Surface EMG Data Aggregation Processing for Intelligent Prosthetic Action Recognition

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Abstract: In the current development and design of sports rehabilitation equipment or biomimetic prostheses, in addition to pay attention to the development and design of the structure, the more core is how to realize the accurate and effective control of the rehabilitation equipment or intelligent prosthesis, and the current research is based on data process and pattern recognition. This paper designs 9 kinds of actions that can react effectively to the function of the hand and extracts the original EMG signals, which are based on the sEMG of the forearm muscles of human hand movement, and uses the 20 order comb filter and wavelet threshold to preprocess the signal, and uses the root mean square, wavelength and nonlinear characteristics sample entropy in time domain as three eigenvalues to construct the input feature vectors of the subsequent action classifier. Finally, the recognition of the hand movements is realized successfully through GRNN and SVM. The recognition rate is 98.64% in SVM classifier and 96.27% in GRNN classifier. Experimental results show that the SVM classifier is better than the GRNN classifier.

Keywords: data aggregation; signal processing; support vector machine; generalized regression neural network.

1 Introduction

Intelligent prosthesis is a very important rehabilitation equipment in medicine, directly related to the rehabilitation of the disabled, involving a large population[1]. Most amputees suffer from a variety of maladjustments in their daily lives and are under tremendous stress psychologically, so more and more people are choosing to install intelligent prostheses[2]. In recent years, the development of many rehabilitation robots, bionic prostheses and other rehabilitation equipment to assist the human body in restoring limb movement function has been paid more and more attention[3]. The sample is of great significance. Some of the prosthetic hand functions are poor, control sensitivity and accuracy are unsatisfactory, and usually require coordinated control of other parts of the body. Because of the heavier materials, the quality of these prosthetic hands is also large, which is likely to cause fatigue[4]. Further research on prosthetic limbs is very necessary for the disabled to have a normal life and better integration into society. The anthropomorphic prosthetic limbs have attracted more and more researcher's attention. In the current development and design of sports rehabilitation equipment or bionic prosthesis, besides the need to pay attention to the development and design of the structure, the core is how to realize the accurate and effective control of rehabilitation equipment or intelligent prosthesis[5]. In recent years, electromyography (EMG), as a bioelectrical signal reflecting muscle activity, has been widely used in clinical diagnosis of muscle diseases, sports medicine, rehabilitation engineering and other fields. The specific joint movement of the limbs is controlled by the corresponding muscle groups. The SEMG signals of the corresponding muscle groups are collected by the acquisition equipment to capture the skeletal muscle activity information of the corresponding movement. The corresponding signals can reflect the degree of extension and bending of the human joints, and also reflect the shape, position and movement of limbs in the process of action completion, so EMG signals can identify different human movements. Gesture is the most frequently used and widely used way to convey information. It is very important for the accurate recognition of human gesture. The selection of classifier has a very important impact on the accuracy of recognition. Reasonable selection of classifier can achieve accurate recognition of various gestures.

In the remainder of this paper, Section2 is the research of feature extraction and gesture recognition at home and abroad. Section3 is about EMG signal acquisition and signal de-noising. The noise is classified and processed by the combination of digital filtering and wavelet transform. Section4 is about the feature extraction of EMG signals. sample entropy, time domain feature RMS and WL are used as feature vectors. Section5 is action recognition based on SVM and GRNN, and analyzes the performance of the two methods through experiments. In the last section, conclusions are presented.

2 Related works

In order to realize motion recognition accurately, feature extraction and pattern classification are the keys of bionic hand control system. Angkoon Phinyomark et al[6] have proposed two novel mean and median frequencies (MMNF and MDF) for robust feature extraction. Englehart et al[7] have proved that LDA (Linear Disehminat Analysis) is better than MLP in terms of temporal features, which are distinguished by the principal element analysis (PCA) in the spatial domain; in addition, the probability analysis method has been successfully used. A. Phinyomark et al[8] use different levels of various mother wavelets to obtain the useful resolution components from the EMG signal. Optimal EMG resolution component (sub-signal) was selected and then the reconstruction of the useful information signal was done. J.Rafiee et al[9]presents a new technique for feature extraction of forearm electromyographic (EMG) signals using a proposed mother wavelet matrix (MWM). A MWM including 45 potential mother wavelets is suggested to help the classification of surface and intramuscular EMG signals recorded from multiple locations on the upper forearm for ten hand motions. ABMSU Doulah et al[10] proposed a feature extraction scheme based on some statistical properties of the DWT coefficients of dominant MUAPs. For the purpose of classification, the K-nearest neighborhood (KNN) classifier is employed. Extensive analysis is performed on clinical EMG database for the classification of neuromuscular diseases and it is found that the proposed methods provide a very satisfactory performance in terms of specificity, sensitivity, and overall classification accuracy.

Most of the research on recognition of human behavior intention by sEMG is focused on classification of human action. J U Chu et al[11] used a multilayer perceptron (MLP) as the classifier. Using an analysis of class separability by feature projections, they show that the recognition accuracy depends more on the class separability of the projected features than on the MLP's class separation ability. Consequently, the proposed linear-nonlinear projection method improves class separability and recognition accuracy. Mahdi Khezri et al[12] demonstrate the capability of an EMG pattern recognition system using ANFIS as classifier with a real-time learning method. Their results reveal that the utilized real-time ANFIS approach along with the user evaluation provides a 96.7% average accuracy. Aaron J. Young et al[13] introduces a novel classifier based on Bayesian theory to provide classification of simultaneous movements. This approach and two other classification strategies for simultaneous movements were evaluated using nonamputee and amputee subjects classifying up to three DOFs, where any two DOFs could be classified simultaneously. Similar results were found for nonamputee and amputee subjects. The new approach, based on a set of conditional parallel classifiers was the most promising with errors significantly less (p <; 0.05) than a single linear discriminant analysis (LDA) classifier or a parallel approach. Al-Quraishi MS et al[14] employed three classifiers to assess the two feature sets, namely linear discriminant analysis (LDA), k nearest neighborhood, and Naïve Bayes. Results indicated the LDA classifier outperformed the other two classifiers considered in this study.

