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Intelligent Human-Computer Interaction Based on Surface EMG Gesture Recognition

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ABSTRACT Urban intelligence is an emerging concept which guides a series of infrastructure developments in modern smart cities. Human–computer interaction (HCI) is the interface between residents and the smart cities, it plays a key role in bridging the gap in applicating information technologies in modern cities. Hand gestures have been widely acknowledged as a promising HCI method, recognition human hand gestures using surface electromyogram (sEMG) is an important research topic in the application of sEMG. However, state-of-the-art signal processing technologies are not robust in feature extraction and pattern recognition with sEMG signals, several technical problems are still yet to be solved. For example, how to maintain the availability of myoelectric control in intermittent use, since pattern recognition qualities are greatly affected by time variability, but it is unavoidable during daily use. How to ensure the reliability and effectiveness of myoelectric control system also important in developing a good human–machine interface. In this paper, linear discriminant analysis (LDA) and extreme learning machine (ELM) are implemented in hand gesture recognition system, which is able to reduce the redundant information in sEMG signals and improve recognition efficiency and accuracy. The characteristic map slope (CMS) is extracted by using the feature re-extraction method because CMS can strengthen the relationship of features cross time domain and enhance the feasibility of cross-time identification. This study is focusing on optimizing the time differences in sEMG pattern recognition, the experimental results are beneficial to reducing the time differences in gesture recognition based on sEMG. The recognition framework proposed in this paper can enhance the generalization ability of HCI in the long term use and it also simplifies the data collection stage before training the device ready for daily use, which is of great significance to improve the time generalization performance of an HCI system.

INDEX TERMS Urban intelligence, human-computer interaction, sEMG, gesture recognition.

I. INTRODUCTION

With the emerging of novel information technologies such as Internet of things, cloud computing, big data, remote sensing telemetry and geographic information systems, the research of urban intelligence is booming. As a front-end application technology in urban intelligence, HCI is also been intensively studied [1]. When we talking about HCI in urban management, more attentions should be paid on humanity, since HCI is the direct interface for residents to interact with cities. In order to construct a more intelligent and livable city, the demands of residents can be obtained dynamically by HCI [2], [3]. Developing the front-end HCI technologies of smart cities can promote efficiency and accessibility of transportation, environment, security, management, service, culture, medical and other industries in modern cities. Improving the level of intelligent and refining management in the field of urban operation management is very important to the development of intelligent urban [4], [5].

The sEMG signal can be used to indicate the active states of the muscles, through the analysis, the information of the neural activities can be obtained. The advantages of sEMG

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is non-invasive, so it performs well in the field of artificial control, clinical diagnosis, motion detection and neurological rehabilitation [6]. Gesture recognition based on sEMG signal is an important research topic in the practical application of surface electromyography, also the reliable and effective gesture recognition help to develop a good human-machine interface. The main challenges of pattern recognition today are the weak signal intensity with noise and high dimension, frequent interferences [7], usually the amplitude range is 0∼105mV and the bandwidth is 0.5∼2 kHz, it is easily perturbated by the external noise source and the acquisition device itself, and shielded by the surface skin [8].

At present, the research on sEMG signal mainly focuses on the spatial non-stationarity of sEMG, but the time non-stationarity of sEMG has always been a big challenge. In this paper, LDA is used to reduce the dimensionality of high-dimensional signals and eliminate the redundant information in sEMG. The method of feature re-extraction is adopted to extract the characteristic slope value, and the ELM is optimized by genetic algorithm to establish a gesture recognition system across time dimensions. This paper studied the compatibility of sEMG classifier in time dimension, which is conducive to reduce the difference in time dimension of gesture recognition based on sEMG and improve the generalization ability of classifier in time dimension.

The reminder of the paper is as follows, the second section reviews the basic methods of gesture recognition, including feature extraction, feature reduction and pattern recognition based on neural network. The third section elaborates the whole experimental process, including the sEMG signal collection plans. We proposed a feature extraction method for reducing time non-stationarity, establishes GA-ELM optimization recognition network, and analyzes the algorithm process of each step. In fourth section, we illustrated the gesture recognition experiment based on this algorithm and concluded the experimental results in the last section.

II. RELATED WORK

The sEMG is random in nature, which is made up of the action potential of the motion unit [1], [9]. These action potentials exist in the electrode pick-up area and the detected voltage is the sum of the action potentials of the single electrode elements [10]. The pattern recognition process can be divided into three stages: signal detection, signal representation and signal classification. In general, the long-term recognition accuracy can only reach 50-70%, which still have a long way to practical application [11]–[14].

Recently, there are many existing schemes on feature extraction, feature dimensionality reduction and pattern recognition. The time-domain processing method is to process the surface EMG as a function of time and obtains some statistical characteristics through time-domain analysis [15]. The time-domain method is simple in principle and low in computational complexity, but it can effectively represent the signal characteristics and is widely used in feature extraction of surface EMG. However, time-domain features are not robust enough to interferences [16], even small changes in muscle states will result in huge variance in features [17]. At present, the time-domain characteristics most frequently used are as follows: integrated electromyography (iEMG), root mean square (RMS), absolute value (AVI), zero crossover (ZC), variance (VA), Willis amplitude, wavelength (WL), etc.

