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PHYSICAL ACTIVITY RECOGNITION BASED ON TIME WINDOW SELECTION AND ONLINE SEQUENTIAL ELM

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Abstract. *Physical activity recognition in daily life plays an important role in healthcare and fostering healthy lifestyle. This paper is devoted to using the data from wearable sensors to recognize physical activities accurately. Time window segmentation is an essential stage in the process of physical activity recognition, but no clear consensus exists on which window size should be preferably employed. The autocorrelation function divides the physical activities into quasi-periodic and non-periodic, and we propose time window selection which adopts adaptive time window and fixed time window for quasi-periodic and non-periodic activities respectively. Adaptive time window size is determined by a period extraction algorithm based on autocorrelation function (ACF) and cepstrum (CEP). Furthermore, in this paper, an activity classifier based on online sequential extreme learning machine (OS-ELM) is presented, and used to recognize falling down, running, upstairs, lying, downstairs, walking, standing and sitting, and the experiment results are encouraging for physical activity recognition.*
Keywords: Physical activity recognition, Wearable sensors, Autocorrelation function (ACF), Cepstrum (CEP), Time window selection, Online sequential ELM

1. **Introduction.** According to the World Health Organization, there will be 1.2 billion people aged 60 or above by 2025 and 2 billion by 2050 [1], the ageing issues cannot be ignored. In addition, high-risk diseases tend to be younger and sub-health has become a major factor affecting people's health and quality of life, health care plays an increasingly important role in modern life. Physical activities contain a wealth of information that can reflect physical condition and movement, the information is closely related to health, and physical activity recognition plays an important role in health care.

Now the use of wireless sensor network in health care is mainly in two ways at home and abroad. On the one hand, wireless sensors can be arranged in external environment. People in [2] arranged different types of sensors in household devices to assess the status in daily activities of older people and analyze the wellness of the elderly. However, using a large number of sensors in external environment costs a lot and the equipment maintenance is difficult. Hence, wearable sensor network is presented. The wearable sensor is easy to use and convenient to bring and has a reduced form. For instance, 9-DOF inertial motion unit was tied on the wrist to recognize eleven kinds of arms-related activities using linear discriminant analysis [3]. Various types of sensors were placed on the limbs and back to monitor the posture and gait of Parkinson's sufferers and assess their physical condition [4].

The size of time window determines how much data is used to extract features each time. Small time window size cannot describe the activity fully and simple physical activities in daily life need not large time-window size [5]. However, in many researches, the impact of time window size on recognition accuracy is ignored, and they place more focus on extracting features to improve the recognition accuracy.

Many learning algorithms have been used in human daily activity recognition and classification. In [6], support vector machine (SVM) was used to distinguish walking and falling down, and the recognition precision was above 85%. People in [7] used cell phone accelerometers to recognize activities including walking, jogging, climbing-up stairs, climbing-down stairs, sitting, and standing, and decision trees (J48), logistic regression and multilayer neural networks have been used to recognize these activities respectively, but the result showed that climbing-up and climbing-down stairs were difficult to recognize, so they combined ascending stairs and descending stairs into one activity and used decision trees to recognize these 5 activities and the average precision was 91.06%. In [8], hidden markov model (HMM) was used to recognize activities including standing, sitting, walking and running, etc. And the experimental results on 6 subjects achieved an average accuracy of 96.7%. We used BP neural networks to recognize four activities including standing, sitting, waling, and falling down, and the average correct rate was 98.5% [9]. However, above algorithms all adopt batching learning to train the network, which is time-consuming and the network weights cannot be updated online.

In this paper, we propose time window selection which adopts adaptive time window and fixed time window for different activities. Furthermore, motivated by online sequential ELM [10], we present a classifier based on OS-ELM algorithm. The training data of activity data can be input to the network chunk-by-chunk or one-by-one, and in the process of training network, network weights are updated based on the current input data.

The paper is structured as follows. We first describe the proposed method in this paper and then present the results of recognition of activities and discussion. Finally, the last part concludes the paper.