With the deepening of theoretical research, the demand for EMG prostheses is getting higher and higher. Not only the number of recognizable limb movement patterns should be increased, but also the motion response of prosthesis should be fast and accurate[15-16]. However, there are not many kinds of EMG prosthesis used in clinic, and the recognition rate needs to be improved. In addition, the recognition of continuous movements is still in its infancy, and there is still a long way to go to completely replace the function of human hands. Therefore, how to obtain the features of EMG signals with higher accuracy and less classification and recognition time and the method of pattern recognition have become the most concerned issues in the current research of surface EMG signals[17-19].

3 Data acquisition and noise reduction

3.1 Acquisition of surface electromyography signal

In this paper, because the research is mainly about the basic movements of the hand, we choose the forearm which is closer to the hand distance to extract the signal. In practice, the fingers of the hand can be divided into three parts according to the motion correlation degree, that is, the distribution of the thumb and the index finger as a single motion part and the other three fingers together to form a motion part; Kapandji test ,which is a widely used evaluation criterion for the dexterity of the prostheses in the world[20-22]. The core of the standard is whether the thumb of the bionic hand can touch the fingertips and of the other four fingers conveniently. Therefore, this article selects the 9 actions shown in Figure 1 to extract EMG signals, and the 9 actions are defined as Rest (Re), Hand close (HC), Hand open(HO), Pronation(PR), Wrist Extension(WE), Wrist Flexion(WF), Thumbs up(TU), Thumb and index finger contact(TI), Thumb and middle finger contact(TM), such an action combination has basically covered the common hand movements and all freedom in daily life. At the same time, these 9 movements can also satisfy the discrimination of dexterous hands of Kapandji test to a certain extent. Therefore, we can extract representative features from these 9 hand movements of sEMG to control bionic prosthesis or rehabilitation equipment. In this paper, electromyogram (EMG) signals of forearms of two healthy subjects aged 23 and 24 were collected by cross-pump electromyograph. Because the amplitude and waveform information of signals controlling different groups of motor muscles are often very different, a unified sampling mode was adopted in this experiment: 16 channels, 1 kHz and 12 Bits. In this mode, the sampling frequency of sEMG signal is 1000Hz. In order to eliminate the influence of individual differences, two healthy subjects were used to complete nine different movements independently, with an interval of 2 seconds and 20 repetitions each. At the same time, in order to reduce the fatigue effect signal stability of the experimenter after completing multiple movements, a minute rest was taken after collecting two sets of data.

Fig. 1 Hand action planning

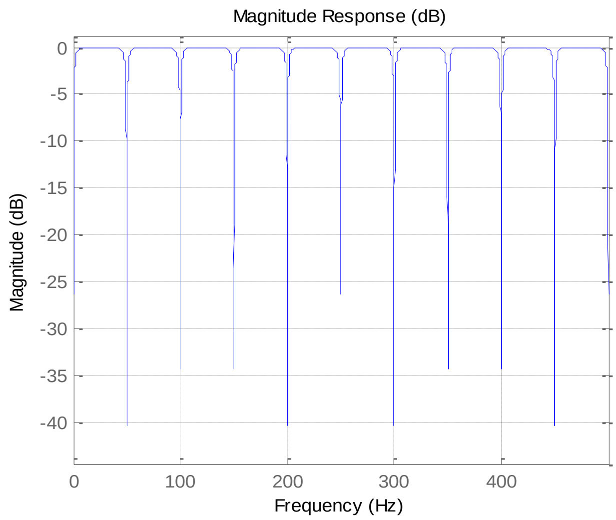
3.2 Noise reduction of original surface EMG signal

In order to achieve high recognition rate of classification results, the original surface EMG signals need to be pre-processed before final classification. The preprocessing includes two stages of noise reduction and feature selection; the EMG signal contains many kinds of noise due to its interference[23-25]. In this paper, the noise is classified and the noise is processed with digital filtering and wavelet transform, and the true signal wave is reduced as much as possible. At the same time, feature selection and feature vector are selected[26-28]. The formation is also the key point for the implementation of the rehabilitation equipment and intelligent prosthetic control strategy. This paper will compare a variety of features and select the better separable data to make up the feature vectors for the next step.

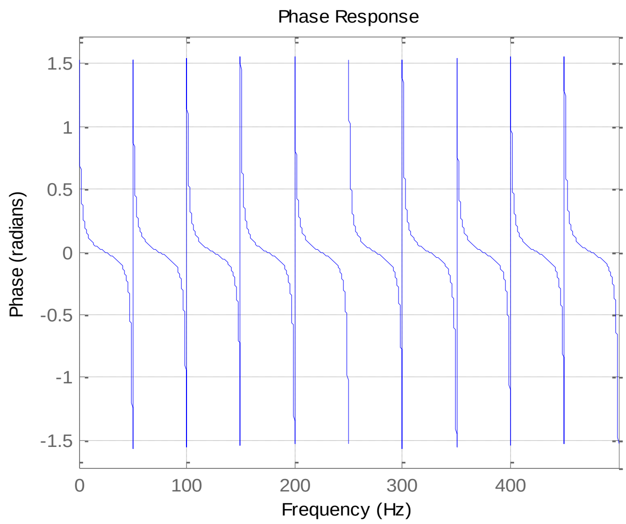
3.2.1 Filtering and noise reduction of surface EMG signal

In a variety of sEMG noise, power frequency interference is the main noise in the whole frequency range of EMG, because it is first considered. Although most EMG signal acquisition instruments have taken some hardware measures to deal with it, such as trap filter and high mode rejection ratio amplifier, the power frequency noise still exists[29-30]. The power frequency noise is mainly caused by the nonlinear characteristics of electronic devices, such as switching power supply, electronic fluorescent lamp ballast, uninterrupted power supply and so on. So a 50Hz comb filter (comb filter) is designed to filter the power frequency interference[31-33].