The frequency domain analysis method is realized by Fourier transform, which transforms the signal into frequency spectrum or power spectrum. Now scholars mainly study the two characteristics of average power frequency and median frequency [18]. The signal is transformed into frequency spectrum or power spectrum by fast Fourier transform, and its waveform changes little. Therefore, the descriptions of sEMG in frequency domain are relatively stable [19]. The stability of sEMG power spectrum waveform directly leads to the stability of frequency domain features extracted by power spectrum. Therefore, the extracted frequency domain features are beneficial to the subsequent sEMG pattern recognition.

Although the first two methods can be used to extract some typical features of EMG, they have ignored the instability and chaotic EMG [20]. In the process of exercise, the number of motor units, action potential and conduction rates involved in neuromuscular process are different, and the motor nervous system are non-liner [21]. Non-liner dynamic method can construct multi-dimensional dynamic model based on one-dimensional time series to extract more hidden information [22]. The main non-liner characteristics include correlation dimension, entropy, complexity and Lyapunov exponent.

The training of the sEMG pattern classifier relies on a large training database, but the diversity of these samples slow down the training speed of the model. Hence, efficient feature or high-quality data from certain channels will be selected but they have significant uncertainty for different gestures or acquisition methods [23]. Therefore, it is necessary to improve data efficiency through dimension reduction to avoid overloading the classifier. Besides, dimensionality reduction can eliminate redundant information and prevent unnecessary information from interfering with the correct judgment of the classifier. Therefore, when performing pattern recognition, it is necessary to adopt the method of feature dimension reduction [24].

There are two common methods for dimensional reduction for extracted features: one is to obtain a subset of the original features without losing the classification information, and the other is to create a new subset of features by transforming the original features. The first method is called feature selection, which reduces the number of features to be calculated and the computational complexity [25], [26]. The second method is called feature transformation, which reduces the dimension of the feature space through data transformation to avoid the loss of classification information, so it can be used by the same classifier to achieve a higher classification accuracy compare with the feature selection method [27]–[29], because feature transformation can reduce the dimension of the feature space regardless of the attributes or memberships of the features, while keeping the maximum separability, on the contrary, the former is greatly limited in this respectively [30], [31]. In feature transformation, the original N-dimensional date are projected to a lower n-dimensional space through a certain optimization process, so as to achieve the purpose of reducing the dimension [32]. The representative algorithms of feature transformation are linear discriminant analysis (LDA) and principal component analysis (PCA). For example, the combination of PCA and SOFM improves the accuracy of sEMG pattern classification [33], [34], saves the running time and it's more applicable to real-time control of prosthesis. The feature transformation also includes non-negative matrix factorization, factor analysis, singular value decomposition, etc. The disadvantage of the feature dimension reduction is that when the original features contain physical meanings, the new feature may loss them, the advantage is that these new features have high compression efficiency [35], [36].

At present, the widely used pattern recognition methods of sEMG mainly include support vector machine (SVM), radial basis function (RBF) algorithm, artificial neural network (ANN), hidden Markov model (HMM) and linear discriminant classifier [37]–[39]. Among these classification methods, the theory of ANN technology is the most mature and widely used. In the late 1980s and early 1990s, ANN was introduced to motion recognition of sEMG [40]. Without explicit inferences of the calculation process, ANN can achieve the non-linear mapping of input and output, which satisfied the demand performance of the classifier in motion recognition of sEMG [41]. Therefore, ANN plays a dominant role in the research of gesture recognition of via sEMG. However, there are still have many problems lie in ANN, such as relative long response time and instability [42], [43]. Regarding to the above problems, an ELM with simpler model structures, faster training speed and fewer adjustment parameters is introduced in sEMG gesture recognition, compared with feed-forward neural networks, ELM is much quicker in finding the global optima.

III. METHOD

The whole process from the acquisition of surface EMG to pattern recognition is shown in Figure 1. Firstly, collect surface EMG $X1$ and hand motion n synchronously, then preprocess surface EMG. Signal preprocessing consists of feature extraction, feature dimension reduction with LDA and feature re-extraction. Matrix $[X4, n]$ is obtained after preprocessing, and non-linear mapping of network input is used to recognize hand motion n through ELM. Finally, the genetic algorithm is used to optimize the structural parameters of ELM network for the best network structure and better classification accuracy of the network.

A. ACQUISITION OF sEMG

The design of gesture dataset effects the classification accuracy in the experiment. The gestures in experiment must be typical and with as more moving joints involved as possible.

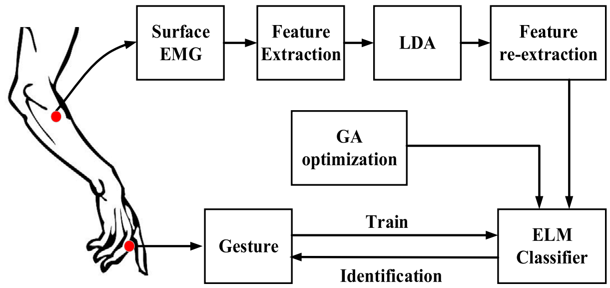

FIGURE 1. Gesture recognition process block diagram.

