Four-channel sEMG for Elbow Load Recognition

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Four-channel sEMG for elbow load recognition

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In order to help patients after surgery to carry out reasonable rehabilitation training, avoid joint adhesions and movement disorders, the relationship between surface electromyograph (sEMG) signal changes and the size of the patient ' s joint force in the process of rehabilitation exercise was studied, hoping to use the relationship between them to redesign the control mode of the rehabilitation robot, and a method was proposed to identify the size of the elbow load based on wavelet packet. Firstly, s EMG signals of human elbow joint during stretching and bending under different loads were collected by 4-channel surface electromyography. Then, the wavelet packet decomposition method was used to obtain the feature vector composed of energy(E), variance(VAR) and mean absolute value(MAV) of wavelet packet coefficient. Finally, the improved support vector machine (ISVM), BP neural network and RBF neural network were used for pattern recognition of three different forces. The experimental results show that the change of sEMG signal is indeed related to the size of joint force. It is feasible to identify the load of s EMG signal.

Keywords: Wavelet packet; surface electromyography(s EMG); load identification; improved support vector machine(ISVM); BP neural network; RBF neural network.

1. Introduction

Surface Electromyography (s EMG) is a non-stationary physiological signal, which is superimposed on the skin surface by the potential of the motor unit during muscle contraction. The limbs have different muscle contraction modes under different loads, and the signals under different modes contain abundant muscle contraction force information. There are also differences between s EMG signal characteristics. The s EMG signal characteristics can be effectively used to distinguish the different load modes of limbs. Therefore, s EMG signal can be applied to sports medicine, rehabilitation medical training and other fields, and is an ideal control signal for medical prosthetics and intelligent boosters.

Xiuwu Sui et al. used the improved SVM algorithm to effectively identify six kinds of daily upper limb movements [1]. The average recognition rate reached 90.66 %, and the training time was shortened by 0.042 s. The problem of low recognition rate and long recognition time of three-degree-of-freedom prosthesis was solved. Junkai Shao et al. first proposed a hybrid classification model based on singular value decomposition and wavelet deep belief network, which allows the machine to identify the single joint motion of the upper limb through a single channel [2]. The fully connected feedforward DNN model was used to classify eight different hand movements by Anand Kumar Mukhopadhyay and his group, and they compared it with the existing machine learning tools [3]. They used the time domain power spectrum descriptor (TDPSD) as the feature set to train the DNN classifier. Firas AlOmari et al. proposed an intelligent hybrid pattern recognition system to classify eight hand movements, which was a combination of genetic algorithm, particle swarm optimization and support vector machine [4]. The new model (GAPSO-SVM) had higher prediction accuracy and reliability, with an average accuracy of up to 98.7 %. According to Jiho Noh and others, wavelet packet was used to decompose s EMG signal, and extracted the energy and variance of wavelet packet coefficients of s EMG signal as feature vectors [5]. SVM classifier was used to effectively identify six commonly used upper limb movements, and the average recognition rate was 90.66 %. Navleen Singh Rekhi et al. used wavelet packet transform to extract wavelet packet energy and singular value of s EMG signal as feature vector [6]. SVM classifier was used to classify six different hand movements, and the average recognition accuracy was 93.33 %. The amplitude of s EMG signal can be used as the control input of EMG prosthesis and the measurement method of muscle force. Karimi combined genetic algorithm (GA) with artificial neural networks (ANNs), and proposed a new pattern recognition method, which was used to identify the types of hand movements, and identified 10 hand movements. The recognition accuracy reached more than 98 % [7]. See Refs.8,9,10,11,12 for more details.

The current rehabilitation training robots have only a fixed trajectory. In this case, patients either fail to achieve the purpose of training muscles due to insufficient exercise, or cause secondary injury due to excessive exercise. Therefore, it is urgent to study the sEMG signal generated by patients in the process of rehabilitation training, and then redesign and upgrade the training robot. In order to help patients with better rehabilitation training after surgery, avoid joint adhesions and movement disorders, the relationship between sEMG signal changes and joint force of patients in the process of rehabilitation exercise was studied, hoping to use the relationship to reset the control mode of the current rehabilitation training robot, and a method was proposed to identify the size of the elbow load. The size of the elbow load was identified by improved support vector machine(ISVM), BP neural network and RBP neural network.