The power frequency of the EMG acquisition instrument is 50Hz, and the frequency of the industrial frequency noise can be predicted to be about 50Hz, 100Hz, 150Hz and so on. At the same time, the amplitude of the power frequency noise is stable in the time domain. Because the sampling frequency of the signal is selected as 1000Hz in this experiment, and the interference of the power frequency is in the 50Hz and its integer times, the design order of the filter must be set to 1000/50=20, so this paper designs a 20 order 50Hz comb filter to remove the noise of the power frequency. The frequency response diagram of this filter is shown as fig.2.



a) frequency response in frequency domain



b) time domain response

Fig. 2 Frequency response diagram of 20 order comb filter

The filter result diagram of the comb filter, such as Fig. 3, and the contrast two diagram can be found that the filter mainly filters the integer multiple signal of the frequency 50Hz, and the other frequencies are not changed.

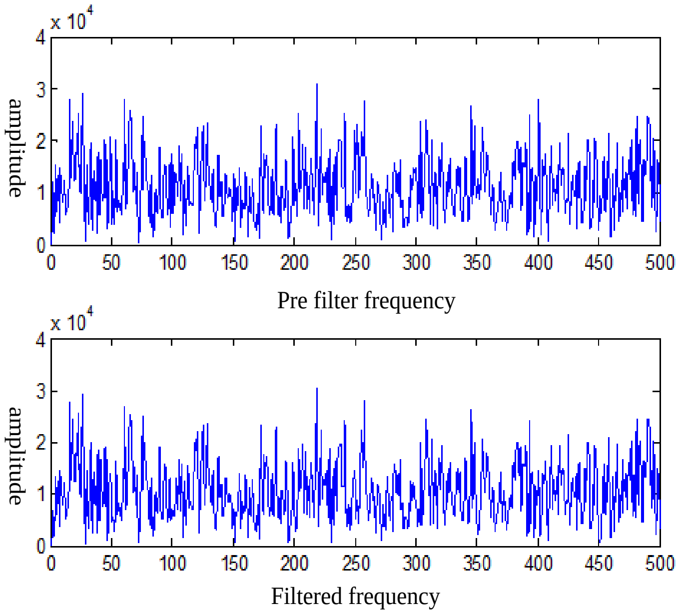


Fig. 3 Filter results of a dresser filter

3.2.2 Wavelet threshold noise reduction of surface EMG signal

Wavelet threshold noise reduction is based on wavelet decomposition, and wavelet decomposition is a multi-frequency hierarchical decomposition of sEMG through a series of wavelet basis functions or specific wavelet basis functions, and then sets a certain threshold to deal with specific frequency components, and finally integrated into the original signal to achieve noise reduction[34-37].

In order to remove the noise contained in the collected signal and achieve the purpose of wavelet de-noising, three steps should be taken: wavelet decomposition, wavelet threshold quantization and wavelet reconstruction. Wavelet decomposition is to decompose the original signal by choosing the appropriate benchmark function and the appropriate analytical scale. Since the decomposed high frequency bands are not pure useless interference, it is necessary to select appropriate thresholds to quantify each high frequency component. The waveform after threshold quantization is basically the useful EMG signal in the original signal, but because it still exists in the form of each component, it is necessary to reconstruct and synthesize the EMG signal with high signal-to-noise ratio by wavelet reconstruction.

(1) The selection of the small wave basis function

Generally, the selection of basic functions is generally considered by its orthogonality, support set, regularity, and the order of vanishing moment. Because the sEMG signal is weak and low frequency, its energy is very weak. This paper focuses on the effective preservation of the energy, mainly based on the orthogonality to select the wavelet basis function, in which the dbN wavelet is used. In this paper, the dbN wavelet system is selected as the base function of signal de-noising, so the energy of the dbN wavelet is not lossless when the other small wave base functions do not have the orthogonality[38-40].

(2) Wavelet threshold noise reduction and effect test

When the wavelet analysis is performed on the basis of the same wavelet basis function, the effect of wavelet noise reduction depends mainly on the decomposition scale and threshold setting. Unfortunately, there is a lack of authority on how to determine and select the two, which is mainly dependent on the result of the actual noise reduction effect of the researchers according to their experimental results[41-43]. The current actual noise reduction effect is mainly evaluated from the angle of the signal itself and the noise, and this paper is based on the two values of the mean square root and the signal to noise ratio gain in the noise reduction effect to determine the appropriateness of the number of decomposition layers; the noise reduction effect is negatively correlated with the mean square root error and is positively related to the signal to noise ratio gain[44-46].

After repeated tests and actual results, the db5 wavelet basis function of three layers is selected to process EMG signals. As shown in Fig.4, three different threshold rules are used to quantify the noise reduction effect of a certain channel signal after noise reduction, and the signal to noise ratio gain and the mean square root error calculation results of the three threshold processing methods are shown in Table.1.

