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IMAGE & SIGNAL PROCESSING

# Virtual Rehabilitation Training System Based on Surface EMG Feature Extraction and Analysis

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**Abstract**
Aiming at the characteristics that electromyography (EMG) signals can reflect the human body's motive intention and the information of muscle's motive state, this paper makes a thorough study on the evaluation of surface electromyography signals' motive state. At the same time, EMG signals can reflect the characteristics of limb movement and its changing rules, and can acquire the functional characteristics of limb movement so as to accurately evaluate the rehabilitation status of patients. In this paper, EMG signal analysis and feedback control are introduced into the virtual rehabilitation system to study the methods of EMG parameter identification and dynamic feature extraction, and obtain the EMG characteristics and variation rules related to human motion patterns. In this paper, a rehabilitation training system based on EMG feedback and virtual reality is built, and the validity of the system is verified by patient experiment. The feasibility of the system is verified by the methods of validity of the algorithm, recognition rate of the system action pattern and fatigue evaluation.

**Keywords** EMG feature extraction · Virtual technology · Rehabilitation training system · Function evaluation

## Introduction

In recent years, with the development of science and technology, virtual reality has come into people's attention. It has become a new means of rehabilitation therapy because of its advantages such as repeated rehabilitation training without guidance, interactivity and immersion with virtual environment, autonomous rehabilitation and physician-assisted guidance [1, 2]. EMG signals can reflect the state of limb muscle activity, including movement intention and movement functions information, and have the characteristics of real-time interaction, skin non-invasive, safe and convenient operation, which are widely used in stroke rehabilitation treatment [3]. EMG signal is a kind of non-stationary weak signal which can reflect the movement state of skeletal muscle and the command information of nervous system. Therefore, EMG signals can be used to classify and recognize different limb movements, which can provide effective help for the analysis of limb movements and their state characteristics [4]. It is widely used in medical rehabilitation robots, human-machine interface, biomedical research and other fields. Among them, how to accurately and accurately and accurately collect EMG signals and extract features is one of the hotspots of current research.

EMG signal and virtual reality technology are combined to fuse the real-time, security and immersion and interesting characteristics of virtual reality [5]. Designing a targeted rehabilitation program to address the deficiencies of traditional rehabilitation requires only the guidance and assistance of a doctor, saving a significant amount of recovery time, while real-time data, records and assessments, and developing a correct rehabilitation strategy. Greatly reducing the labor intensity of doctors, can effectively improve the rehabilitation training effect of stroke patients.

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## Human EMG signal processing and feature extraction

### Surface EMG signal feature extraction

The principle of feature extraction method of EMG signal is to ensure the maximum discriminability of sample features. The quality of feature extraction method has a direct impact on the recognition effect of classifier. Therefore, researchers have done a lot of research on feature extraction of EMG signal, respectively from the time domain, frequency domain and time-frequency domain of EMG signal [6]. Typical time-domain analysis methods use time-domain statistical information such as absolute mean, absolute mean slope, zero-crossing point, slope symbol change rate, waveform length, variance and autoregressive model (AR) as characteristic frequency domain analysis methods of EMG signals. Fourier transform is usually used to complete the conversion between discrete sequences and spectrum [7]. Commonly used indicators include power spectral density, average power frequency (MPF), median frequency (MF), etc. In recent years, the use of time-frequency domain analysis method to extract the characteristics of electromyography signals has also made great progress.

Since the EMG acquisition card designed in this paper loses more energy in the frequency domain, the AR parameter model method is used to model the EMG signal in the time domain. Generally, AR parametric model regards random signal as the output response of a given system caused by white noise signal as a specific parameter. Therefore, the study of the characteristics of random signal can be converted to the study of the characteristics of the output response system [8]. That is to say, the characteristics of random signals can be represented by the coefficients of AR parameter model. Therefore, by establishing the AR parameter model of EMG signals, the AR coefficients will contain a large number of EMG signal sample features. Taking AR coefficient as the feature vector of action samples, it can effectively distinguish different action samples.

AR model is a linear prediction model, that is, known N data, can be derived from the model before or after the N point of the data. The corresponding relation between the transmission function of the AR model and the AR coefficient is shown in Formula (1).

$$H_{AR}(Z) = \frac{1}{1 + \sum_{k=1}^{p} a_k Z^{-k}} \tag{1}$$

P is the order of the selected AR model and $a_k$is the P order AR model coefficient. P and $a_k$jointly determine the characteristics of spectral estimation.

In this paper, we extract the parameters of 4-channel 4-order AR model and combine the AR coefficients of 4-channel into one-dimensional vector $\mu = \{a_{11}, a_{12}, a_{13}, a_{14}, a_{21}, ..., a_{44}\}$ as the feature vector of SVM pattern recognition.

$$\varepsilon = \sum_{i,j=0}^{p} a_{pj} R(i-j) a_{pj} = a^T Ra \tag{2}$$

In formula (2), R matrix is obtained by sampling autocorrelation function, and the calculation method of sampling autocorrelation is shown in formula (3).

$$R(k) = \frac{1}{N} \sum_{k=0}^{N-1-k} x(n)x(n+k), 0 \le k \le N-1 \tag{3}$$

In formula (3), $x(n)$ represents the value of the sampling sequence at the n point and the length of the N table sampling sequence.