2. s EMG Signal Acquisition

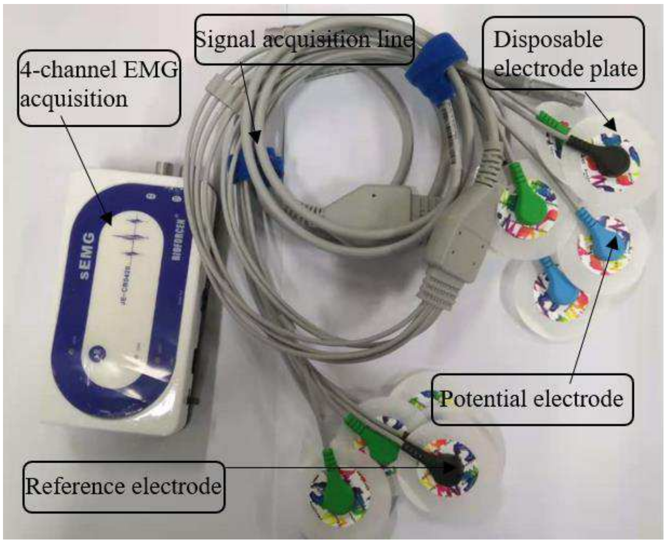


Fig.1. EMG acquisition equipment.

In this paper, four-channel surface EMG acquisition instrument was used for s EMG signal acquisition, the sampling frequency was 1000 Hz. First of all, the subjects were experimented to standardize the course of action. The s EMG signals of the corresponding biceps brachii, brachial Tricep, brachioradialis, and flexor carpi ulnaris were collected by four-channel EMG acquisition instrument. Then the s EMG signals were uploaded to the computer through the USB interface for relevant data pre-processing and analysis. The acquisition equipment is shown in Fig.1.

Table 1. Test details.

Gender, number of the experimental objects		Muscle name	Load
Male	5	biceps	0kg
Female	4	triceps	1.5kg
		flexor carpi ulnaris	4kg
		brachioradialis	

The experimental objects in this study are five healthy males and four healthy females, aged 20-30 years old. There was no strenuous exercise within 24 hours before the experiment to prevent the influence of muscle overfatigue on the test results. The details are shown in Table 1. Before the test, the object was naturally sitting in a chair, and the right arm was placed flat on the table to relax. First of all, the alcohol was used to clean the electrode position of the acquisition site (biceps brachii, brachial Tricep, brachioradialis, and flexor carpi ulnaris), the glycerin was applied to reduce skin surface impedance and enhance conductivity . Then, the four-channel EMG acquisition electrodes were respectively attached to the test site of the arm, in which the test electrodes (2 electrodes) of each channel were attached to the corresponding muscles in parallel to the direction of muscle fibers, and the reference electrode (1 electrode) was attached to the non-muscle near the test electrodes. The three electrodes were placed in triangles, and the spacing between the three electrodes should not be too large to ensure more accurate test signals. Finally, under the condition of no load, 1.5kg load and 4kg load, the objects performed elbow bending (elbow bending to 90 °) and stretching (flat to the desktop) according to the experimental standard action. Each person repeated ten bending and stretching exercises under each load condition. When the testers completed one bending and stretching exercise every time, the rest interval was 1-2s. It took 3 minutes to relax to prevent muscle fatigue when completed a group of load tests. The s EMG signal acquisition process is shown in Fig.2.

Fig.2. Data acquisition experiment.

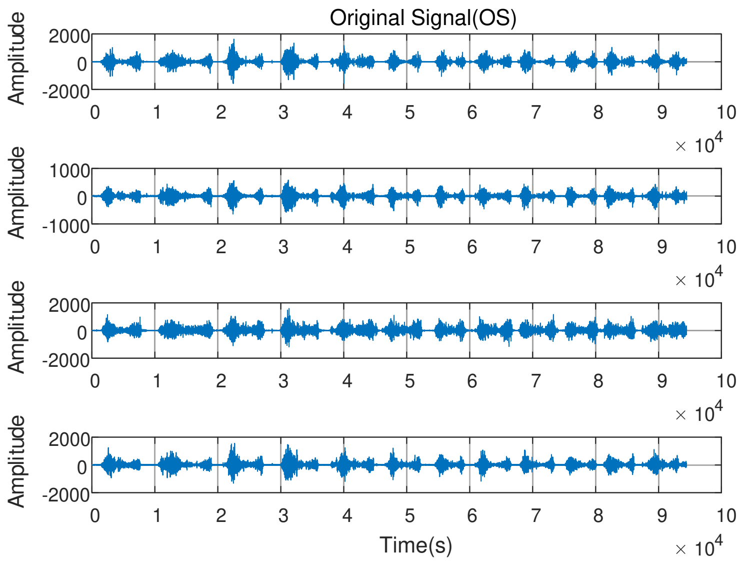
A total of 27 groups of experiments were carried out by 9 objects, and 270（9×3×10）groups of experimental data were recorded repeatedly for 10 times under each load. A total of 1080（9×3×10×4）groups of s EMG signals were collected from 4 corresponding muscles. The s EMG signals of biceps brachii, brachial Tricep, brachioradialis, and flexor carpi ulnaris were collected during elbow flexion and extension under three loads.