Table.1 Results of GSNR and RMSE after three threshold quantization methods

	Gain signal noise ratio (GSNR)	Root mean square error (RMSE)
Mandatory threshold	7.1256	1.8632
Default threshold	7.0792	1.8667
Given soft threshold	8.8151	3.699

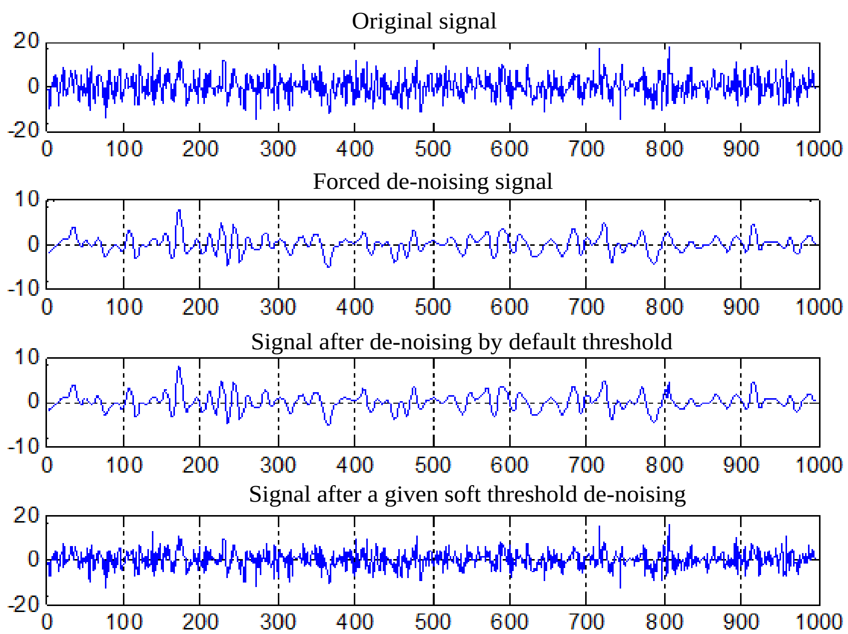


Fig.4 Contrast diagram of signal noise reduction effect

To sum up, fig.4 and Table.1 show that the effect of the mandatory threshold and the default threshold is quite close, but it can be seen that the effect of the mandatory threshold is slightly better than the default threshold, and the effect of the given soft threshold is not ideal because of the improper setting of the specific threshold.

4 Feature extraction of surface EMG signal

The main purpose of feature extraction is to map complex signals from high dimensional space to low dimensional space by using signal characteristics, and make classification simple and intuitive in data background[47-49]. Therefore, after a long period of exploration and research, many related researchers have divided the feature extraction into three main directions: time domain analysis, frequency domain analysis, time frequency analysis[50-51].

In this paper, sample entropy, time domain features RMS and WL are used as eigenvalues to form eigenvectors, as shown in formula.1. The RMS value of EMG signal actually represents the instantaneous electric power of the signal. Its waveform is similar to the linear envelope waveform of EMG signal, but it is more linear with muscle force. It is a better mathematical expression than the linear envelope of EMG signal. Waveform length is the statistics of waveform length in an analysis window. Wavelength can reflect the duration, amplitude and frequency characteristics of the sample. Sample Entropy measures the probability of generating new patterns in time series complexity. Sample Entropy overcomes data deviation, has stronger anti-noise ability and excellent consistency, and can obtain stable entropy value by using less data segments.

$$feature = \{RMS, WL, SampEn\} \tag{1}$$

Since this paper uses 16 channels to collect EMG signals at the same time, any single eigenvector dimension is: 1*48. After collecting 9 action 16 channel signals, the eigenvalue of one channel is calculated to carry out the validity of the eigenvector. As shown in Table.2, it is the three eigenvalues of this channel under 9 actions. The mean value, in order to be more intuitive to observe the difference between the same eigenvalues under different movements, take a histogram for differential description, as shown in fig.5~ 7.

Table.2 Three eigenvalues of a single channel under 9 actions

	RMS	***WL***	***SampEn***
Re	7.1262	1.8368*e3	0.9410
HC	183.1176	4.3872*e4	0.9133
HO	125.5576	2.5299*e4	1.5337
PR	102.8147	2.1140*e4	0.9705
WE	42.9087	1.1577*e4	1.1249
WF	50.0360	1.3359*e4	1.3516
TU	28.5878	6.6026*e3	1.0930
TI	58.4510	9.3138*e3	1.1672
TM	75.1499	1.3223*e4	1.4571