Hand motions are delivered by the bending of wrist and finger joints (especially the thumb and index finger), so the motion of these joints should be included in the design of gestures [44], [45]. In addition, each finger is in the state of linkage when in the work, so the design of gesture should consider the combination of finger movements.

As shown in Figure 2 [46], nine gestures involve the whole hand movement, including palm closure (SH) and palm opening (SK), wrist movement including inward bending (NQ) and outward bending (WQ) and finger movement including thumb acting on index finger (MS), middle finger (MZ), ring finger (MW) and small finger (MX) respectively. Except those test gestures, rest state (RE) is include as the control group. These gestures were defined to include the movements of all the major joints on one hand, such as wrist, finger and palm movements. A three-day dataset was collected, the data collect in the first and second day were serves as training set and the data collected in third day were treated as test set.

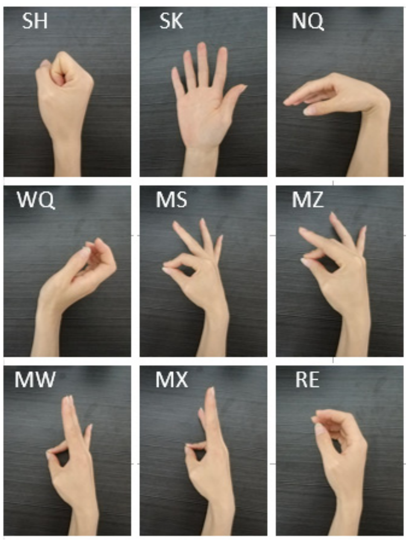

FIGURE 2. Nine static gestures (involve wrist movements, finger movements, palm opening and closing).

B. DIMENSION REDUCTION AND FEATURE FUSION

1) PRELIMINARY FEATURE EXTRACTION

In order to facilitate feature extraction in the future, window functions are used to segment these continuous signals into appropriate sizes. After that, features were extracted from the intercepted signal in a single window. The attributes of extracted features affect the performance of gesture recognition system. For example, the number and type of features affect the real-time and accuracy of the system. In the field of signal analysis, the main feature types are time domain feature and frequency domain feature. According to the references [15]–[18], [20], two time-domain features are extracted, including root mean square (RMS) and waveform length (WL), and a frequency-domain feature median amplitude spectrum (MAS). Using these three features, good classification results can be obtained. Therefore, these three parameters are used as input parameters of the identification network.

Taking signal data from the single channel as an example, the waveforms of three features are displayed in Figure 3. Obviously, these three features are various with different gestures, which provided evidences for the follow-up gesture recognition. Because of the magnitude differences of each feature and the sensitivity of the classifier, the features need to be pre-processed before dimension reduction, in order to unify the order of parameters of each feature. As shown Figure 3, it can be seen that the WL features are of the highest order from Figure 3a, if unification is missing RMS and MAS will be covered by WL, when gesture recognition is performed.

2) FEATURE FUSION AND DIMENSION REDUCTION

The direct extracted features, RMS, WL and MAS, are in high dimensional feature spaces, which is not suitable for classification. In order to improve the accuracy of gesture recognition and generalize the classifier, reducing the dimension of the feature space is very important. In this paper, three features are integrated into a feature set, which build on a fused feature with 48 dimensions (16 channels × 3 features).

Before dimension reduction, the data of the first day and the second day are averaged to get the new dataset X_2. Equation 1 represents the process of feature fusion.

$$X_2 = [RMS_1 + RMS_2, WL_1 + WL_2, MAS_1 + MAS_2] \quad (1)$$

X_3 will be applied to dimension reduction, which is obtained by normalizing X_2. LDA is used to eliminate the matching problem between channels and features, while weakening some channels with less correlation or more redundant information and improving the recognition rate. Specifically, ignoring the feature data of 16 channels of each feature and the relationship between the channel and the feature, the variance within the same classes is the smallest after projection, and the variance between different classes is the largest. The process of dimension reduction is as follows.

Input dataset $X_2 = [x_1, x_2, \ldots, x_c]$, where any sample x_i is a c-dimensional vector.

Computing of intra-class divergence matrix S_ω.

Computing inter-class divergence matrix S_b

Computational matrix $S_\omega^{-1}S_b$.