In order to reduce the solution dimension of Yule-Walker equation, the famous Levinson-Durbin algorithm is used to solve the equation. The idea is to derive the parameters of AR(k + l) model iteratively from the parameters of AR(k) model. The iterative formula of Levinson-Durbin algorithm is as follows.

$$\sigma_k^2 = R(0) + \sum_{i=1}^{k} a_{k,i} R(i) \tag{4}$$

$$D_k = \sum_{i=0}^{k} a_{k,i} R(k+1-i), a_{k,0} = 1 \tag{5}$$

$$\gamma_{k+1} = \frac{D_k}{\sigma_k^2}, \sigma_{k+1}^2 = \left(1-\gamma_{k+1}^2\right)\sigma_k^2 \tag{6}$$

$$a_{k+1,i} = a_{k,i} - \gamma_{k+1} a_{k,k+1-i}, i = 1, 2, ..., k; a_{k+1,k+1} = -\gamma_{k+1} \tag{7}$$

For the AR (p) model, the AR coefficient of the P order AR model can be derived from recursive computation until k + 1 = p is known.

## Design of surface electromyography classifier

Another important factor affecting the accuracy of limb movement recognition is the characteristics of pattern classifier. The role of EMG pattern classifier is to establish a classification model for the characteristics of surface EMG signals to accurately determine the classification of the samples to be identified. In recent years, the classifiers used to study pattern recognition of surface electromyography (SEMG) signals mainly include linear classifiers, neural networks, and support vector machines [9]. Linear classifier is suitable for the application of sample eigenvectors with certain linear relationship. It is widely used because of its simple structure and convenient calculation. By simulating the thinking of human brain image, neural network has strong adaptive, self-organizing and generalization ability, and can establish nonlinear mapping relationship between input and output of the system, which is beneficial to solve the classification problem of complex system [10]. Support Vector Machine (SVM) is a new pattern classification method based on statistics and structural risk minimization theory, which has strong generalization ability [11].

Because the support vector machine classification algorithm has great advantages in small sample, nonlinear and high-dimensional pattern recognition, this topic selects support vector machine classification machine to complete the recognition of action. Because the support vector machine classification algorithm has great advantages in small sample, nonlinear, high-dimensional pattern recognition and recommendation [11]. This topic selects support vector machine classification machine to complete the recognition of action.

Support Vector Machine (SVM) was first used to solve the problem of linear classification. The essence of SVM is to find a hyperplane to complete the segmentation of samples. At the same time, the sum of the minimum distances between two classes of samples from the hyperplane is maximized, that is, the classification distance is maximized. Let the linear separable sample set$\{X_i, d_i\}$, where $X_i$ is the input sample feature and $d_i$ is the sample class, and the optimal hyperplane$\omega^T X_i + b = 0$is solved. Its essence is to satisfy the formula (8):

$$\begin{cases} \omega^T x_i + b > 1, d_i = 1 \\ \omega^T x_i + b < -1, d_i = -1 \end{cases} \tag{8}$$

The minimum$\|w\|^2/2$value is solved under the condition. The schematic diagram of hyperplane is shown in Fig. 1. Therefore, the goal of the optimal hyperplane transformation formula (9) is:

$$\begin{cases} y_i\left[\omega^T x_i + b\right] \geq 1, i = 0, \dots, m \\ \min[J(w)] = \|w\|^2/2 \end{cases} \tag{9}$$

The above objective is to solve the optimization problem under a series of inequality constraints. The Lagrange function method [10] can be used to solve the problem.

$$L(\omega, b_0, \lambda) = \frac{1}{2}\omega^T\omega - \sum_{i=1}^{N} \lambda_i\left[y_i\left(\omega^T x_i + b_0\right) - 1\right] \tag{10}$$

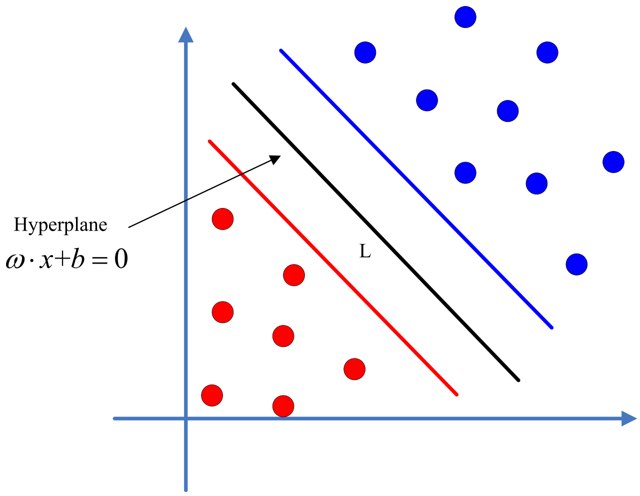



**Fig. 1** Schematic diagram of hyperplane

It is converted to Lagrange's dual problem, and finally the classification function formula is obtained [12].

$$f(x) = \operatorname{sgn}\left(\sum_{SV}^{m} y_i \lambda_i^* (x_i \cdot x) + b^*\right) \tag{11}$$

$x_i$is the support vector, $\lambda^*$is the Lagrange multiplier corresponding to the support vector, and $b^*$is the constant. For linear nonseparable systems, the relaxation variable$\xi \geq 0$ is introduced, and the target is transformed into a formula (12):

$$J(w, \xi) = \frac{1}{2}(w \cdot w) + C \sum_{i=1}^{m} \xi_i \tag{12}$$

In the above formula (4–14), CC > 0 is the penalty factor to solve the optimal interface in the case of non-linear separability, and finally converts to the same solution method as in the case of linear separability. These are all ideal solutions in linear space. For nonlinear cases, the problem is usually mapped to high-dimensional linear space by the selected nonlinear transformation, i.e. kernel function. The kernel functions commonly used at present include polynomial kernel, radial basis function kernel and hyperbolic tangent kernel. According to the previous research on electromyography, the radial basis function formula (13) is chosen as the kernel function.

$$K(x, z) = \exp\left(-\frac{\|x - z\|^2}{\delta^2}\right) \tag{13}$$

In the algorithm implementation, this paper uses the open source LIBSVM software to realize the support vector basis classification algorithm.