3. The pretreatment of s EMG

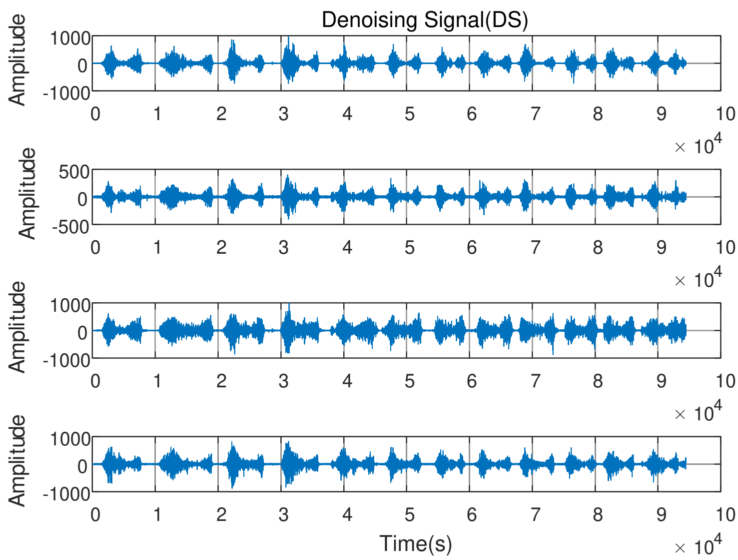
3.1. *Signal filtering*

The original s EMG signal is preprocessed to remove the interference of various environmental noise in the measurement, such as ECG signal and motion distortion noise. The s EMG signal is a low frequency weak signal, and its useful components are mainly concentrated in 0 Hz-500 Hz, and the energy is mainly concentrated in 20 Hz-300 Hz. According to the actual situation of s EMG signal acquisition, the Butterworth band-pass filter and 50Hz notch filter are designed. The original s EMG signal is processed by 10Hz-450Hz band-pass filter and 50Hz power frequency interference removal, and the pure s EMG signal is obtained. As shown in Fig.3, Fig.(a) is the original signal figure that has not been filtered, and Fig.(b) is the filtered s EMG signal figure.

Compared with the original s EMG signal, the high frequency and low frequency noise parts of the filtered s EMG signal are filtered, and the energy of each peak is more concentrated and the peaks are more clear, which makes the signal segmentation and feature extraction become convenient and reliable.



(a)



(b)

Fig.3. Comparison of s EMG signal before and after filtering.

3.2. *Segmentation of s EMG*

To study the relationship between s EMG signal of the elbow joint and different load size, it is necessary to continuously measure the s EMG signal during repeated stretching and bending under different loads. Only the EMG signal obtained during a complete cycle of stretching and bending movement of the elbow has certain analytical value, so the original signal needs to be divided into

10 complete stretching and bending movements.

In this paper, the double threshold method is used for data segmentation. The principle of the double threshold method is as follows : the s EMG signal is measured only when it exceeds the first threshold. If the continuous sample number or time length of the s EMG signal exceeds the second threshold, the sample or time of the s EMG signal that exceeds the first threshold for the first time is set to the beginning of the activation time [13]. The formula is as follows :

$$\tilde{x}(n) = F(x(n)), \tag{1}$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} \tilde{x}(n), \tag{2}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (\tilde{x}(n) - \mu)^2}, \tag{3}$$

$$H(\tilde{x}(n)) = \frac{1}{\sigma}(\tilde{x}(n) - \mu), \tag{4}$$

$$\tau_0 = \min\{n, H(\tilde{x}(n)) \geq h_1\}, \tag{5}$$

$$\tau_{0_n} = \tau_0 \quad if \quad m \geq h_2 . \tag{7}$$

where $x(n)$ is the original signal, $\tilde{x}(n)$ is the signal obtained after filtering, h_1 is the first threshold, h_2 is the second threshold, τ_0 is the time when the detected signal is greater than the first threshold, and τ_{0_n} is the starting time of segmentation.

In view of the test in the experiment, each complete extension action has a time interval of about 1 s, during which the s EMG signal is in a relatively flat stage, so the s EMG signal is analyzed separately. According to the above formula, $H(\tilde{x}(n))$ is calculated between -3.1979 and 4.1143. Therefore, the first threshold h_1 = 0.4582, between -3.1979 and 4.1143. Since each stretch action has a time interval of about 1 s, the second threshold h_2 is set to 40 ms.