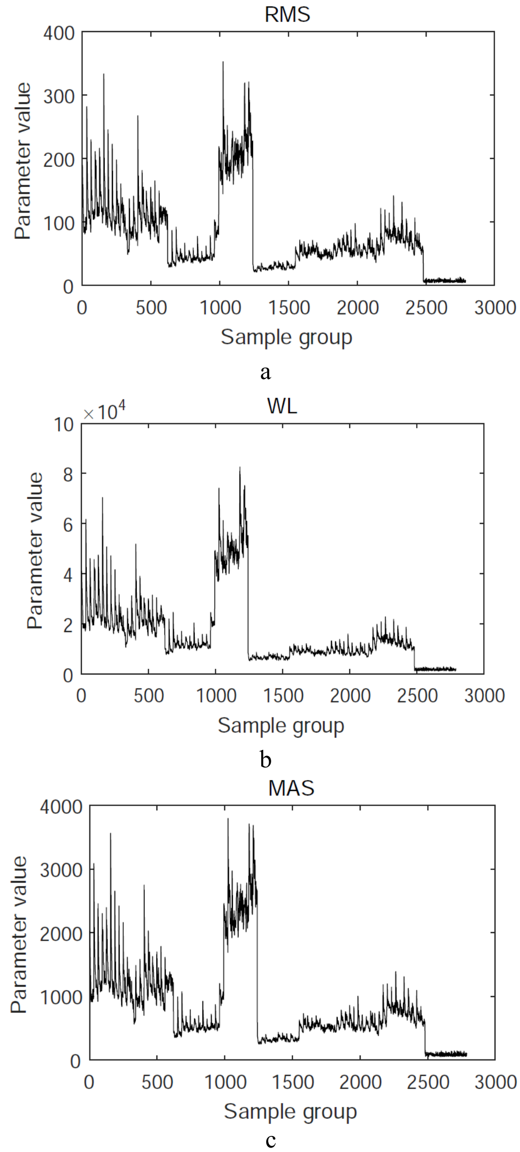

FIGURE 3. RMS, WL, MAS features extracted from one sample.

Calculating the maximum d eigenvalues of $S_\omega^{-1}S_b$ and corresponding d eigenvectors $\omega_1, \omega_2, \ldots, \omega_d$ and the projection matrix W.

For each sample x_i dataset, it is transformed into a new sample $z_i = W^T x_i$.

Outputting sample set $X_3 = [z_1, z_2, \ldots, z_c]$.

After dimension reduction by LDA, the dimension of fused feature becomes d.

3) FEATURE RE-EXTRACTION

Because of the sEMG signals have great differences in time domain, which leads to the differences of features. Therefore, it is difficult to train an ANN with time generalization performance simply by using the reduced dimension-reduced feature as the input of network training.

Figure 4 shows the first three-dimensional feature scatter plots of the training set and the test set. After dimension reduction by LDA, the training set and the test set have a good separability. But obviously, there are no significant effects between training set and test set. The ANN trained by the training set cannot identify the gestures in test set accurately and the time generalization performance of neural network is not obvious.

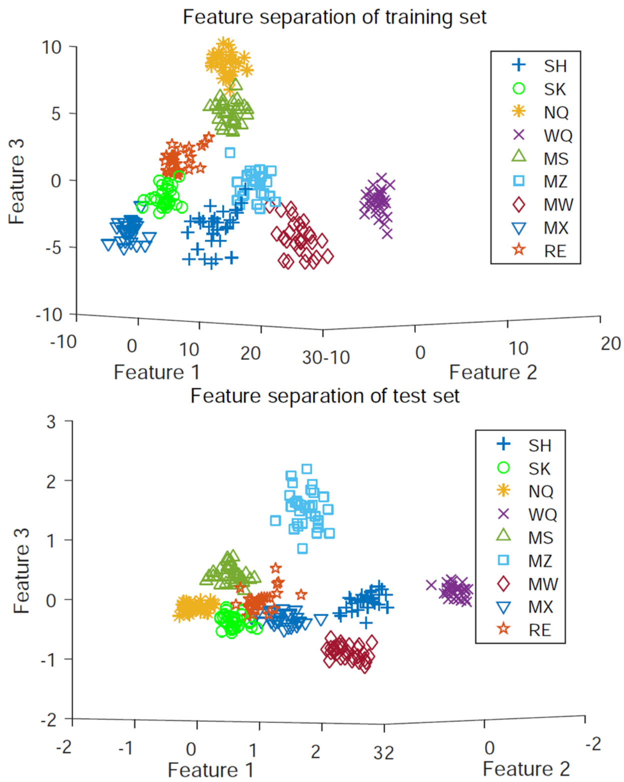

FIGURE 4. Pre-three-dimensional feature scatter plot of training set and test set.

As shown in Figure 5, two sets of features of training set and test set are visualized. Obviously, there is little overlap between training set and feature set. The data in test set and training set are not well integrated, which brings great difficulties in recognition.

As shown in Figure 6, the data of a gesture test set and a training set are selected, among which ten sets of data are chosen, and a line graph is drawn. The trend of data in training set and test set are similar, but the values are different.

Therefore, we can use the fluctuations of the characteristic polylines to represent the difference between different gestures.