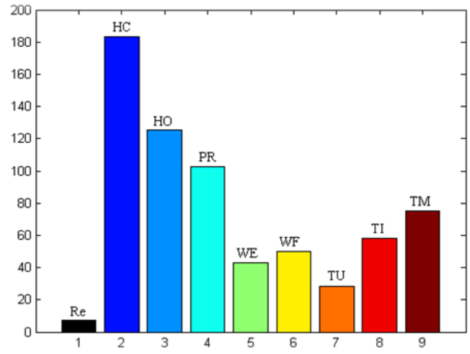


Fig.5 The RMS mean of different actions under a single channel

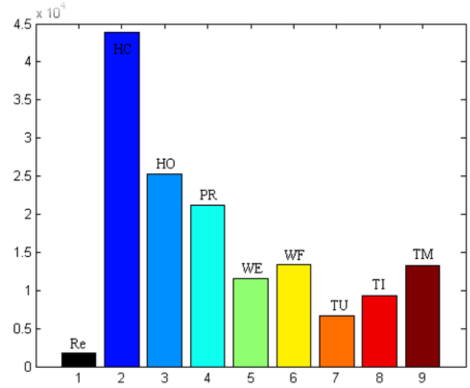


Fig.6 The WL mean of a single channel under nine actions

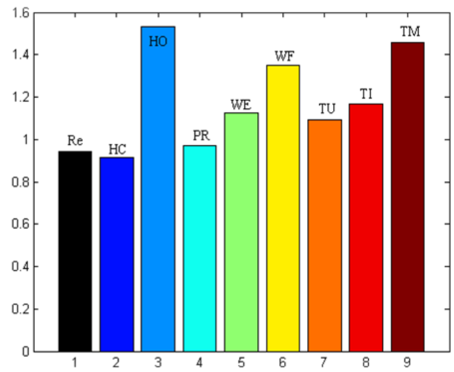
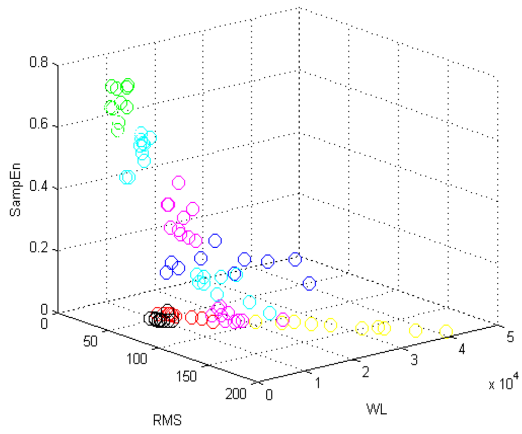
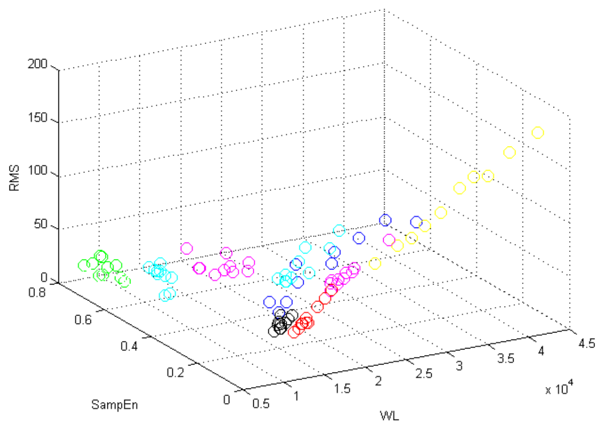


Fig.7 The SampEn mean of a single channel under nine actions

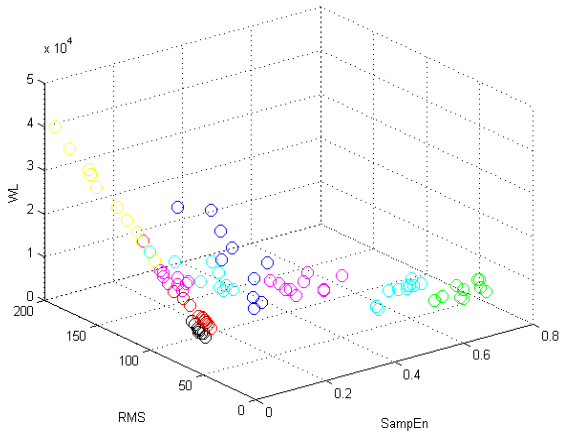
From fig.5~ 7, it can be clearly seen that there are obvious differences between the three eigenvalues extracted from the multiple actions of the channel. In order to further illustrate the separability of the resulting eigenvector, this paper draws the scatter plot of the 10 sample points of the 9 movements, as shown in Fig.8.



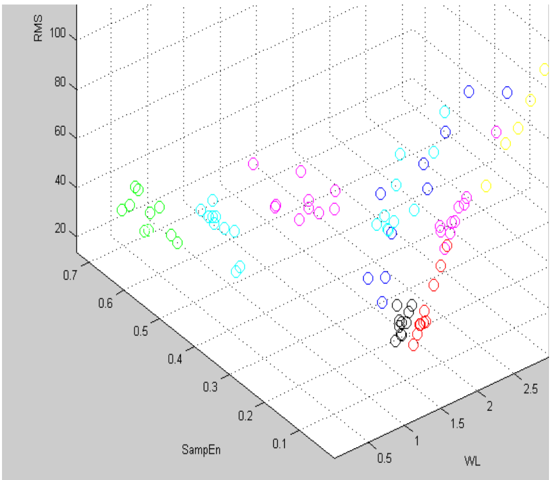
A) set up a scatter point map in a coordinate system with RMS-WL- SampEn



B) set up a scatter point map in a coordinate system with SampEn-WL- RMS



C) set up a scatter plot of coordinate system with RMS-SampEn-WL



D) black and red local big map

Fig. 8 Scatter points of 9*10 sEMG eigenvectors in a single channel

Because in Matlab, the color three tuples have only 8 colors, one of which is white, so in Fig.8, two separate blue colors and two separate purple are set to represent different movements; from Fig.8, nine hand movements are found to be discrete, and there is a very different movement (black and red in the map). To be close, but Fig.8 (d) of the part of Fig.8(b) still can be found that there is an obvious separation in the distribution area. In summary, it is feasible to extract the sample entropy, the time domain feature RMS and the WL as the characteristics of the 9 action patterns of the hand.

5 Hand movement recognition based on SVM and GRNN

After the preparation of sEMG noise reduction and feature extraction, in order to realize the final classification of hand movements, the feature vectors need to be input into the appropriate classifier, and the final recognition rate is very high with the separators, so the selection and design of the classifier is particularly important[52]. However, many kinds of classifiers are used at present, and both of them are in their own advantages and short boards. It is necessary to choose the best hand action classifier by a certain comparative experiment.