A set of peaks of s EMG signal segmentation is a complete stretching and bending movement. It can be seen that the energy of the signal is mainly concentrated in the elbow bending part, which is consistent with the experiment. And the analysis of the segmented signal is reliable.

3.3. *Feature extraction based on wavelet packet*

3.3.1. *Theory of Wavelet Packet Algorithm*

In this paper, wavelet packet transform is used to extract the feature of s EMG signal. Wavelet packet transform is a more refined time-frequency analysis method based on wavelet transform. The difference between wavelet packet transform and wavelet transform is that the wavelet packet is decomposed into high frequency and low frequency for the first time, and the high frequency and low frequency for the first time are decomposed into high frequency and low frequency for the second time.Taking 3-layer wavelet packet decomposition as an example. Compared with wavelet transform, wavelet packet transform not only analyzes the low frequency of s EMG signal, but also decomposes its high frequency components to improve the high frequency resolution of s EMG signal [14].

Wavelet packet transform is composed of a set of linear combination of wavelet functions, the two-scale variance is as follows :

$$\omega_{2n}(t) = \sqrt{2}\sum_{k \in Z} h_{0k}\,\omega_n(2t-k), \tag{8}$$

$$\omega_{2n+1}(t) = \sqrt{2}\sum_{k \in Z} h_{1k}\,\omega_n(2t-k). \tag{9}$$

In the formula, h_{0k} and h_{1k} are a set of filter coefficients related to scale function and wavelet function, satisfying the relationship of $h_{1k}(n)=(-1)^n h_{0k}(1-n)$, that is, the group coefficients are orthogonal. When $n=0$, $\omega_0(t)=\phi(t)$ is a scale function and $\omega_1(t)=\varphi(t)$ is a wavelet function.

The formula of wavelet packet coefficients :

$$d_k^{j+1,2n}=\sum_l h_{0(2l-k)} d_n^{j,n}, \tag{10}$$

$$d_k^{j+1,2n+1}=\sum_l h_{0(2l-k)} d_l^{j,n}, \tag{11}$$

In the expression $d_l^{j,n}$ denotes the j th wavelet packet on layer l, $h_{0(2l-k)}$, $h_{1(2l-k)}$ is a filter.

3.3.2.*Feature extraction of s EMG*

According to the above formulas, it is very important to select the appropriate wavelet packet basis function for s EMG signal feature extraction. The db series wavelet is the most similar to the biological signal in the wavelet packet basis function. The db3 basis function is simple in structure and similar to the shape of s EMG signal. Therefore, db3 wavelet is used as the basis function to transform s EMG signal. According to the literature, when the s EMG signal is decomposed by wavelet packet, the decomposition layer is more suitable in 3-4 layers. After repeated tests, the test results show that it is much better that the s EMG signal is decomposed by three layers of wavelet packet.

A tester ' s s EMG signal of elbow joint was collected during flexion and extension movement under the load of 1.5 kg. The collected s EMG of biceps brachialis was taken as an example for wavelet packet decomposition. The db3 wavelet basis is used to decompose the preprocessed s EMG signal into three layers of wavelet packet.

According to the definition of energy, variance and mean absolute value, the wavelet packet reconstruction coefficient of s EMG signal obtained by wavelet packet transform can be used to calculate the energy, variance and mean absolute value, which can reflect the magnitude and severity of s EMG amplitude strength of muscle contraction under different loads in the process of elbow flexion and extension. The calculation formulas of energy, variance and mean absolute value of wavelet packet coefficient are as follows :

$$E_j=\sum_{j=1}^{N}\left|S_j\right|^2, \tag{12}$$

$$VAR_j=\frac{1}{N-1}\sum_{j=1}^{N}(S_j-\bar{S})^2, \tag{13}$$

$$MAV_j=\frac{1}{N}\sum_{j=1}^{N}S_j . \tag{14}$$

In the above formulas, j ($j=1,2,3,4,5,6,7,8$) is the number of wavelet packet coefficients, S_j is the wavelet packet decomposition coefficient, E_j is the energy of wavelet packet coefficients in the j th band, VAR_j is the variance of wavelet packet coefficients in the j th band, and MAV_j is the mean absolute value of wavelet packet coefficients in the j th band.

According to the above calculation formulas, the average and standard deviation of wavelet packet coefficient energy, mean absolute value and variance after logarithmic processing are shown in Table 2-4.

Table 2. Average and standard deviation of energy feature of wavelet packet coefficients.