Therefore, we designed a new feature, characteristic map slope, CMS, which used slope to represent the trend of eigenvalue in the fused feature map. Specifically, it calculates the slope of adjacent two-dimensional data and combines these slopes into a new feature matrix. The slope here is not a derivative but a value defined in Formula 2.

$$h_i = \frac{z_{i+1} - z_i}{z_{i+1} + z_i} \quad i = 1, 2, \ldots, d-1 \tag{2}$$

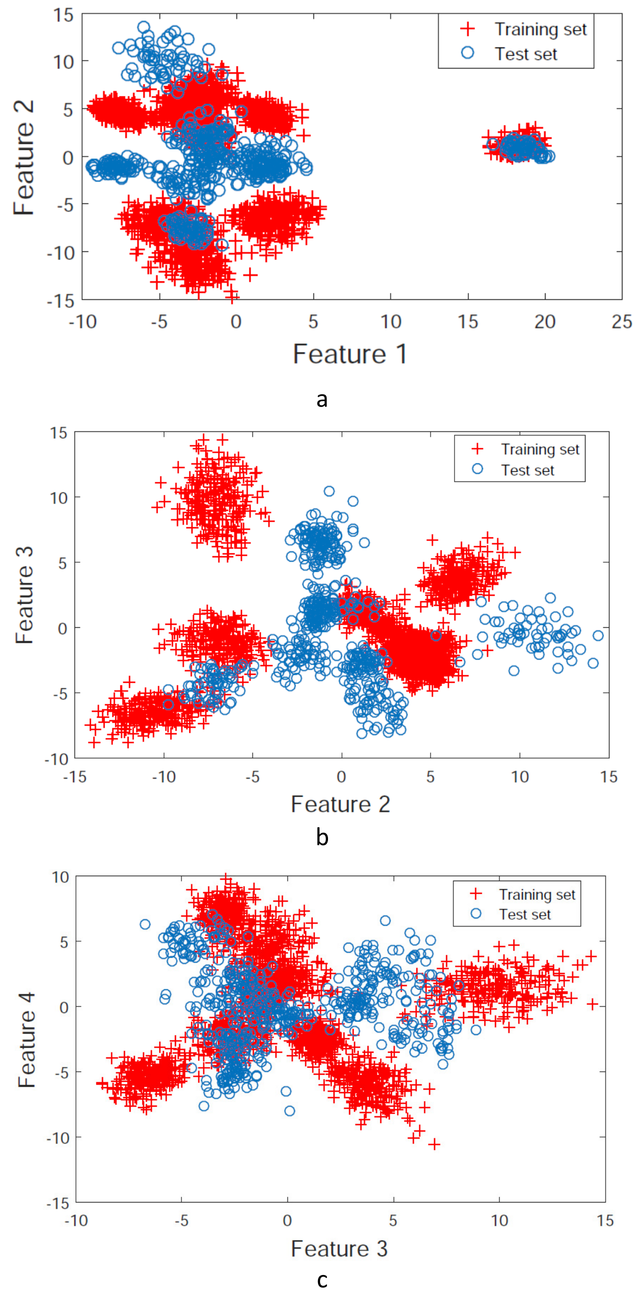

FIGURE 5. Characteristic coincidence degree between training set and test set after dimension reduction of LDA. The three graphs a, b and c are scatter graphs with three sets of features respectively.

$$X_4 = [h_1, h_2, \ldots, h_{d-1}] \tag{3}$$

Then, we can get that the dimension of $X4$, which is one dimension lower than that of $X3$. A new eigenvector $X4$ is used as the input of the neural network to reduce the time variance.

C. CLASSIFIER DESIGN AND PARAMETER OPTIMIZATION

Genetic algorithm in GA-ELM network is designed to optimize the initial weights and thresholds of the network, due

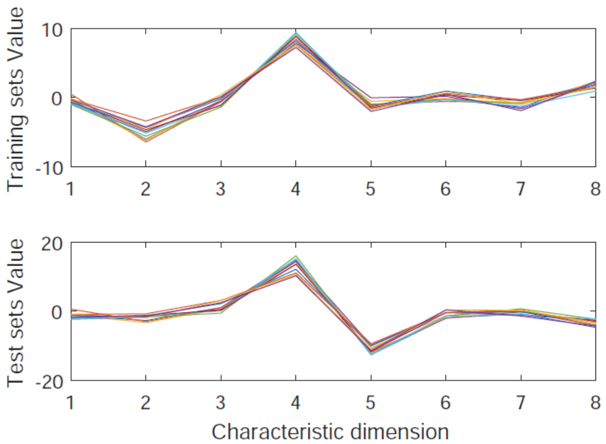

FIGURE 6. Ten sets of characteristic polygons of the first gesture. Data representing training set and test set respectively.

to the excellent performance in global search. Then the optimized training set was used to train the network and establish a reliable gesture recognition model for better recognition results.

1) EXTREME LEARNING MACHINE AND GENETIC ALGORITHMS

Extreme learning machine (ELM) is a fast learning method based on single-hidden layer feedforward neural network proposed by Hu *et al.* [47]. It can randomly select the hidden layer nodes of a single-hidden layer feedforward neural network and the parameters of corresponding. In the training process, only the output weights of the network need to be adjusted by the regularized least squares algorithm [48]. Therefore, it can achieve good network generalization performance with extremely high learning speed. The expression cost function of ELM can be described as:

$$E = \sum_{J=1}^{n} \left(\sum_{I=1}^{l} \beta_I g(d_I * x_J + b_I) - f_J \right)^2 \tag{4}$$

Among them, n as the number of the input layer, l is the number of the hidden layer, βI as the weight vector which is connected between hidden layer and output layer, $g(x)$ indicates the activation function, dI as the weight vector which is connected between input layer and hidden layer, XJ is the input data, bI is the bias and f_J is the output data of the single-hidden layer feed forward neural network.