2. **Proposed Method.** The wearable sensor system for recognition of physical activities is composed of a tri-axial accelerometer and two pressure sensors, a coordinator and a personal computer (PC). The tri-axial accelerometer is placed on the waist and the pressure sensors are placed under the insoles respectively. Each sensor is connected with a wireless transceiver module. The data from sensors is sent to the coordinator via a wireless

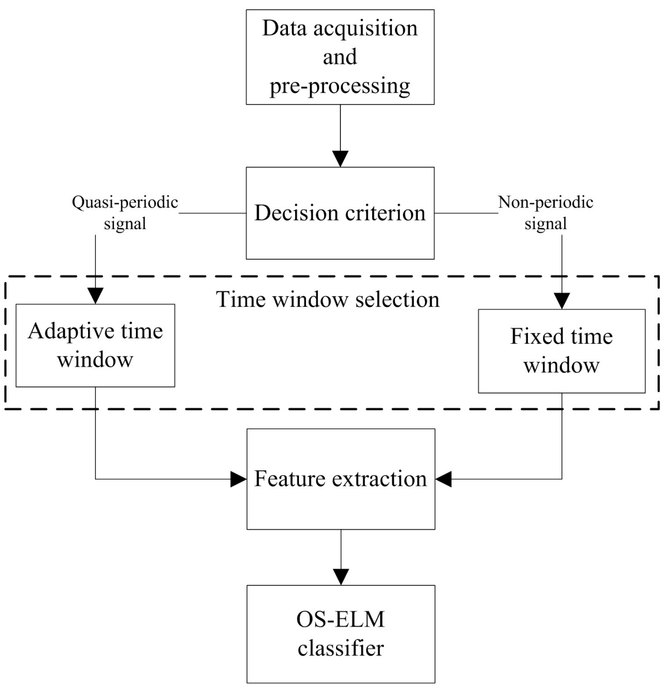

Figure 1. Flowchart for physical activity recognition

connection, and then the coordinator sends the data to PC via a wired connection, the data is then processed in the PC.

2.1. **Data acquisition and pre-processing.** The wearable sensor system records acceleration and pressure data. The acceleration data contains x-axis, y-axis and z-axis acceleration, and the pressure data includes forefoot and heel pressure. Therefore, each group signal contains seven kinds of data. We can get the output voltage in (1), and then turn output voltage into pressure and acceleration according to Formulas (2) and (3) respectively.

$$v = \frac{x}{X} \times V_+ \tag{1}$$

$$p = \exp((v + 1.1569) \div 0.6522) \tag{2}$$

$$a = \frac{v - v_0}{\rho} \tag{3}$$

where variable x represents activity data, parameter $X = 127$, $V_+ = 33$mv, v_0 equals 1.7mv, 2.3mv, 1.7mv respectively for x, y, z axis, and $\rho = 800$mv/g.

2.2. **Decision criterion.** By analyzing the sensor data of different activities, physical activities involved in this paper can be divided into quasi-periodic and non-periodic, and the method we present here is autocorrelation function. Activity data is first segmented into several windows, each window contains the same number of simples m, and the length of each window should be not less than 1s as the stride frequency of a person is usually 60 steps in 1 minute [5].

$$R(k) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(n)x(n+k) \tag{4}$$

The variable $\max R(k)/R(0)$ of different activities in the window $N_1, N_2, N_3, \ldots, N_n$, $n = length(N)/m$ are shown in Figure 2, and then we present the decision criterion.

For non-periodic activity:

$$\max R(k) >= 90\% R(0) \tag{5}$$

For quasi-periodic activity:

$$\max R(k) < 90\% R(0) \tag{6}$$

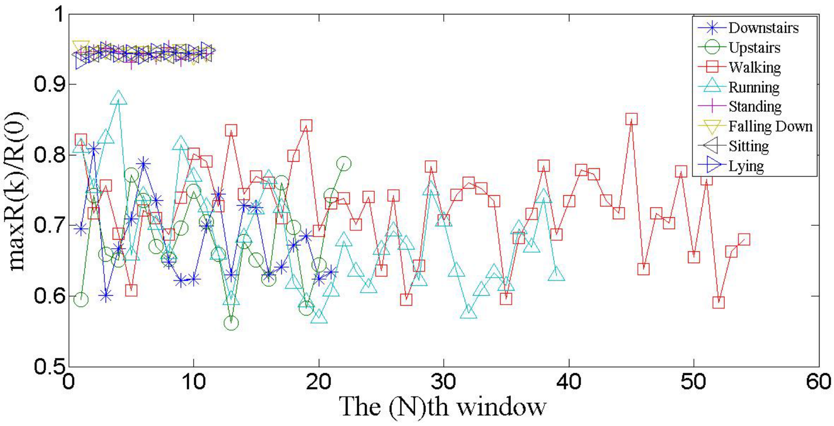

FIGURE 2. The variable $\max R(k)/R(0)$ of different activities in the N_ith window

2.3. **Time window selection.** As shown in Figure 3, the impact of time window size on non-periodic activity is little, so we choose a fixed time window for them. However, for quasi-periodic activity, in order to describe the activity adequately, we choose adaptive time window. The window size is determined by its period, and the period extraction algorithm is based on ACF and CEP.

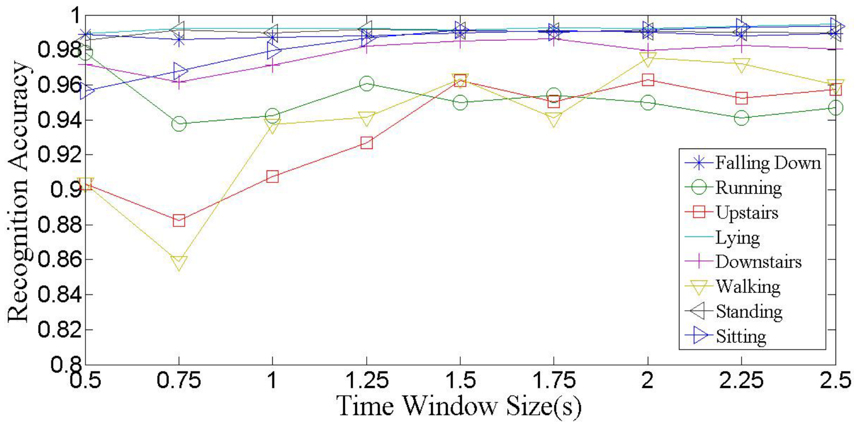

FIGURE 3. The impact of time window size on different activities

As a common method of the time domain analysis, ACF can be used to detect the similarity of signal in time domain and determine the period of signal by detecting the peak value of autocorrelation function [11]. For periodic signal, the autocorrelation function is defined as follows.

If the period of $x(n)$ is T, and $x(n) = x(n+T)$, so

$$\begin{aligned} R(k+T) &= \lim_{N\to\infty} \tfrac{1}{2N+1} \sum_{n=-N}^{N} x(n)x(n+k+T) \\ &= \lim_{N\to\infty} \tfrac{1}{2N+1} \sum_{n=-N}^{N} x(n)x(n+k) \\ &= R(k) \end{aligned} \tag{7}$$

Thus it can be seen that the autocorrelation function $R(k)$ has the same period with $x(n)$ and we can get the period of the signal by the period of its autocorrelation function.

CEP is a traditional method to extract period, which makes use of the spectral characteristics of signals [12]. The cepstrum can extract the spectrum envelop, and the peak value will appear at the period point of signal, so the period can be determined by detecting position of the peak value. It can be defined as

$$C(n) = IDFT(\ln(|DFT(x(n))|)) \tag{8}$$

In this paper, we propose a period extraction algorithm based on ACF and CEP, the position of first peak value is defined as period of signal and it can be defined as

$$RC(k) = [a \times C(k) + \alpha] \times [b \times R(k) + \beta] \tag{9}$$

where variables $RC(k)$ represents weighted ACF and CEP, $C(k)$ and $R(k)$ represent CEP and ACF respectively, in order to get appropriate amplitude, variable $a \in [1, 10]$, α should not be too big, and b and β should be less than 1.