Eigenvalue	Channel	Three load modes of elbow joint		
		No load	Load 1.5 kg	Load 4 kg
		Average± Standard deviation	Average± Standard deviation	Average± Standard deviation
$\log_{10} E_{31}$	1	632.8218±8.4137	1086.8465±2.1077	1607.8957±2.8656
	2	510.1075±9.2791	708.8240±12.8495	955.4142±15.1296
	3	490.6964±18.8921	1059.1653±1.7850	1662.2980±5.9451
	4	678.7305±9.6908	1027.1500±1.9901	1463.4796±2.086

Table 3. Average and standard deviation of mean absolute value feature of wavelet packet coefficients.

Eigenvalue	Channel	Three load modes of elbow joint		
		No load	Load 1.5 kg	Load 4 kg
		Average± Standard deviation	Average± Standard deviation	Average± Standard deviation
$\log_{10} MAV_{31}$	1	1.3868±0.0685	1.5113±0.0454	1.5998±0.0275
	2	1.3468±0.0349	1.4186±0.0379	1.5984±0.0545
	3	1.3306±0.0766	1.5072±0.0375	1.6063±0.0335
	4	1.3894±0.0347	1.4991±0.0452	1.82342±0.0581

Table 4. Average and standard deviation of variance feature of wavelet packet coefficients.

Eigenvalue	Channel	Three load modes of elbow joint		
		No load	Load 1.5 kg	Load 4 kg
		Average± Standard deviation	Average± Standard deviation	Average± Standard deviation
$\log_{10} VAR_{31}$	1	1.0135±0.0736	1.0324±0.0301	1.0164±0.023
	2	0.965±0.0910	1.013±0.0661	1.0027±0.0317
	3	1.0054±0.1377	0.9813±0.0414	0.9772±0.0331
	4	0.9905±0.1149	1.0061±0.0788	1.0121±0.0398

From the distribution of coefficient energy characteristics, coefficient variance characteristics and coefficient mean absolute value characteristics of four muscles (Fig. 4-6), it can be seen that although the coefficient variance characteristics have a little blend, the three characteristics have a good discrimination on the whole. And with the increasing load, coefficient energy and mean absolute value characteristics also show an increasing trend,which is more obvious, while the change of the coefficient variance characteristics is slightly gentle, in general, the distribution shows a unified increasing trend. Moreover, as shown in Fig.6, with the increase of load, the coefficient variance characteristics also show a trend from dispersion to aggregation. It can be seen from the figure that the coefficient variance characteristics are relatively dispersed without load, but when the load increases to 4 kg, the coefficient variance characteristics show extremely aggregation.

Therefore, the characteristic changes of muscle s EMG signal can directly reflect the changes of muscle force.

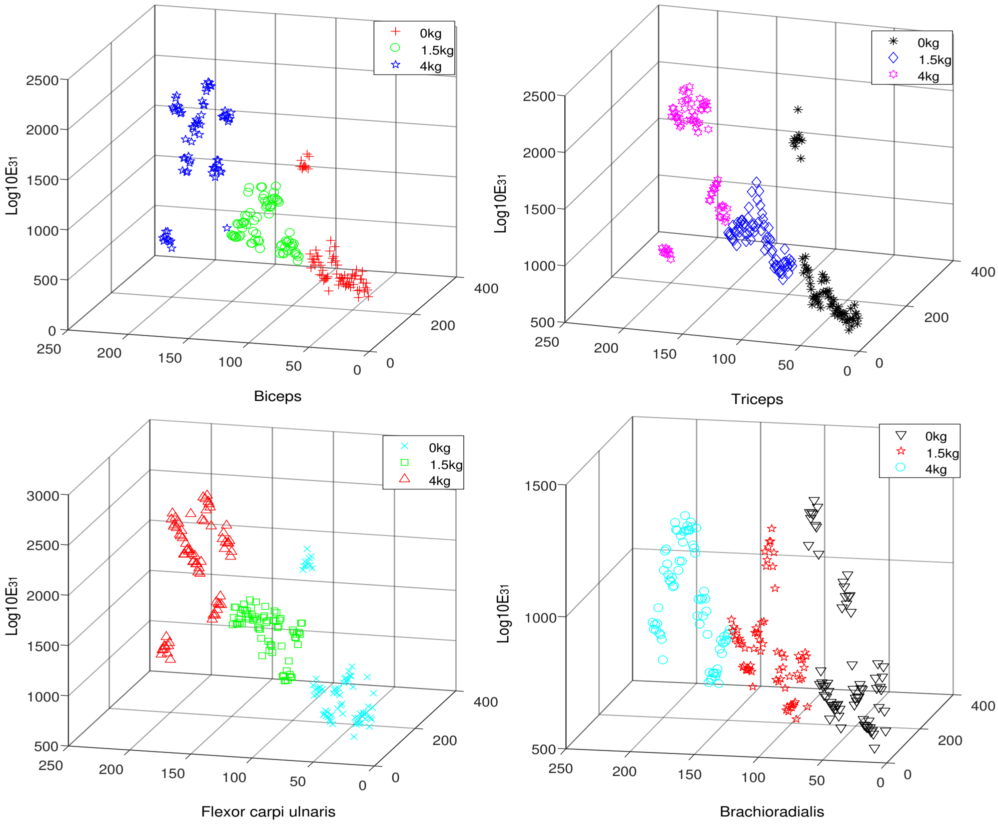


Fig.4. Distribution of s EMG signal coefficient energy characteristics of different muscles under different loads.