## Motion pattern recognition based on surface electromyography signal

### Electromyography acquisition

As a noninvasive physiological signal, electromyography (EMG) is widely used in rehabilitation medicine. However, the EMG signal is very weak, low signal-to-noise ratio with many noise characteristics, making the acquisition of EMG signal difficult, the main doped noise includes: the noise of the electronic acquisition equipment itself; skin and electrode contact makes EMG signal change and acquisition line touch [13]. Therefore, EMG signal is a complex and non-stationary physiological signal. In order to improve the quality of EMG signal acquisition and enhance the spatial and temporal resolution, the key problem is to solve the signal acquisition and pre-processing.

The EMG signal acquisition is mainly divided into two parts: the lower part includes the electrode, the EMG signal amplifier, the EMG signal acquisition device, and the wireless transmission module. Differential amplification of EMG electrode can effectively control CMRR and SNR, and obtain more accurate EMG information reflecting limb movement. The amplifier amplifies the EMG signal, restrains the temperature drift and zero drift. The wireless acquisition module is the hub connecting software and hardware. The portable performance of rehabilitation training can be achieved by wireless transmission. The upper computer mainly refers to the system acquisition software, responsible for receiving EMG data, analysis and processing, display, control, storage and historical query functions. The flow chart of EMG acquisition system is shown in Fig. 2.

## EMG signal preprocessing

Because the EMG signal is affected by the environment, physiological and equipment noise, as well as power frequency interference such as motion trajectory and power supply, the collected EMG signal contains a lot of useless information. Therefore, using proper preprocessing methods for baseline drift, power frequency and harmonics removal and weakening of useless frequency signals can greatly facilitate the follow-up information processing and analysis process, and obtain good recognition results.

Firstly, the low-pass filter is used to notch the EMG signal in 10–200 Hz band to retain the main EMG information. Secondly, to remove the baseline drift, EMG signal detection is basically based on the baseline of its amplitude, baseline drift as a common noise, if the baseline drift will lead to EMG signal detection bias, affecting the quality of EMG signal. As an effective filtering method, adaptive high-pass filtering can be used as a variety of filters, such as FIR, IIR filter and so on. In the case of baseline drift, adaptive high-pass filtering can effectively weaken the voltage error caused by baseline drift by extracting DC voltage signal and eliminating it from EMG signal. Poor. Finally, adaptive 50 Hz filtering is used to

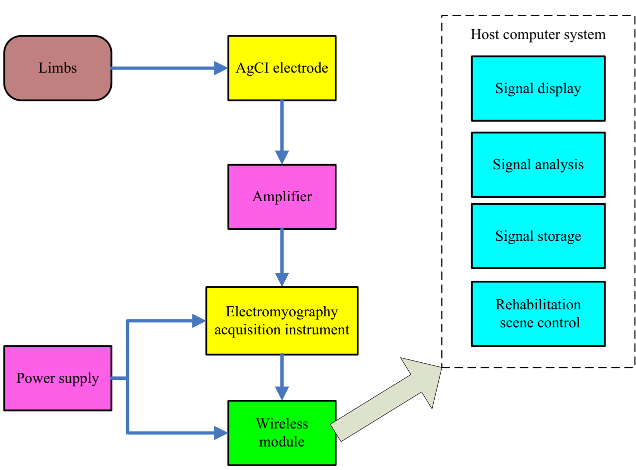



**Fig. 2** Flow chart of electromyography acquisition system

eliminate 50 Hz power frequency and harmonic noise in EMG. The adaptive filter can also adjust parameters intelligently, track the mixed noise in EMG when the input is unknown, and adjust its own coefficients in real-time during the signal processing automatically.

Therefore, the above methods are used to denoise and remove baseline wander. The basic process is shown in Fig. 3.

In this paper, the EMG signals of arm flexion and extension in a healthy patient were collected and preprocessed. Compared with the original EMG signals shown in Fig. 4 and the EMG signals after preprocessing in time domain and frequency domain, the 50 Hz power frequency and the baseline drift were removed obviously.

Through the above pretreatment methods, the quality of EMG signal can be effectively guaranteed, which is convenient for subsequent signal feature processing.