Before extracting period, we first adopt non-linear processing for the signal. Non-linear processing is defined as:

$$x'(n) = \begin{cases} [\gamma \times x(n)]^2 & x(n) > 0 \\ -[\gamma \times x(n)]^2 & x(n) \le 0 \end{cases} \tag{10}$$

where variable γ should be small as the amplitude of activity signals is big, and $\gamma = 0.003$ in this paper.

2.4. **Feature extraction.** Before the sensor data is input to classifier, we extract features from the sensor data as characteristics of different activities are not obvious. A total of 25 features are extracted from each window, consisting of mean, the standard deviation (STD), the angle between tri-axial accelerometer and axes [13], energy [14], norm [15], root mean square (RMS) and the max value. These features are usually extracted from the tri-axial acceleration data and pressure data.

2.5. **OS-ELM classifier.** OS-ELM is improved on the basis of the ELM [16], and it adopts online learning mode, the training data is input to the network to learn in the form of chunk-by-chunk or one-by-one [10], and the input weights and biases of hidden nodes are randomly generated and the output weights are analytically determined. Thus online learning model is more suitable for large data sets and real-time data sets in real applications. In practice, not all training data arrives together, if adopting batch learning to learn the real-time data sets, it needs a long time to learn and the results are not satisfactory. Thus, we adopt the classifier based on OS-ELM algorithm to recognize 8 daily activities, and it can be described as follows.

The output of network with N hidden nodes can be represented by

$$f_N(\mathbf{x}) = \sum_{j=1}^{N} \beta_i G(\boldsymbol{\alpha}_i, b_i, \mathbf{x}) \quad \mathbf{x} \in \mathbf{R}^n,\ \boldsymbol{\alpha}_i \in \mathbf{R}^n \tag{11}$$

where $\boldsymbol{\alpha}_i$ and b_i are the learning parameters of hidden nodes and β_i the weight connecting the ith hidden node to the output node. $G(\boldsymbol{\alpha}_i, b_i, \mathbf{x})$ is the output of the ith hidden node with respect to the input $\mathbf{x}$.

Through selecting the type of node, the activation function, and the number N of hidden nodes, the OS-ELM can be implemented with data $\mathbf{N} = \{(\mathbf{x}_i, \mathbf{t}_i), \mathbf{x}_i \in \mathbf{R}^n, \mathbf{t}_i \in \mathbf{R}^m,\ i = 1, 2, \ldots, N\}$ arrived one-by-one or chunk-by-chunk. The algorithm steps are as follows.

Initialization phase: Select $\mathbf{N}_0 = \{(\mathbf{x}_i, \mathbf{t}_i)\}_{i=1}^{N_0}$, $N_0 \geq N$ randomly from the training data set $\mathbf{N} = \{(\mathbf{x}_i, \mathbf{t}_i), \mathbf{x}_i \in \mathbf{R}^n, \mathbf{t}_i \in \mathbf{R}^m,\ i = 1, 2, \ldots, N\}$ as initial data set.

Step 1. Assign random input weights $\boldsymbol{\alpha}_i$ and bias b_i, where $i = 1, \ldots, N$.

Step 2. Calculate the initial hidden layer output matrix $\mathbf{H_0}$.

$$\mathbf{H_0} = \begin{bmatrix} G(\boldsymbol{\alpha}_1, b_1, \mathbf{x}_1) & \ldots & G(\boldsymbol{\alpha}_N, b_N, \mathbf{x}_1) \\ \vdots & \ldots & \vdots \\ G(\boldsymbol{\alpha}_1, b_1, \mathbf{x}_{N_0}) & \cdots & G(\boldsymbol{\alpha}_N, b_N, \mathbf{x}_{N_0}) \end{bmatrix}_{N_0 \times N} \tag{12}$$

Step 3. Estimate the initial output weight β^0.

Considering using the batch ELM algorithm, the solution to minimizing $\|\mathbf{H}_0\beta - \mathbf{T}_0\|$ is given by $\beta^0 = \mathbf{P}_0\mathbf{H_0^T}\mathbf{T_0}$, where $\mathbf{P_0} = \left(\mathbf{H_0^T}\mathbf{H_0}\right)^{\mathbf{-1}} = \mathbf{K}_0^{-1}$ and $\mathbf{T_0}=(\mathbf{t}_1, \mathbf{t}_2, ..., \mathbf{t}_{\mathbf{N_0}})^{\mathrm{T}}$.