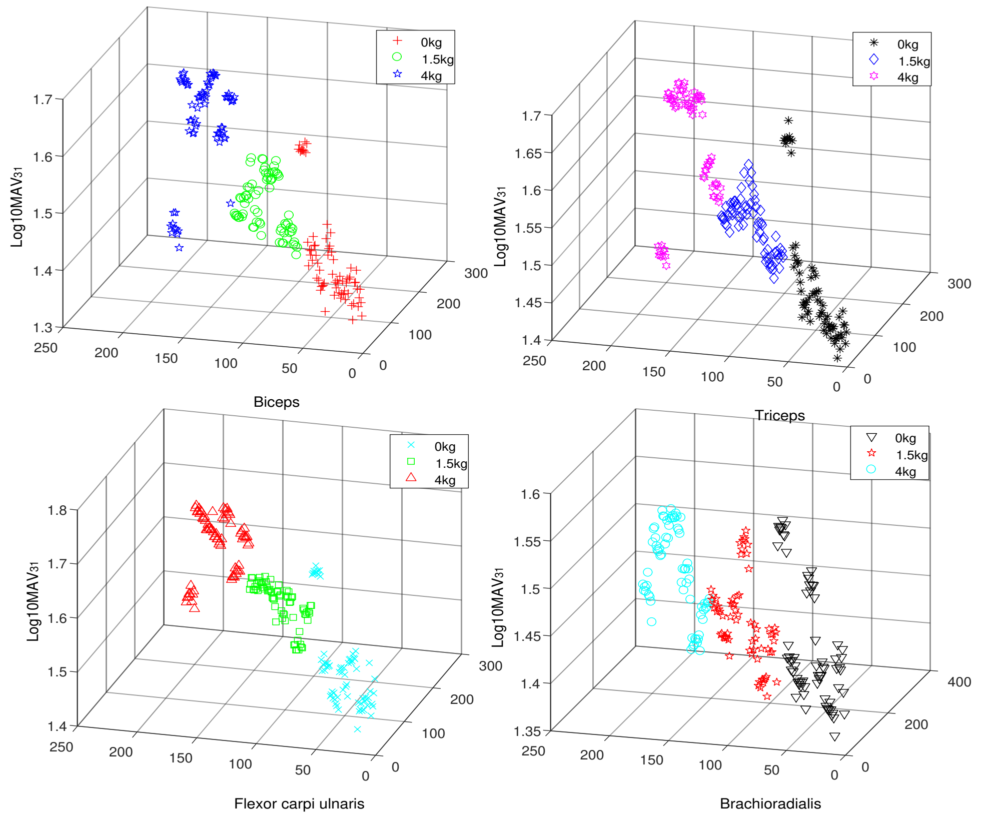


Fig.5. Distribution of s EMG signal coefficient MAV characteristics of different muscles under different loads.