## Moving segment detection of electromyography signals in limb movements

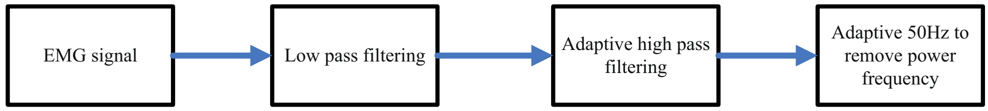
Active segment detection is mainly used to detect the data segments corresponding to the corresponding movements in the collected EMG signals. It is an effective means to extract the limb movements. The collected EMG signals contain some noise and other disturbances, so parts of the signals are not entirely generated by limb movements. Accurate and effective detection of limb movements start and end time lays a foundation for subsequent feature extraction and pattern recognition. Therefore, it is very important to select a suitable and effective detection means to extract active segments. The existing methods mainly include Self-organizing Artificial Neural network, moving average window, short-time Fourier transform and other commonly used active segment detection methods.

Based on the requirement of real-time maneuverability and portability of rehabilitation training system, this paper selects moving average window to detect the moving segment, and sets a threshold to judge whether it is an effective movement segment. When the limb moves, it will produce large random fluctuations. The moving average window can smoothly smooth its changing trend and solve the impact of short-term signal fluctuations. By setting the size of sliding window, the noise can be effectively removed, and the information of limb movements can be retained, which is convenient for the detection of moving segments.

The specific steps of the activity segment detection are as follows:

In this paper, the electromyogram (EMG) signals obtained from wrist flexion and extension movements of healthy volunteers were used, and the moving average window was used to detect the active segments. As shown in Fig. 5, the EMG signals before and after the active segment interception are detected. It is known that the sliding window can effectively

**Fig. 3** Preprocessing of EMG signals




intercept the effective data segments of the action. This method plays an important role in subsequent feature extraction and pattern recognition of the action.

## General design of virtual rehabilitation system

### The general framework of virtual rehabilitation interaction system

For stroke patients, the traditional treatment mainly relies on the guidance of doctors for rehabilitation training, patients training initiative is not strong, lack of interesting, not only physician intensity, and patients with poor rehabilitation training effect. In this paper, a virtual rehabilitation system based on EMG feedback is designed for rehabilitation training of stroke patients, which combines virtual reality technology and EMG signal characteristics. The principle frame of this system is shown in Fig. 6.

The system mainly includes four parts: front-end acquisition module, data processing and display module, model control module and virtual environment module.

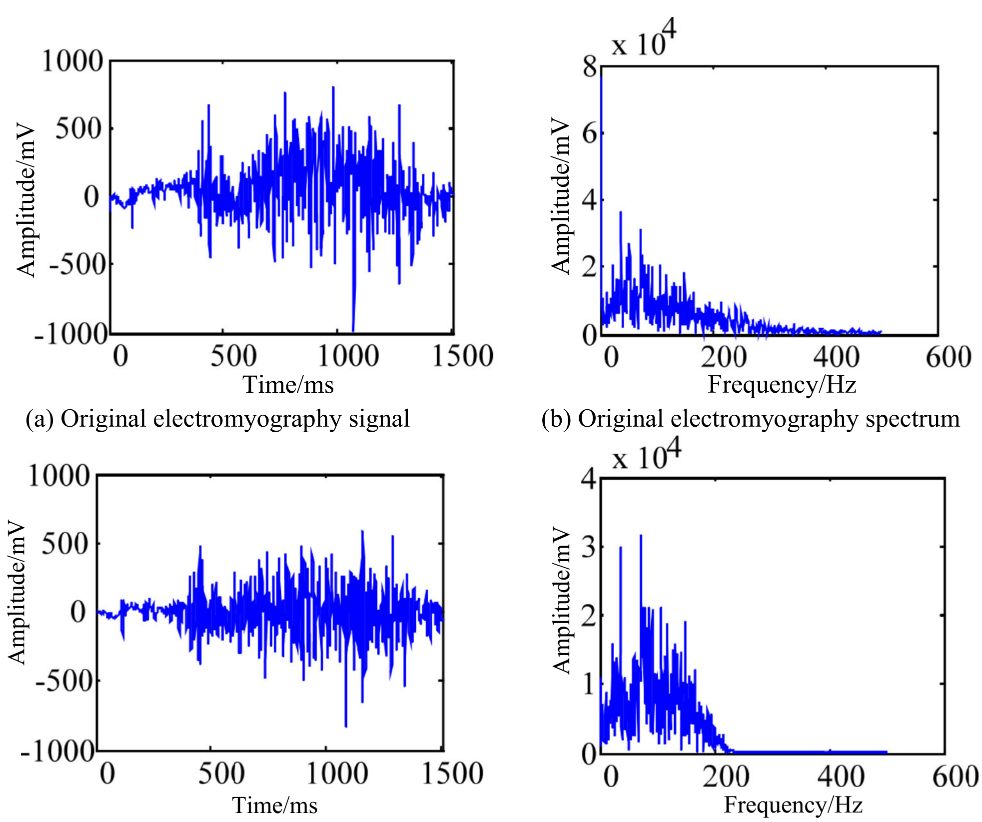
(1) Front end acquisition module

Using disposable electrode AgCl to acquire EMG information and transmit it to EMG acquisition instrument, after the signal is conditioned by the acquisition module, the analog signal is converted into digital signal by digital-to-analog converter, and the data is packaged and sent to the host computer. TCP wireless transmission protocol is used in the transmission process. It can transmit data safely and reliably. It can save EMG information completely. At the same time, wireless transmission ensures the portable performance of rehabilitation.