Step 4. Set $k = 0$, where k is the number of chunks that is trained currently.

Sequence learning phase: The $(k+1)$th chunk of training data $\mathbf{N}_{k+1} = \{(x_i,t_i)\}_{i=\sum_{j=0}^{k} N_j+1}^{\sum_{j=0}^{k+1} N_j}$ arrives, where N_{k+1} denotes the number of observations in the kth chunk.

Step 1. Calculate partial hidden layer output matrix $\mathbf{H}_{k+1}$ for the $(k+1)$th chunk of data $\mathbf{N}_{k+1}$.

$$\mathbf{H}_{k+1} = \begin{bmatrix} G\left(\boldsymbol{\alpha}_1, b_1, \mathbf{x}_{\left(\sum_{j=0}^{k} N_j\right)+1}\right) & \ldots & G\left(\boldsymbol{\alpha}_N, b_N, \mathbf{x}_{\left(\sum_{j=0}^{k} N_j\right)+1}\right) \\ \vdots & \ddots & \vdots \\ G\left(\boldsymbol{\alpha}_1, b_1, \mathbf{x}_{\sum_{j=0}^{k+1} N_j}\right) & \cdots & G\left(\boldsymbol{\alpha}_N, b_N, \mathbf{x}_{\sum_{j=0}^{k+1} N_j}\right) \end{bmatrix}_{N_{k+1} \times N} \tag{13}$$

Step 2. Set $\mathbf{T}_{k+1} = \left[t_{\left(\sum_{j=0}^{k} N_j\right)+1}, \ldots, t_{\sum_{j=0}^{k+1} N_j}\right]^T$.

Step 3. Calculate the initial output weight β^{k+1}. We have

$$\mathbf{k}_{k+1} = \mathbf{k}_k + \mathbf{H}_{k+1}^{\mathrm{T}} \mathbf{H}_{k+1} \tag{14}$$

$$\beta^{k+1} = \beta^k + \mathbf{K}_{k+1}^{-1} \mathbf{H}_{k+1}^{\mathrm{T}} \left(\mathbf{T}_{k+1} - \mathbf{H}_{k+1}\beta^k\right) \tag{15}$$

From Equation (15), we find that $\mathbf{K}_{k+1}^{-1}$ is used to compute β^{k+1} from β^k. The update formula for $\mathbf{k}_{k+1}^{-1}$ is derived using the Woodbury formula [17].

$$\begin{aligned} \mathbf{k}_{k+1}^{-1} &= \left(\mathbf{k}_k + \mathbf{H}_{k+1}^{\mathrm{T}} \mathbf{H}_{k+1}\right)^{-1} \\ &= \mathbf{k}_k^{-1} - \mathbf{k}_k^{-1} \mathbf{H}_{k+1}^{\mathrm{T}} \left(\mathbf{I} + \mathbf{H}_{k+1} \mathbf{k}_k^{-1} \mathbf{H}_{k+1}^{\mathrm{T}}\right)^{-1} \times \mathbf{H}_{k+1} \mathbf{k}_k^{-1} \end{aligned} \tag{16}$$

Let $\mathbf{P}_{k+1} = \mathbf{k}_{k+1}^{-1}$, then the equations for updating β^{k+1} can be written as

$$\mathbf{P}_{k+1} = \mathbf{P}_k - \mathbf{P}_k \mathbf{H}_{k+1}^{\mathrm{T}} \left(\mathbf{I} + \mathbf{H}_{k+1} \mathbf{P}_k \mathbf{H}_{k+1}^{\mathrm{T}}\right)^{-1} \mathbf{H}_{k+1} \mathbf{P}_k \tag{17}$$

$$\beta^{k+1} = \beta^k + \mathbf{P}_k \mathbf{H}_{k+1}^{\mathrm{T}} \left(\mathbf{T}_{k+1} - \mathbf{H}_{k+1}\beta^k\right) \tag{18}$$

Step 4. Set $k = k + 1$, and return to the sequence learning phase until all the training data has been learned.

