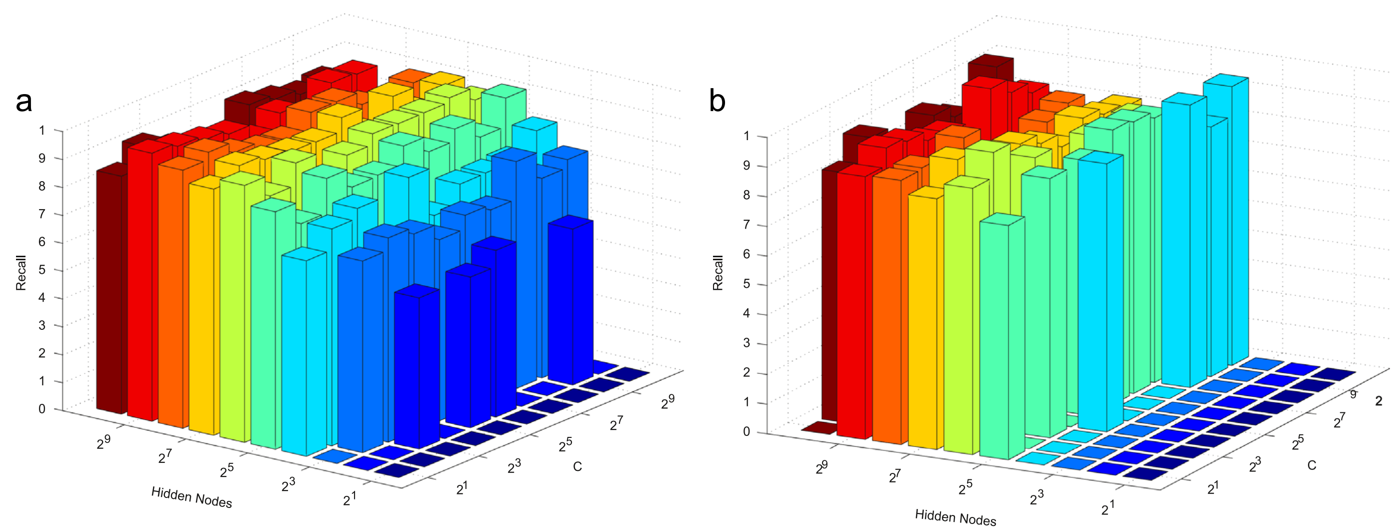

Fig. 7. The optimal parameter selection of weighted ELM classifier in the second stage. (a) Eyeglass. (b) Eyeglass–watch.

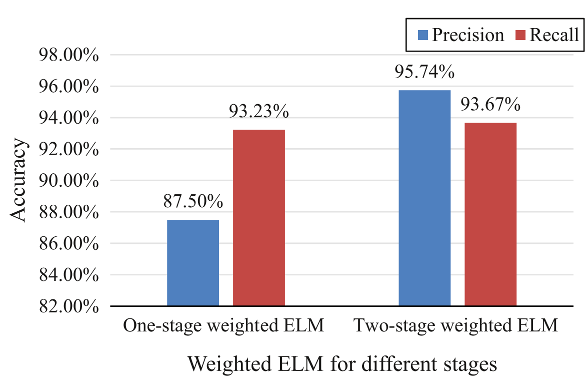

Fig. 8. The performance comparison of precision and recall for different stages of weighted ELM methods.

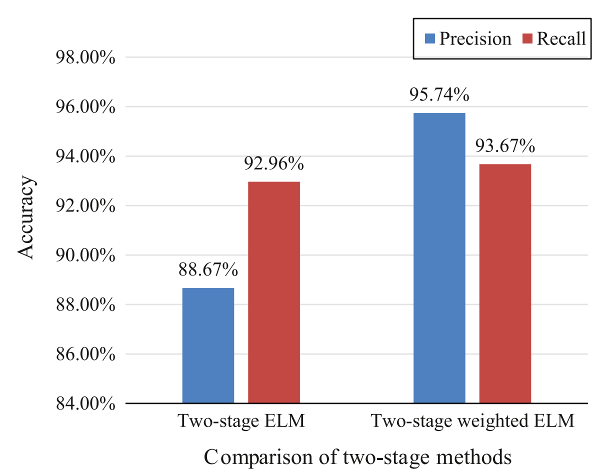

Fig. 9. The performance comparison of precision and recall for two-stage scheme between ELM classifier and WELM classifier.

detection. In particular, we explore the initial WELM classifier to detect the suspected fall in the first stage, then in the second-stage WELM classifier is employed to refine the former detection result. From our preliminary study, we can conclude that our proposed two-stage AWELM method is effective for imbalance learning problem, and is efficient for wearable device with resource constraint computation, also is able to detect the fall with high detection accuracy and low false-alarm rate simultaneously. Our encouraging results contribute towards the on-going development of mHealth technology, which enables large-scale mHealth applications, and especially helps the elderly people to greatly reduce the risk of fall accidents.

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Xingyu Gao is a Ph.D. candidate of Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China. His research interests focus on machine learning, multimedia information retrieval, and ubiquitous computing.

Zhenyu Chen received his Ph.D. degree in computer application technology at Institute of Computing Technology, Chinese Academy of Sciences (ICT-CAS), China, in 2015. His current research interests include pervasive computing, wearable computing, mobile sensing, data mining.

Sheng Tang received his Ph.D. degree in computer application technology at Institute of Computing Technology, Chinese Academy of Sciences (ICT-CAS), China, in 2006. He is now an associate professor in the ICT-CAS. He visited National University of Singapore (NUS) for participating in TREC Video Retrieval Evaluation (TRECVid) tasks in 2006. From 2006 to 2008, he was TRECVid team (MCG-ICTCAS) leader of the Multimedia Computing Group at ICT-CAS. From Feb., 2009 to Feb., 2010, he worked as a visiting research fellow in NUS under the instruction of Prof. Chua Tat-Seng. His current research interests are in the fields of pattern recognition and content-based multimedia retrieval and indexing. He served as the reviewer for Journal of Visual Communication and Image Representation, Neurocomputing, Multimedia Tools and Applications, Journal of Computer Science and Technology, etc.

Yongdong Zhang received the Ph.D. degree in electronic engineering from Tianjin University, Tianjin, China, in 2002. He is currently a professor with the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China. His current research interests are in the fields of multimedia content analysis and understanding, multimedia content security, video encoding, and streaming media technology. He has authored over 100 refereed journal and conference papers. He was a recipient of the Best Paper Awards in PCM 2013, ICIMCS 2013, and ICME 2010, and the Best Paper Candidate in ICME 2011. He serves as an Editorial Board Member of Multimedia Systems Journal and Neurocomputing.

Jintao Li received the Ph.D. degree from the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China, in 1989. He is currently a professor with the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China. His research interests focus on multimedia technology, virtual reality technology, and pervasive computing.