(2) Data processing and display module

Data processing includes moving segment detection, feature extraction and feature recognition of EMG signals

**Fig. 4** Preprocessing of EMG signals




(a) Original electromyography signal (b) Original electromyography spectrum

(c) EMG signal after pretreatment (d) EMG spectrum after pretreatment

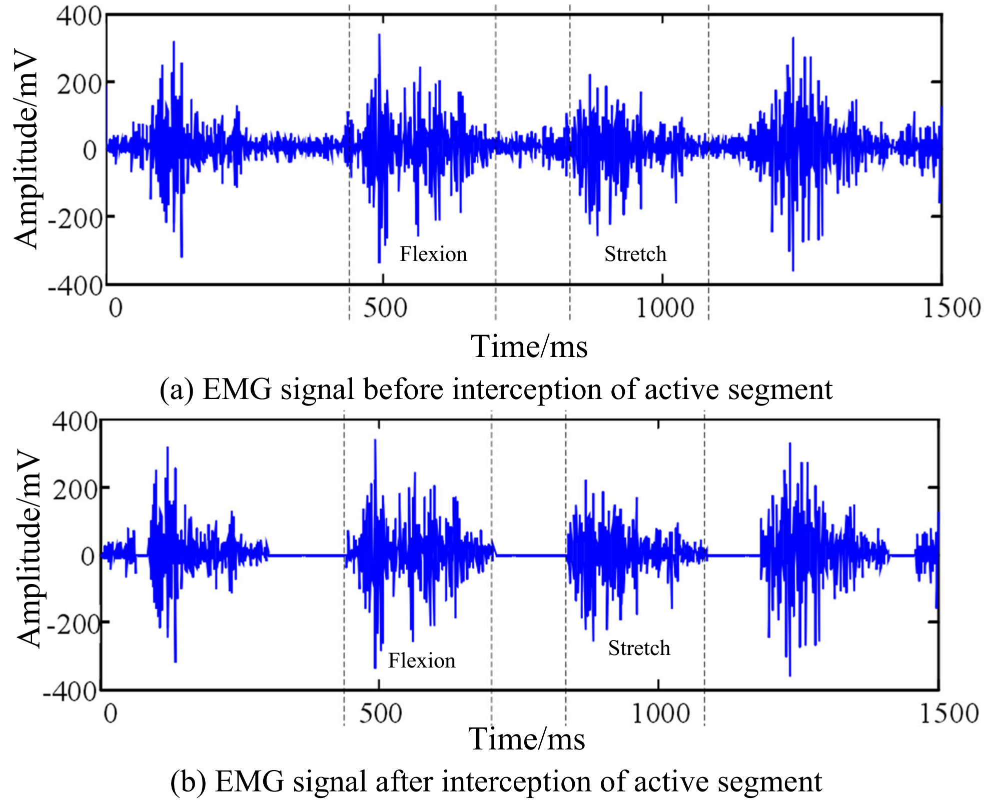



**Fig. 5** Active segment extraction process of electromyography signal

collected. Since the surface electromyogram (SEMG) signals collected are not entirely representative of the limb movements, the active segment detection is mainly used to distinguish the effective EMG data corresponding to the upper limb movements, determine the starting and ending positions of the movements and intercept their EMG signals for feature extraction. Feature extraction is used to calculate and analyze the intercepted data to get corresponding motion intention and motion function feature vector. The display module mainly aims at the intuitive display of original EMG signal, related rehabilitation evaluation index and historical data query.

(3) Scene control module

The scene control module can be divided into two modes: the EMG control mode and the Kinect control mode. According to the EMG control mode, the extracted features are analyzed by intelligent classifier, and the