The procedure of algorithm is composed of initialization and sequence learning. The parameters of the network are selected randomly, while the weight vector between hidden layer and output layer is calculated by output matrix of hidden layer and output sample, and constantly updated based on new chunk until all the training data has been learned, and when, OS-ELM is equal to ELM.

3. **Experimental Results and Discussion.** In order to evaluate the performance of the proposed method in this paper, we choose twenty healthy volunteers for data collection including ten males and ten females, aged from 20 to 25 years and weighted from 44 to 75kg. Each volunteer is required to place the tri-axial accelerometer on the waist and wear the shoes with pressure sensors under the insoles, then they imitate 8 activities, and the sensor signals from different activities are recorded. The experiments are carried out in the laboratory. The time window selection and fixed time window will be applied to the classifier based on OS-ELM and BP neural network respectively to classify the physical activities.

In Tables 1 and 2, FD, R, U, L, D, W, SD, ST represent falling down, running, upstairs, lying, downstairs, walking, standing and sitting respectively.

The confusion matrices of 8 classes of activities are shown in Tables 1 and 2. In the confusion matrices, the row represents actual class and the column represents the recognized class by the classifier respectively, and the data at the ith row and jth column represents the probability of actual class i is recognized as j class by the classifier. From the confusion matrices, we can find that for classifier based on OS-ELM and BP neural

Table 1. The confusion matrices using OS-ELM classifier

	OS-ELM based on time window selection								OS-ELM based on fixed time window							
	FD	R	U	L	D	W	SD	ST	FD	R	U	L	D	W	SD	ST
FD	0.993	0	0	0.007	0	0	0	0	0.986	0	0	0.014	0	0	0	0
R	0	0.988	0	0	0.006	0.006	0	0	0	0.986	0.014	0	0	0	0	0
U	0	0	0.962	0	0.019	0.019	0	0	0	0	0.834	0	0.033	0.133	0	0
L	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
D	0	0.007	0.014	0	0.979	0	0	0	0	0.006	0.006	0	0.963	0.025	0	0
W	0	0	0.012	0	0	0.988	0	0	0	0	0.091	0	0	0.909	0	0
SD	0	0	0	0	0	0	1	0	0	0	0	0	0.006	0	0.994	0
ST	0	0	0	0	0	0	0	1	0	0	0	0	0	0.006	0	0.994

Table 2. The confusion matrices using BP neural network classifier

	BP neural network based on time window selection								BP neural network based on fixed time window							
	FD	R	U	L	D	W	SD	ST	FD	R	U	L	D	W	SD	ST
FD	0.987	0	0	0.013	0	0	0	0	0.993	0.007	0	0	0	0	0	0
R	0	0.986	0	0.007	0.007	0	0	0	0	0.814	0.048	0	0.076	0.055	0.007	0
U	0	0.014	0.699	0	0.055	0.226	0	0.006	0	0.006	0.655	0	0.137	0.202	0	0
L	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
D	0	0.054	0.094	0	0.685	0.167	0	0	0	0.007	0.079	0	0.671	0.214	0	0.029
W	0	0	0.128	0	0.155	0.717	0	0	0	0	0.076	0	0.153	0.733	0.015	0.023
SD	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
ST	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1

Table 3. Comparison of classifier based on OS-ELM and BP neural network

Classifier	Training time (S)	Testing time (S)	Accuracy (%)
OS-ELM	0.734	0.056	0.988
BP neural network	16.606	0.107	0.818

network, time window selection can lead to better results than fixed time window, and the classifier based on OS-ELM can distinguish activities better than the classifier based on BP neural network.

For further discussion, we conduct 100 trials to compare the classifier based on OS-ELM and BP neural network in detail. The results are shown in Table 3.

Table 3 compares the performance of classifier based on OS-ELM and BP neural network in training time, testing time and accuracy, and we can find that classifier based on BP neural network spends much more time training data than the classifier based on OS-ELM, while the testing time has no obvious difference between them. Furthermore, the average recognition accuracy of 100 trials of classifier based on OS-ELM is 98.8%, much higher than the classifier based on BP neural network.