Common classifiers include KNN classifier, K-means classifier, SVM classifier, Bayesian classifier, neural network classifier and so on. The KNN method mainly relies on the limited neighboring samples, not on the method of discriminating the class domain to determine the category. Therefore, the KNN method is more suitable than other methods for the sample set with more overlap or overlap of the class domain. The K-means algorithm makes each cluster satisfy the internal object similarity higher, while the object similarity in different clusters is smaller. SVM algorithm is to find a hyperplane. For the training samples that have been marked, the SVM training gets a hyperplane, which makes the vertical distance between the samples nearest to the hyperplane in the training set of two categories maximize. The classification principle of Bayesian classifier is to calculate the posterior probability of an object by using the prior probability of the object, that is, the probability that the object belongs to a certain class, and select the class with the maximum posterior probability as the class to which the object belongs. Neural network has a good ability to deal with non-linear characteristics. As a classifier, neural network can complete the classification of actions very well.

In this chapter, the standard support vector machine and neural network are used as classifiers for comparison, and the optimal classifier for hand motion pattern recognition is obtained[53].

5.1 Action recognition based on support vector machine classifier

5.1.1 Establishment of support vector machine classification model

After the EMG data is divided, the grid search method is used to optimize the SVM parameters. The optimal parameters are shown as shown in Fig.9. When the parameters are C=2, σ=3.0518e-5, the correctness rate of the 50 percent off cross validation recognition of the training set is 99.8827%, and the C σ is the best value at this time.

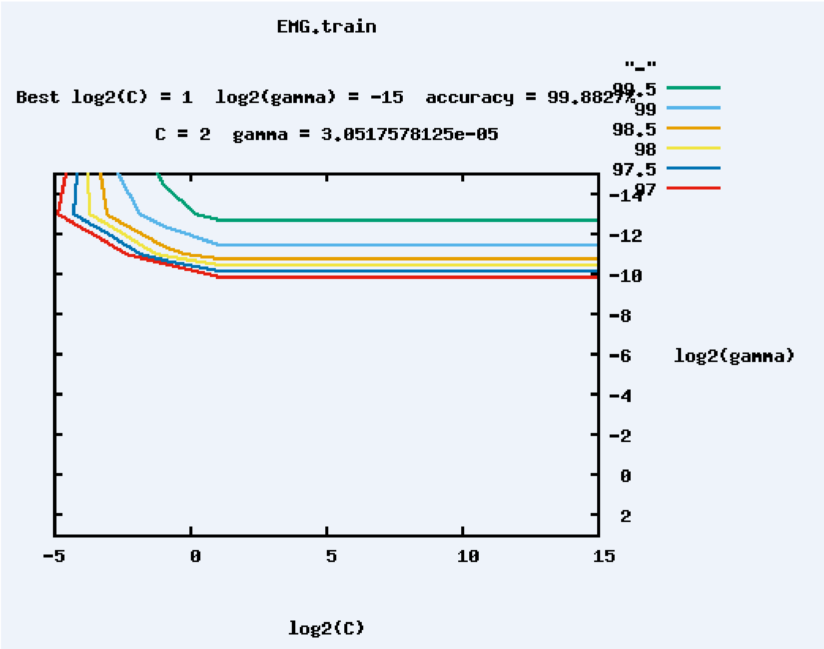
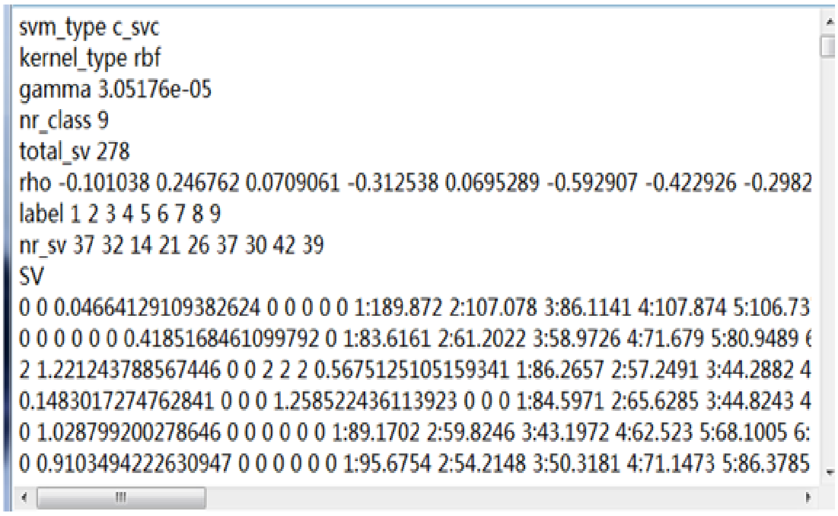


Fig.9 Grid method to obtain the best SVM parameter diagram



svm_type c_svc
kernel_type rbf
gamma 3.05176e-05
nr_class 9
total_sv 278
rho -0.101038 0.246762 0.0709061 -0.312538 0.0695289 -0.592907 -0.422926 -0.2982
label 1 2 3 4 5 6 7 8 9
nr_sv 37 32 14 21 26 37 30 42 39
SV
0 0 0.04664129109382624 0 0 0 0 0 1:189.872 2:107.078 3:86.1141 4:107.874 5:106.73
0 0 0 0 0 0 0.4185168461099792 0 1:83.6161 2:61.2022 3:58.9726 4:71.679 5:80.9489 6
2 1.221243788567446 0 0 2 2 2 0.5675125105159341 1:86.2657 2:57.2491 3:44.2882 4
0.1483017274762841 0 0 0 1.258522436113923 0 0 0 1:84.5971 2:65.6285 3:44.8243 4
0 1.028799200278646 0 0 0 0 0 0 1:89.1702 2:59.8246 3:43.1972 4:62.523 5:68.1005 6:
0 0.9103494222630947 0 0 0 0 0 0 1:95.6754 2:54.2148 3:50.3181 4:71.1473 5:86.3785