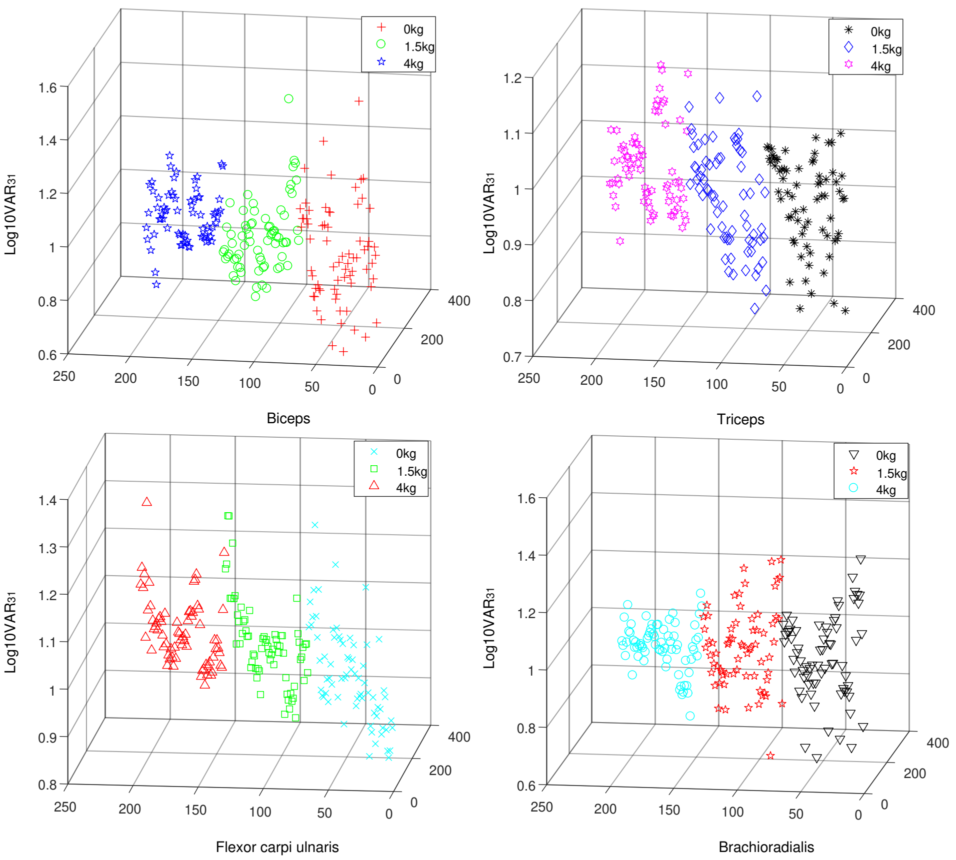


Fig.6. Distribution of s EMG signal coefficient VAR characteristics of different muscles under different loads.

4. Pattern recognition

4.1. *SVM*

Support vector machine is mainly used in linear separable data set. For linear non-separable data, kernel function is introduced for mapping operation, and penalty factor C and relaxation variable ξ_i are introduced. Penalty factor is to balance the relationship between classification loss and maximum classification interval, so as to realize the conversion of linear non-separable data points to linear separable. The kernel function used in this paper is radial kernel function, and the calculation formula is as follows :

$$K(x,x_i)=\exp\{-\frac{x-x_i^2}{\sigma^2}\}, \tag{15}$$

Let the sample data set to be classified be (x_i, y_i), i=1,2,3…,n ; $x_i \in R$; Among them, y_i is the classification number of each category. According to the requirement of maximizing the classification interval, the optimal hyperplane function is :

$$\begin{cases} \min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \\ s.t.\ y_i\left[w * x + b\right] \geq 1-\xi_i, i=1,2,\ldots n \end{cases}. \tag{16}$$

Lagrange optimization method is introduced to solve the dual problem. The Lagrange function is constructed as follows :

$$L(w,b,\alpha,\xi,\mu)=\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i + \sum_{i=1}^{n}\alpha_i(1-\xi_i - y_i(w*x_i+b)) - \sum_{i=1}^{n}\mu_i\xi_i . \tag{17}$$

The optimal hyperplane after solution is :

$$f(x) = \sum_{i}^{n} \alpha_i^* C_i K(x, x_i^*) + b^* . \tag{18}$$

In the formula, α_i^* is the Lagrange multiplier and b^* is the displacement of the hyperplane, which determines the distance between the hyperplane and the origin.

It can be seen from the above equation that the optimal hyperplane is only related to the penalty factor *C* and the kernel function. Therefore, through the optimization of parameters, it is essential to find the appropriate penalty factor and kernel function parameters for the selection of the optimal hyperplane for the linear inseparable sample data.

4.2. *Parameter optimization*

In this paper, mainly the grid search method and particle swarm optimization algorithm were applied to select the penalty factor *C* and the kernel function parameter *g* that are most suitable for the experimental data. The grid search(GS) was conducted within the planned numerical range [2^{-10}, 2^{10}] with 0.2 as the step distance.

In the process of particle swarm optimization, the local search speed c_1 took 1.6, the global search speed c_2 took 1.5 and the initial speed weight ω took 0.5 for continuous iterative optimization. And then the iterative operation was terminated until the convergence condition was reached.

According to the above two methods, the parameters of support vector machine were optimized, and the experimental results were compared. Finally, the optimal solution of support vector machine parameters was obtained as shown in Table 5.

Table 5. Grid search algorithm and particle swarm optimization for parameter optimization of support vector machine.