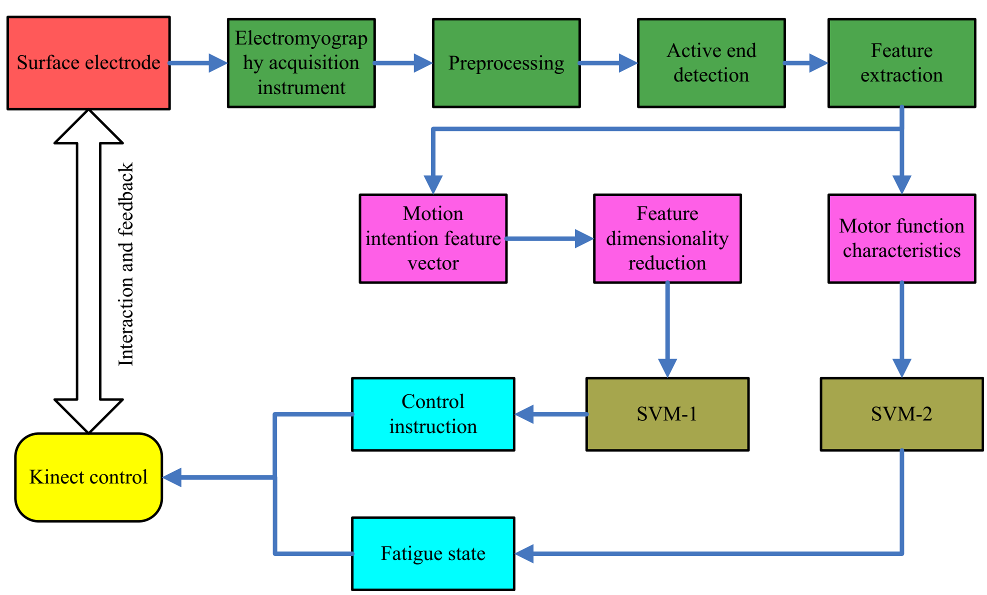



**Fig. 6** System design block diagram

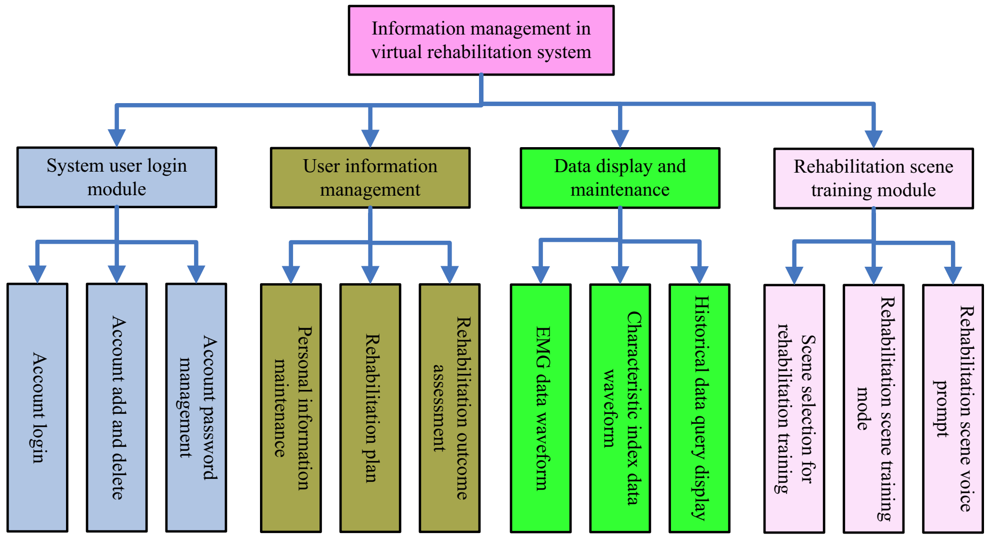



**Fig. 7** Figure Information management module of virtual rehabilitation system

recognition results are output. And according to the corresponding control strategy to identify the results of different limb movements, to obtain the corresponding control commands, real-time manipulation of the interaction between limb movements and virtual scenes, to complete the pre-set tasks or goals. For Kinect control mode, the skeleton and depth information of human posture are obtained by Kinect skeleton tracking, and the motion recognition control scene is carried out.

(4) Virtual environment module

The virtual environment module mainly provides a good virtual rehabilitation environment for patient rehabilitation training, and can give patients a sense of immersion through the interaction between human and virtual rehabilitation games. At the same time, based on own perceptions to exert subjective initiative, improve the active participation of rehabilitation patients, and contribute to the improvement of rehabilitation.

## Design of virtual scene and information management system

In the process of virtual environment interaction, virtual scene is a very important part of rehabilitation training for patients in the virtual environment. Virtual scene connects the virtual and real world. Through visual feedback to the user, the scene design directly related to the rehabilitation of patients' willingness and effect, design a good virtual scene is conducive to the rehabilitation of patients.

### Construction of virtual scene

Virtual scene modeling is mainly divided into two methods: Geometric 3D modeling and image environment modeling.

**Table 1** Results of body movement recognition for subjects

| Subjects | Body movements (right / wrong) | | | | | | | | Correct rate |
|---|---|---|---|---|---|---|---|---|---|
| | HO | HC | WF | WE | SU | PR | EF | EE | |
| S1 | 5/2 | 1/1 | 4/1 | 1/1 | 1/1 | 1/1 | 4/1 | 1/1 | 93.4% |
| S2 | 6/1 | 1/1 | 4/1 | 1/1 | 1/1 | 1/1 | 4/1 | 1/1 | 99.1% |
| S3 | 19/1 | 11/3 | 8/2 | 4/1 | 12/2 | 22/3 | 20/1 | 27/2 | 93.8% |
| S4 | 16/2 | 7/2 | 7/2 | 6/2 | 15/3 | 24/2 | 21/1 | 22/2 | 92.3% |
| S5 | 5/1 | 5/1 | 6/1 | 1/1 | 5/2 | 5/1 | 6/1 | 6/1 | 97.2% |
| S6 | 4/1 | 3/1 | 3/1 | 1/1 | 5/1 | 3/1 | 4/1 | 3/1 | 99.3% |
| S7 | 23/1 | 20/2 | 23/2 | 20/1 | 18/2 | 21/1 | 31/2 | 29/1 | 97.8% |
| S8 | 21/1 | 17/3 | 17/2 | 25/1 | 22/1 | 18/2 | 31/1 | 32/2 | 96.8% |
| Total | 99/10 | 65/12 | 72/12 | 79/9 | 79/13 | 95/12 | 121/9 | 121/11 | 96.3% |

Geometric modeling is mainly composed of entity technology of computer control, processing and output, which is composed of geometric elements and topological elements. The shape, location and form of the object are the core of geometric modeling. The geometric elements mainly include points, lines and surfaces, while the topological elements mainly include the connection of vertices, edges and points, lines and surfaces. Image modeling is mainly used to build the background of the virtual scene, such as the sky, the earth and the remote mountains. The main characteristics of image modeling are: [1] the resolution of the image is not high, effectively improve the efficiency of the system; [2] the image and image stitched together, can produce a better sense of reality. Considering the above two construction methods, mainly because the virtual scene and the patient need feedback interactive control, and the use of geometric modeling to build a virtual scene, patients can be intuitive control, so this paper uses geometric modeling to build a virtual scene.