Genetic algorithm is an iterative process. In each iteration, a group of candidate solutions are reserved, and sorted according to their merits and demerits, some solutions are selected according to some index. The genetic operator is iteratively participated to find a new generation of candidate solutions, which is stopped until convergence.

2) IMPROVING ELM WITH GENETIC ALGORITHM

The theory proves that ELM neural network will converge quickly and better generalization ability than traditional gradient descent algorithm and is easy to obtain global optimum. However, two main problems need to be solved if better prediction accuracy is obtained [49].

In training, the weights and thresholds are initialized randomly before training. The randomness is introduced by calculation, which interferes the training quality of the model, thus affecting the performance of prediction. Selection of activation function $g(x)$ and definition of neuron quantity effects the performance of ELM neural network. The activation function $g(x)$ can be *Sin*, *Sigmoidal* or *Hardlim* function, which leads to different prediction capabilities of ELM.

The existing researches on ELM suggest the number of neurons are defined by empirical trial algorithm [50]. In this paper, we used genetic algorithm to optimize the initial weights and thresholds of the ELM. It is necessary to encode the data of the original morphology in advance, since genetic algorithm is used to solve optimization problems. After encoding, the morphology is chromosome. Different chromosomes represent the possible solutions of the problem, all chromosomes constitute a population. In order to distinguish the performance of each individual, different fitness functions are constructed for different problems to evaluate. In fitness estimation, corresponding genetic operator can be implemented. The population can be optimized by repeating the above steps and the best solution of the problem is found in the feasible region.

Genetic algorithm can be run parallelly for selecting the superior, eliminating the inferior and optimizing the population performance step by step. The specific steps, shown in Figure 7, lead to the solution to problems. The pre-processed data are used in sample encoding and the construction of original solutions. The encoded samples are fed into ELM for pattern recognition to accurately recognize the hand gestures. The fitness function of each sample is calculated according to the accuracy of recognition and the size of feature subset.

$$f_i = \frac{1}{E(i)} \tag{5}$$

$$E(i) = \sum_{p} \sum_{k} (V_{pk} - T_{pk})^2 \tag{6}$$

where, $i = 1, \ldots, n$ represents the number of chromosomes, $k = d - 1$, is the number of neurons in the output layer, $p = 1, \ldots, v$ is the number of training samples, V_{pk} is the actual output value, and T_{pk} is the predicted output value.

Population selection, crossover and mutation are carried out in corresponding genetic steps to generate the offspring population.

After many experiments, the population size $N = 40$, the evolutionary algebra $M = 30,000$, the crossover probability $Pc = 0.7$ and the mutation probability $Pm = 0.1$.

IV. RESULT ANALYSIS OF GESTURE RECOGNITION

In order to illustrate the advantages of this method, the data before and after dimensionality reduction are used as input

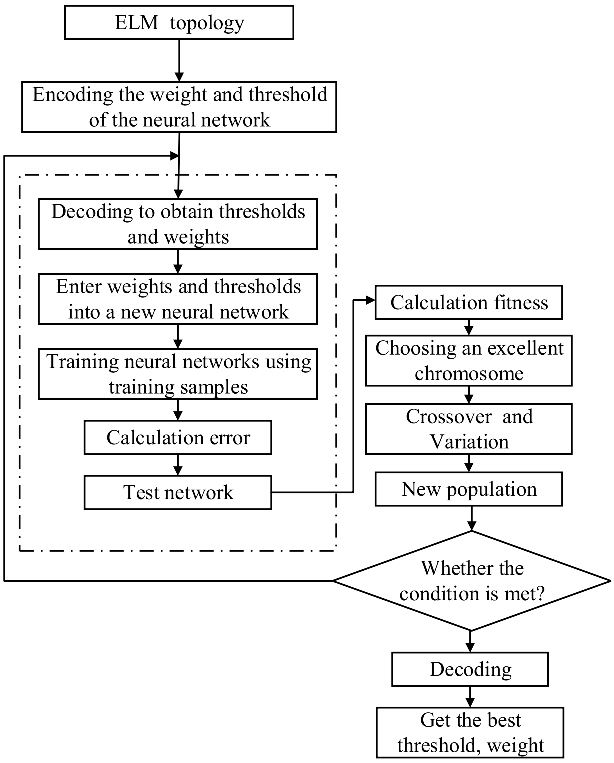

FIGURE 7. Genetic algorithms for optimizing limit learning set processes.