In order to evaluate the performance of time window selection and fixed time window, we adopt following evaluation criteria: accuracy, recall and false positive rate (FPR) [18]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{19}$$

$$Recall = \frac{TP}{TP + FN} \tag{20}$$

$$FPR = \frac{FP}{FP + TN} \tag{21}$$

where the variables TP, TN, FP, and FN represent the number of True Positive, True Negative, False Positive, and False Negative outcomes respectively in the given experiment.

The accuracy of classifier based on time window selection and fixed time window are 98.9% and 95.8% respectively, and as shown in Figure 4, for the evaluation criteria accuracy, recall and FPR, the classifier based on time window selection performs better than the classifier based on fixed time window for almost all activities, especially for the quasi-periodic activities.

4. **Conclusion.** A wearable sensor system based on time window selection and OS-ELM algorithm to recognize physical activities in daily life through tri-axial accelerometer and pressure sensors is presented. Activities are recorded in the form of sensor data, and the sensor data is divided into non-periodic and quasi-periodic through autocorrelation analysis, then a fixed time window is adopted for non-periodic data and adaptive time window for quasi-periodic data, after feature extraction, the feature data is input to the classifier based on OS-ELM to train and classify. 8 activities are used to evaluate the

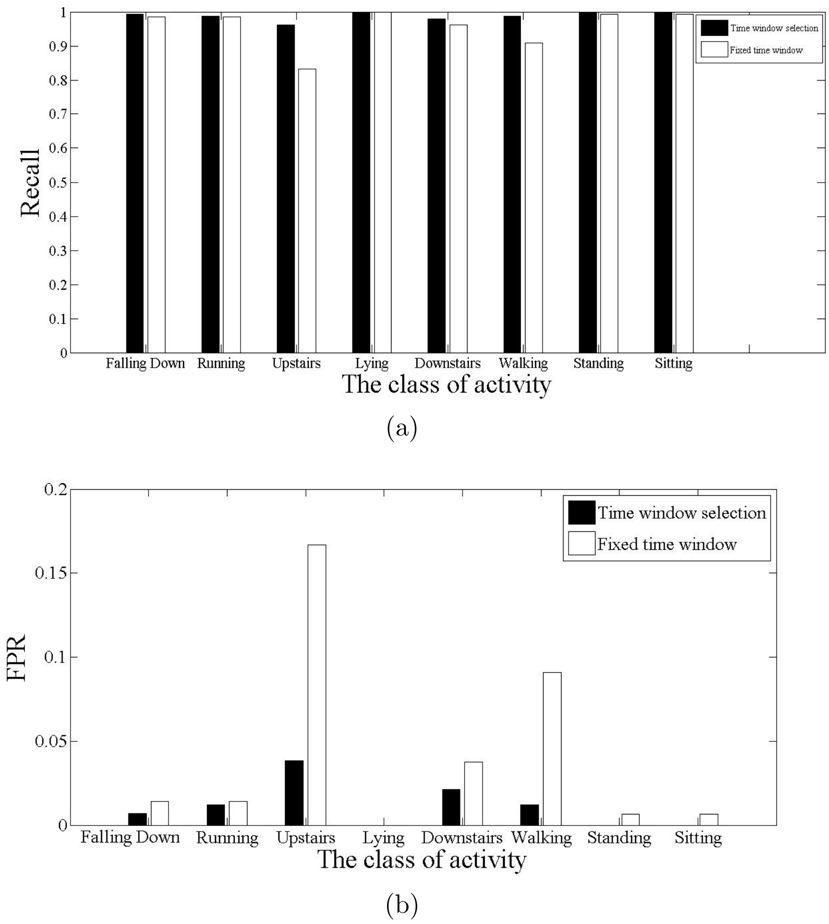

Figure 4. The evaluation results

performance of the proposed method and the results show that the average recognition accuracy of classifier based on OS-ELM is much higher than the classifier based on BP neural network, and it spends less training time, furthermore, the classifier based on time window selection performs better than the classifier based on fixed time window. Therefore, the system proposed in this paper has better practical value and can be used not only in health care but also in other related areas. In our future study, we will try to remove abnormal value from sensor data and extend the current approach to be capable of recognizing more complicated daily activities accurately.

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