## Design of information management system

For the rehabilitation of stroke patients, it is necessary to design a reasonable and suitable information management system. Because patients need long-term rehabilitation and follow-up treatment, it is necessary to preserve the basic information and rehabilitation status information of patients, so as to make rehabilitation evaluation and rehabilitation strategy. On the one hand, keep the basic information of users, facilitate doctors to understand the rehabilitation of patients, take appropriate measures for treatment. On the other hand, in the process of rehabilitation training, the rehabilitation status information of the treated patients is saved in time, and the current rehabilitation situation and rehabilitation process are recorded, so as to adjust the rehabilitation strategy in time. At the same time, the rehabilitation information recorded by the information management system can also be used in rehabilitation research, providing

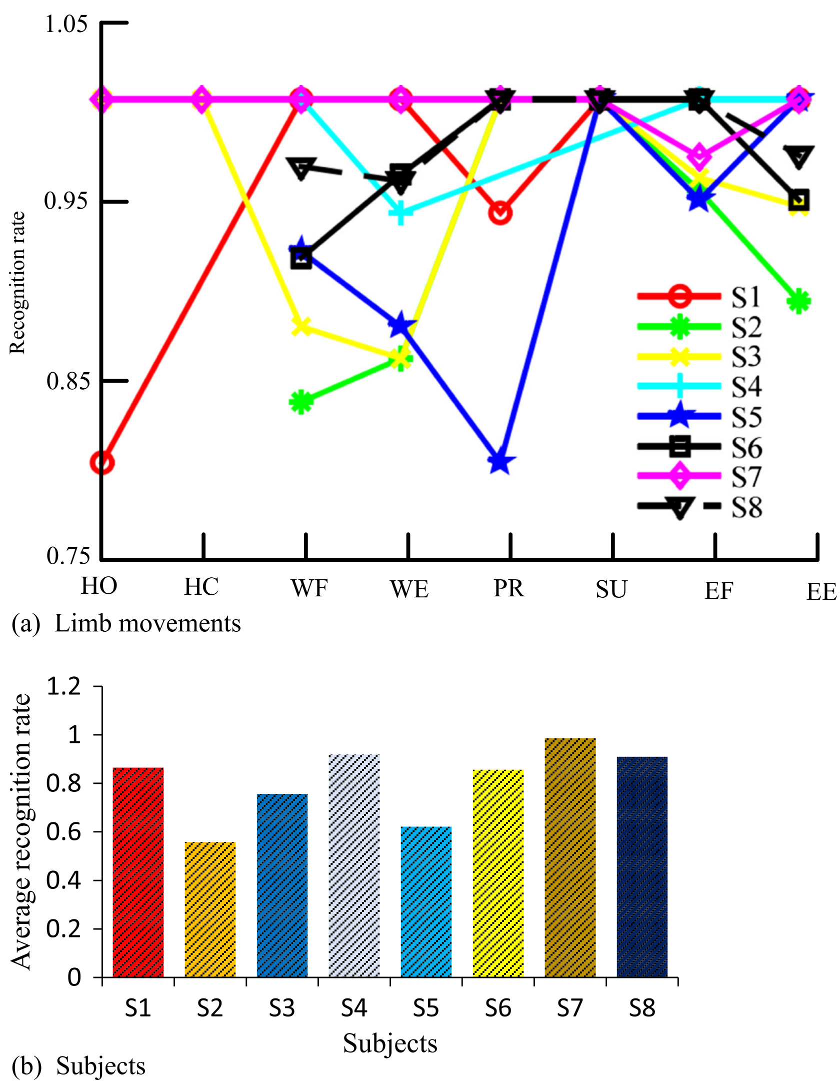



**Fig. 8** Recognition rate of EMG in patients' rehabilitation training

theoretical and experimental basis for rehabilitation medicine by inquiring and analyzing historical data.

This paper uses database information management system for data management, which can effectively solve the problem of data redundancy. Therefore, adding database to the virtual rehabilitation system for patient information management provides a great help for patients to formulate appropriate rehabilitation strategies. At present, the mainstream databases in the market include Access, Oracle, MySQL and SQL Server 2008. Because the virtual rehabilitation system is based on Windows platform, and SQL Server 2008 is simple and cost-effective, this paper uses SQL Server 2008 database to develop user information management module.

The information management part of virtual rehabilitation system mainly includes four modules: user login, user information management, data display and evaluation, and user rehabilitation training. The module of information management is shown in Fig. 7.

Data display and maintenance module mainly includes the acquisition and display of EMG signals, the display of corresponding evaluation indicators and historical data query, including reporting functions. This part can provide patients and doctors with intuitive experience judgment. At the same time, this paper proposes the corresponding EMG processing algorithm to extract movement intention to achieve the control of rehabilitation scene, and the rehabilitation evaluation indicators to reflect the recovery status of patients, through the generation of reports to track the rehabilitation effect.