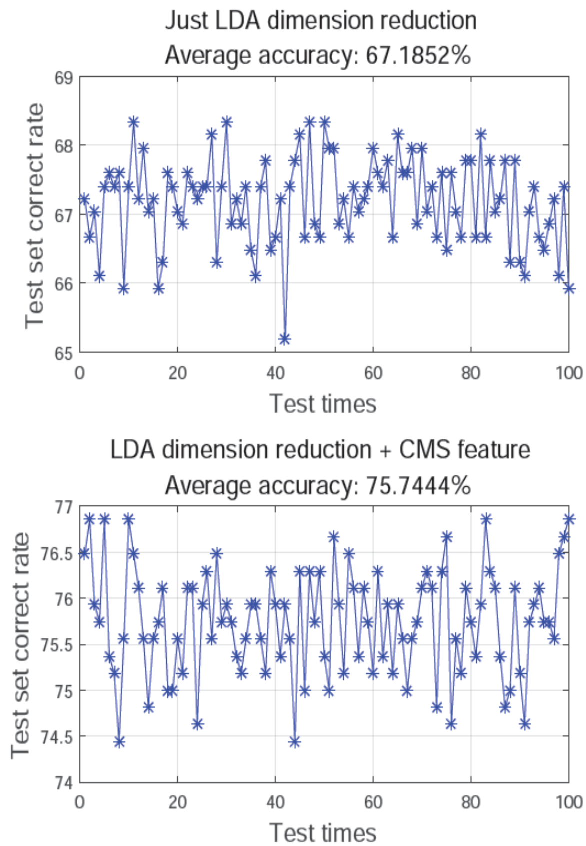

FIGURE 8. Network recognition accuracy after LDA dimension reduction and network recognition accuracy after feature re-extraction.

of ELM classifier, and the experimental results of the two methods are compared. The data of the first day and the second day are used as training set, and the data of the third day are used as test set. The training set is used to learn the parameters of classifier, and the test set is used to test the performance of the classifier.

A. ANALYSIS OF TWO EXPERIMENTAL RESULTS BEFORE GA OPTIMIZATION

By analyzing the ELM network model of each layer, the ELM feature data model is established. The eigenvalues of each gesture are randomly divided into two groups, one is the training set and the other is the test set. The training set consists of data from the first two days, and the test set consists of data from the third day. Each gesture randomly extracts 50 sets of data, a total of 100 times, that is, 100 times of experiments. The number of input neurons is determined by the data dimension after feature extraction, so the number of input neurons is $d - 1$ and the output is 9 neurons. The results are shown in Figure 8.

The average recognition accuracy of ELM network after LDA dimension reduction is 67.18%, and that of ELM network after feature extraction is 75.74%.

Figure 9 shows the degree of feature coincidence after data feature extraction. The first two sets of features of training set and test set are extracted. Compared with Figure 5, the overlap of training set and feature set in Figure 9 increases a lot, which also shows the effectiveness of feature extraction on time generalization performance of classifier.

B. EXPERIMENTAL RESULTS ANALYSIS OF GA OPTIMIZATION

After 30,000 iterations, the mean square error of network training is shown in Figure 10. The optimal threshold and weight obtained by training are loaded into the ELM network to form a GA-ELM correction model. After 18,013 iterations, the error converges to 6.876.

Similarly, the test samples are randomly selected and run 100 times, as shown in Figure 11. The results show that the accuracy is 79.3%. After training the network, the accuracy of gesture recognition is higher than the network without optimization, the relationship between the recognition accuracy of network and the partition of test set is very small.

Compared with the actual data, the GA-ELM network has higher accuracy in gesture recognition than the traditional ELM network. This is because the GA-ELM network spends a longer training time. By training the input and output values separately, the optimal gene chain can be found, based on its global search ability, and the optimal weights and thresholds can be obtained, thus avoiding the emergence of defects in ELM network.