Fig.10 SVM test model parameter diagram

After the optimum parameters are obtained, the SVM classifier is trained with the best parameters combined with the training set. The model test.model is obtained after training, and the related parameters of the model can be opened with the Notepad[54], as shown in Fig.10. The following related information can be obtained from the graph. The support vector machine type is c_scc. The support vector machine is mainly used for multi classification, the kernel function type is RBF (radial basis) kernel function, the kernel function parameter is 3.05176*10-5, the total number of classes is 9, the whole SVM model support vector number is 278, the support vector of each category is numbered. Instead of 37, 32, 14, 21, 26, 37, 30, 42 and 39, the model will list all the support vectors.

5.1.2 Classification and recognition results of SVM classifier

On the basis of the SVM model, we use the model to test the test set samples. The correct classification rate of the 9 hand actions is 98.64%, as shown in Fig.11. At the same time, according to the classification result of the returned test set data, the recognition result of single action is shown in table.3.

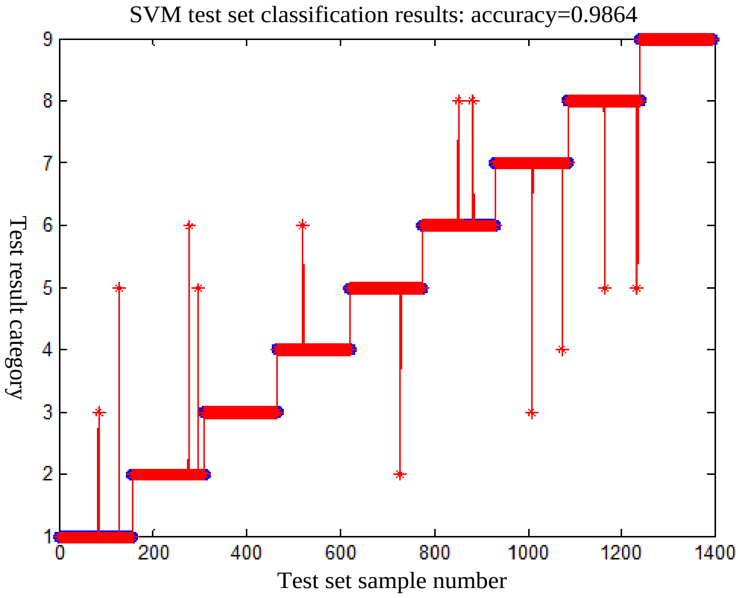


Fig.11 SVM classification result diagram

Table.3 SVM for separate identification results for nine categories

Action mode	Label number	Classification results (Group)	Recognition rate	Overall recognition rate
Rest	1	153/155	98.71%	
HC	2	152/155	98.06%	
HO	3	155/155	100.00%	
PR	4	153/155	98.71%	
WE	5	153/155	98.71%	98.64%
WF	6	151/155	97.42%	
TU	7	152/155	98.06%	
TI	8	151/155	97.42%	
TM	9	155/155	100.00%	

5.2 Action recognition based on generalized regression neural network classifier

Generalized regression neural network is a radial basis function network based on mathematical statistics. Its theoretical basis is nonlinear regression analysis. GRNN has a strong nonlinear mapping ability and learning speed, and has a stronger advantage than RBF. The network converges to the optimal regression with more sample size aggregation. When the sample data is less[55], the prediction effect is very good. The network can also deal with unstable data.

5.2.1 The establishment of generalized regression neural network model (FOA-GRNN) based on FOA.

At the same time, the generalized regression neural network is used for classification and recognition, and the classification results are compared with the support vector machine. At the same time, in order to make the GRNN result more accurate, the FOA is used to find the best smoothing factor Spread for the kernel parameters of the generalized regression network[56]. The target function of the FOA optimization uses the root mean square error (RMSE) of the predicted value of the classification results and the actual value. The FOA algorithm optimizes the smoothing factor results, such as fig.12 and fig.13, where fig.12 is the flight path map of the fruit fly in the optimization process, for example, fig.13 is a convergent process diagram that dynamically adjusts the root mean square error of the predicted value and the actual value of the GRNN after the 200 iteration of the Drosophila algorithm.

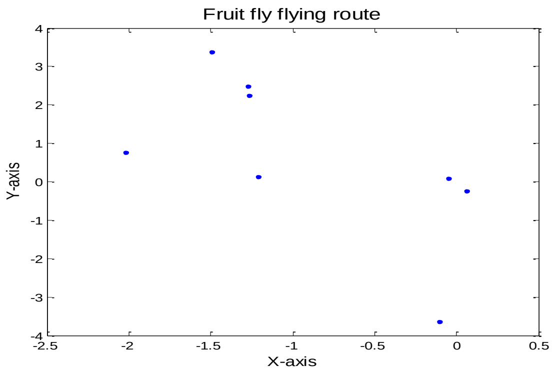


Fig.12 Iterated trajectory of fruit fly in FOA-GRNN model

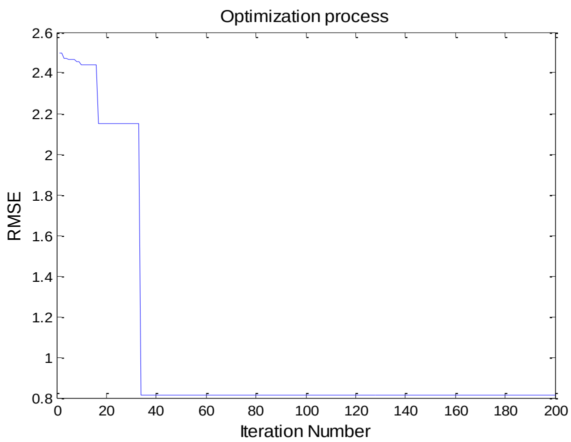


Fig. 13 The optimization of the GRNN process diagram of the fruit fly algorithm

According to figure 4.4 and figure 4.5, RMSE can converge to thirty-third generations in the optimization process and RMSE value is 0.8090. The best smoothness factor Spread is 0.00721. The final location of the Drosophila population is to replace the best smoothing factor at this time into the network architecture of the GRNN, and the test sample is replaced by the optimized GRNN model, and the classification results can be obtained.