The training modes of rehabilitation scenarios mainly include rehabilitation scenarios and scene switching, rehabilitation mode selection and voice prompting. This paper develops a variety of virtual scenes suitable for rehabilitation training of patients, which can enable patients to carry out rehabilitation training in a real changing situation, and provides scene selection, which enhances the interesting, can fully improve the active participation of patients. And according to the rehabilitation needs of different patients, can provide different

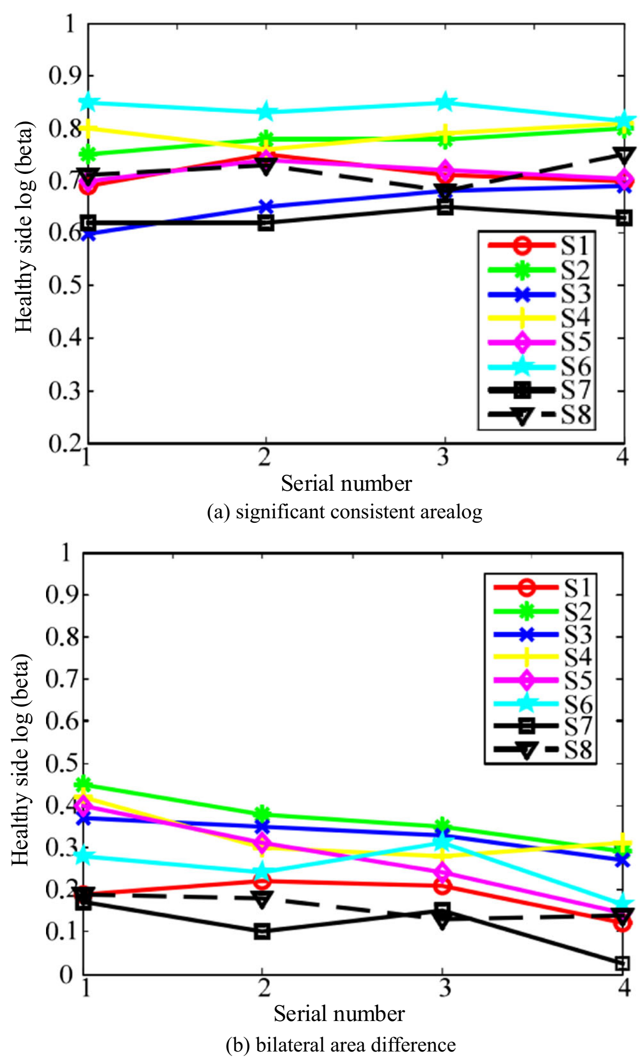



**Fig. 9** Muscle consistency changes in rehabilitation exercise

training mode, rehabilitation mode is more flexible, and easy to repeat, is conducive to improving the intensity of training.

## Experimental results and analysis

### EMG feature extraction and motion intention recognition in rehabilitation exercise

In order to test the effectiveness of EMG control of the system, the recognition results of limb movements of 8 subjects were recorded during the virtual rehabilitation training experiment, as shown in Table 1.

The experimental results show that the rehabilitation training system can accurately receive the subjective motion intention of the subjects after extracting the local entropy feature of wavelet packet and pattern recognition. This shows that the effectiveness of EMG-controlled rehabilitation training system can achieve the autonomous rehabilitation of the subjects. The recognition rate of EMG control is affected by the rehabilitation state of patients. For example, in Fig. 8, S2, S3, S5 patients have high muscle tension, strong joint movement, low quality of wrist flexion, wrist extension, elbow flexion, elbow extension and other movements, and low recognition rate of movement. Therefore, the recognition rate of movement can also be used as a basis for evaluating the state of motor function.

### Virtual rehabilitation effectiveness evaluation

In order to verify the effectiveness of the upper limb rehabilitation system based on EMG feedback and virtual reality, a 20-day follow-up experiment was carried out on the same 8 subjects who used the virtual rehabilitation training system. Four experiments were conducted at intervals of five days each, during which eight subjects did not receive similar upper limb rehabilitation training. The validity of the virtual rehabilitation system was tested by the changes of beta-band significant consistent arealog$A_{Z(beta)}$and bilateral area difference $D_{Z(beta)}$ in the patients' rehabilitation process, as shown in Fig. 9.

With the progress of rehabilitation training, the motor function of affected side of different patients has been improved to varying degrees. From Figs. 5, 6, 7, 8 and 9, it can be seen that with the increase of rehabilitation training time, the significant conformance arealog$A_{Z(beta)}$of beta frequency band increases, and the significant conformance area difference$D_{Z(beta)}$of healthy side decreases gradually. The experimental results show that the rehabilitation system based on EMG feedback and virtual reality has a certain effect on the recovery and evaluation of upper limb motor function of stroke patients.

## Conclusion

The emergence of human rehabilitation training system plays an irreplaceable role in the field of stroke rehabilitation. However, the existing rehabilitation training system still has some shortcomings in the aspects of operational safety, feasibility, active participation of patients, individual adaptability of system training parameters, and effectiveness of rehabilitation evaluation. Aiming at the characteristics that EMG signal can reflect the human motion intention and the information of muscle motion function state, this paper makes a deep research on the recognition of surface electromyogram signal motion intention and the evaluation of surface electromyogram signal motion function state. This paper mainly studies the surface electromyogram signal processing and its feature extraction and action pattern recognition based on surface electromyogram signal, and realizes the rehabilitation training system based on electromyogram feedback and virtual reality. The proposed dimensionality reduction algorithm is applied to the system, and patient experiments are carried out to verify the effectiveness of the algorithm, system action pattern recognition rate and fatigue evaluation methods to verify the feasibility of the system, effectively improving the user experience.

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### Compliance with ethical standards

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors.

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