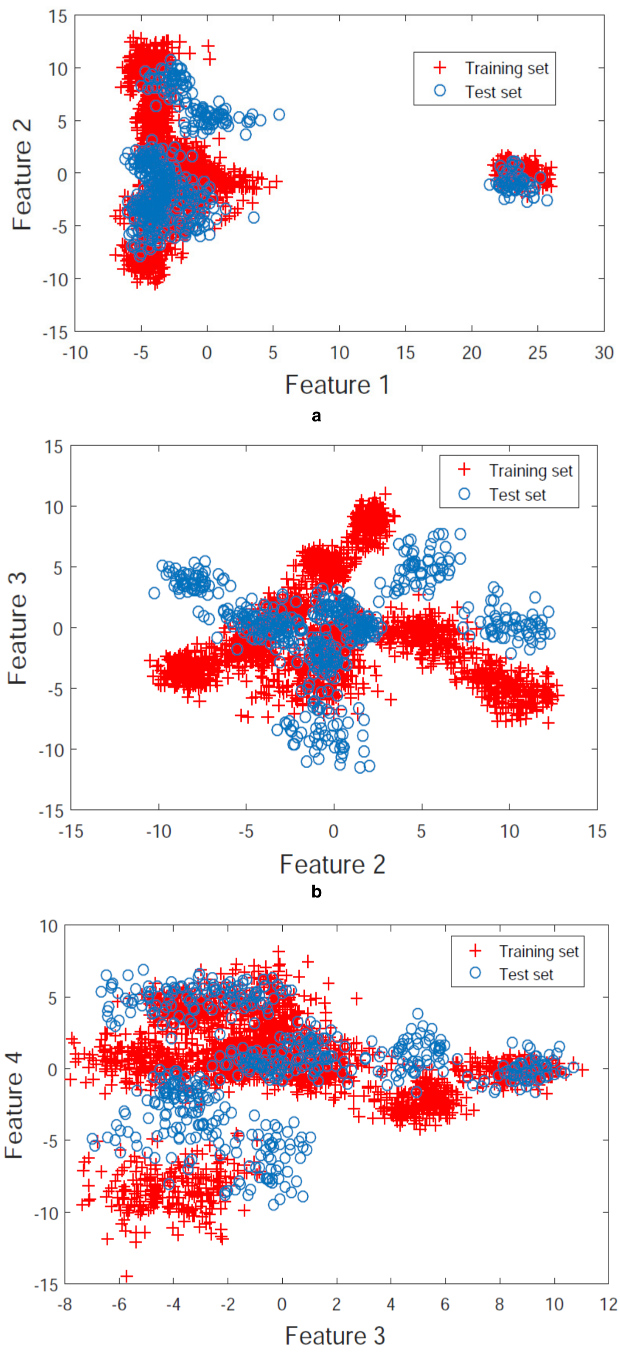

FIGURE 9. Feature coincidence degree between training set and test set after feature extraction. The three graphs a, b and c are scatter graphs with three sets of features respectively.

The average recognition accuracies of the three cases is shown in Table 1.

Items 1, 2 and 3 are the recognition rate after feature dimension reduction, the recognition rate after feature extraction and the recognition rate after network optimization respectively. From Table 1, we can see that the generalization performance of the classifier in time dimension is closely related to the extraction and processing of features and network structure.

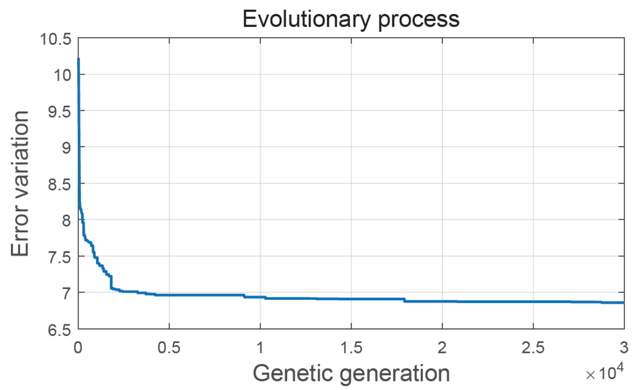

FIGURE 10. Evolutionary process and error relation. The total number of iterations is 30,000, and the error value tends to be stable at 18,013 times.

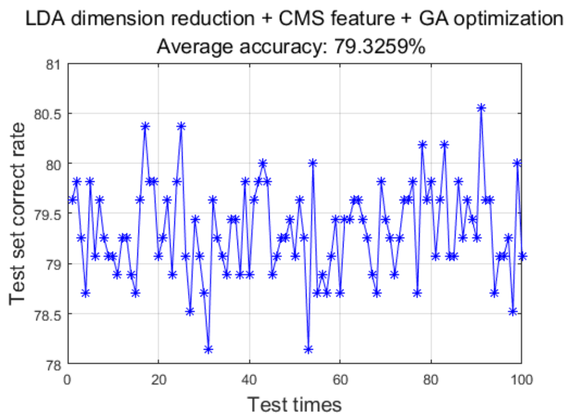

FIGURE 11. Recognition accuracy of 100 times tests of ELM Network Optimized by GA.

TABLE 1. Comparison table of feature classification results.

Item	1	2	3
Discretization error	0.25	0.31	0.26
Average Recognition accuracy %	67.18%	75.74%	79.32%

V. CONCLUSION

In this paper, a front-end application of human-computer interaction method in urban intelligent, based on surface EMG gesture recognition is proposed. Due to the non-stationary, non-linearity and uncertainty of sEMG, it is difficult to extract effective features for pattern recognition. In addition, reducing the differences of sEMG in the long time span also increased the difficulty in pattern recognition. Based on RMS, WL and MAS features, LDA is used to reduce feature dimension and eliminate redundant information. Aiming at the time difference between training set and test set, according to the fluctuation trend of feature data, a new feature, CMS, is designed, which enhanced the relevance of sEMG across time and reduces the error of gesture recognition, which exert positive effects on clinical practice. A classifier based on ELM is constructed, and the initial weights and thresholds of the network are optimized by genetic algorithm, which improves the performance of the classifier. The final accuracy of gesture recognition is significantly improved to 79.32%, which makes long-term gesture recognition possible.

In this paper, the second feature extraction of static gesture based on sEMG is studied. Theoretical and experimental results have been obtained, however there are still problems need to be further explored. The extraction of eigenvalue slope improves the recognition accuracy in our work, to define new features or feature selection methods are promising research directions in the future.

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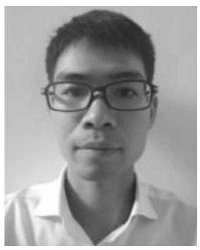

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