5.2.2 Pattern recognition results based on GRNN neural network classifier.

After the best smoothness factor Spread value of the fruit fly algorithm is 0.00721, the initial presupposition value of the GRNN neural network is set to 0.00721, and the data of the test set is input to the classification result. As shown in Fig.14, the result of the classification of the FOA-GRNN model is shown in table 4.

Table.4 FOA-GRNN separate identification results for nine categories

Action mode	Label number	Classification results (Group)	Recognition rate	Overall recognition rate
Rest	1	154/155	99.35%	
HC	2	143/155	92.26%	
HO	3	155/155	100.00%	
PR	4	148/155	95.48%	
WE	5	150/155	96.77%	96.27%
WF	6	145/155	93.55%	
TU	7	153/155	98.71%	
TI	8	147/155	94.84%	
TM	9	154/155	99.35%	

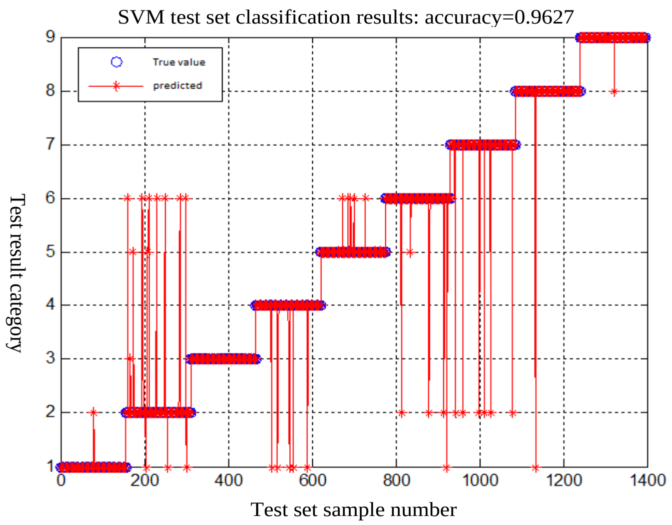


Fig.14 FOA-GRNN test set classification result diagram

5.3 Comparison and analysis of the classification results of two classifiers

By comparing fig.11 and fig.14, table.3 and table.4, it is known that the classification and recognition of the surface EMG signals are excellent and the recognition accuracy is above 96%, However, for rehabilitation medical systems or EMG prostheses with strict diagnostic accuracy, the SVM classifier based on the optimization of grid search parameters is superior and reliable in performance and should be preferred. The body recognition rate is 98.64%.

At the same time, it can be found from table 4.2 and 4.1 that although the overall recognition rate of the two classifiers for the 9 movements reached a high level, there is a great difference in the recognition rate of some hand movements; the recognition effect of the support vector machine on the action 3 (hand) and the action 6 (wrist collecting) is poor, but the classification error is only very individual, and the error is wrong. The cause of error is more accidental.

The main reason for the low recognition rate of neural network classifier is that the neural network has poor recognition effect on action 2 (fist clenching) and action 6 (wrist collecting), and the wrong classification of the generalized regression neural network based on the optimization of the fruit fly algorithm is the error recognition of the action 2 and the action 6. The reason for this problem may be collected. Both wrist and fist action can cause tension contraction in the inside muscles of the wrist so that the neural network classifier can’t be identified correctly; at the same time, a certain amount of action 7 (vertical thumb) is displaced into action 2 (clenching fist), and this part of the error classification may be similar to action 7 and action 2, only the gesture of the thumb. The other four fingers have the same posture, so most of the two involved muscles and the generated electromyogram signals are quite similar.

6 Conclusions

Based on the current research status and problems of surface EMG signals at home and abroad, the surface electromyography signals extracted from the human forearm during hand movement are studied, based on the support vector machine and the generalized regression neural network theory, this paper establish the classifier of hand movement pattern recognition, and the classification and recognition of surface EMG signal of 9 kinds of hand movements are successfully realized by using the established classifier. The classification results show that the classification accuracy of the two classifiers is above 96%, among which support vector machine accuracy of the classifier is 98.64%, and the classification effect is more accurate and reliable than that of generalized regression neural network. Combined with the content of this paper, although the noise reduction, feature extraction and pattern recognition of surface electromyogram (EMG) signals have been studied in this paper, the degree of mining various information contained in EMG signals is still at a fairly early stage. As a control signal source, there is still much work to be done in the practical application of EMG signals. This topic needs further research in the following second aspects:

1) In this paper, only nine representative hand movements are selected under the current understanding of human motion science, and some exquisite hand movements in real life have not been involved. In the future, with the help of human Kinesiology knowledge, the function of the hand will be decomposed in detail, more comprehensive recognition of hand movements is achieved based on representative movements.

2) At present, the classification of EMG signals mostly only discriminates the types of movements, but there are also great differences in the intensity of the same movements. In the

future research, the recognition of EMG signals should be added to meet the needs of rehabilitation equipment for accurate realization of human movements.

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