	Grid search(GS)	Particle swarm optimization(PSO)
Penalty factor *C*	4.2224	0.8643
Kernel function *g*	1.5157	2.9664

5. Experimental results and analysis

In this paper, the energy, variance and mean absolute value of s EMG wavelet packet coefficients were extracted to form the 12-dimensional feature vector V. 70 % of the feature vector was randomly selected as the training set, and the remaining 30 % was the test set.

$$V = \left[\log_{10} E_1, ..., \log_{10} E_4; \log_{10} VAR_1, ..., \log_{10} VAR_4; \log_{10} MAV_1, ..., \log_{10} MAV_4\right]. \tag{19}$$

The prediction and recognition results of s EMG signals by feature vectors in support vector machine classifier are shown in Table 6-7. The average recognition rates of no load, load 1.5 kg and load 4 kg are all above 90 %. Only one group is wrong in no load, and at most two groups are wrong in load 1.5 kg and load 4 kg.

Table 6. Load identification results of GS-ISVM classifier(C = 4.2224 g = 1.5157).

Load category	Number of identifications		Recognition rate/%
	Right number	Wrong number	
No load	27	0	96.3
Load 1.5kg	25	2	92.6
Load 4kg	25	2	92.6

Table 7. Load identification results of PSO-ISVM classifier(C = 0.8643 g = 2.9664).

Load category	Number of identifications		Recognition rate /%
	Right number	Wrong number	
No load	26	1	96.3
Load 1.5kg	26	1	96.3
Load 4kg	25	2	92.6

The feature of s EMG signal is extracted by wavelet packet. The recognition rate in support vector machine is higher, and the accuracy is more than 90 %. The load recognition accuracy of grid search method-ISVM(GS-ISVM) classifier is 93.8 %, and the load recognition accuracy of particle swarm algorithm-ISVM(PSO-ISVM) classifier is 95.1 %.

For the classification of nonlinear data sets, neural network classifier is usually used for prediction and recognition. In this paper, the above feature vectors were predicted and recognized by BP neural network and RBF neural network, respectively. BP neural network was trained to 193 times, and the best mean square error was 0.025. When the RBF network was trained 111 times, the mean square error reached the set target error of 0.001, and the training was completed.

From Table 8-9, it can be seen that there are four groups of errors in the load identification of BP neural network without load, and five groups of errors in the load identification of RBF neural network with 1.5 kg load. The recognition rates are all above 90 %, and the rest are either no errors or only one wrong group. However, the average load recognition rates of BP neural network and RBF neural network are above 90 %.

Table 8. Load identification results of BP neural network.

Load category	Number of identifications		Recognition rate/%
	Right number	Wrong number	
No load	23	4	85.2
Load 1.5kg	26	1	96.3
Load 4kg	26	1	96.3

Table 9. Load identification results of RBP neural network.

Load category	Number of identifications		Recognition rate/%
	Right number	Wrong number	
No load	22	0	100
Load 1.5kg	17	5	77.3
Load 4kg	21	1	95.5

6. Conclusion

From the above, with the increasing load, the energy and mean absolute value characteristics also show an increasing trend, and the change trend is obvious. However, the variance characteristics is slightly flat, but it shows a trend from dispersion to aggregation, and the overall distribution shows a unified increase trend. Therefore, the characteristic changes of muscle s EMG signal can directly reflect the changes of joint load.

Experiments show that the wavelet packet energy, variance and mean absolute value of s EMG signal can be used as feature vectors to identify different loads of elbow joint. The average recognition accuracy of PSO-ISVM is 95.1 %, the average recognition accuracy of RBF neural network is 90.9 %, and the average recognition accuracy of BP neural network is 92.6 %. It is obvious that the classification effect of PSO-ISVM is the best. In summary, s EMG signal based on wavelet packet decomposition is feasible to identify the sizes of load. It can be applied to upgrade and design the rehabilitation training robot, which is of great significance to promote the development of medical training and help patients with reasonable rehabilitation training.

Abbreviations

sEMG: surface electromyograph; E:energy; VAR:Variance；MAV:Mean absolute value；ISVM:Improved support vector machine；BP :Back propagation；RBF:Radial Basis Function；DNN:Deep Neural Networks；TDPSD:Time domain power spectrum descriptor ；GA:Genetic algorithm；GS:Grid search；ANNs:Artificial neural networks；PSO:Particle swarm optimization；ECG:Electrocardiogram；GS-ISVM:Grid search method-ISVM；PSO-ISVM:Particle swarm algorithm-ISVM

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Authors' contributions

Jiabin Cai proposed the original idea of the full text. Junjun Song and Yuanqiang Long designed the experiment. Yuanqiang Long performed the experiment and analyzed the results. Junjun Song wrote and drafted the manuscript. All authors read and approved this submission.

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Availability of data and materials

The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors agree to publish the submitted paper in this journal.

Competing interests

The authors declare that they have no competing interests.

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