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Article

An exoskeleton upper limb rehabilitation robot based on electroencephalography

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Abstract: Today, stroke patients have varying degrees of motor impairment after surgery. An Electroencephalography (EEG) signal is a potential change recorded on the scalp of a human or animal, which can be combined with a rehabilitation robot to help patients complete rehabilitation movements. In this paper, a new exoskeleton-type 6-DOF upper limb rehabilitation robot is designed based on EEG control. The wavelet denoising method based on Gaussian mixture model (GMM) is used for signal pre-processing. The wavelet packet decomposition method is used to extract feature vectors, and the feature performance index based on Mahalanobis distance and Babanobis distance is introduced to test the accuracy of Feature Performance Index (FPI) relativity. The random forest classifier was used to classify and recognize the EEG characteristics and obtain the motion intention of patients. The experimental research shows that the EEG signal processing method proposed in this paper has significant effect, and the upper limb rehabilitation robot based on EEG signal has feasibility. The whole system can significantly improve the patient's rehabilitation enthusiasm.

Keywords: upper limb; exoskeleton robot; EEG control; rehabilitation robot

1. Introduction

Stroke is a disease caused by cerebrovascular problems, usually brain tissue damage caused by blocked or ruptured blood vessels in the brain. Stroke patients can cause symptoms related to the central nervous system such as hemiplegia, aphasia, and sensory disturbances due to ischemia and necrosis of brain tissue. The survey shows that stroke has become the first cause of death in China and the primary cause of disability in Chinese adults, and stroke has the characteristics of high incidence, high disability rate, high mortality rate and high recurrence rate. More than 70 percent of survivors who develop stroke have varying degrees of residual motor dysfunction after surgery, and 40 percent of them have severe disabilities [1].

Rehabilitation exercise is the main measure for stroke patients to restore their ability to perform their daily lives, and the most critical period of rehabilitation is the first three months after the onset of stroke, and the second important recovery time is the subsequent three months [2]. Therefore, rehabilitation training in stroke patients in the early postoperative period can effectively reduce the degree of disability and other complications of stroke patients, and improve the patient's ability to take care of themselves in daily life.

China's medical rehabilitation professionals are very tight. At present, the rehabilitation training methods commonly used in China have problems such as long cycle, large personnel consumption and limited effect, which can no longer meet the needs of Chinese aging for health care, so the development of rehabilitation robots has important practical significance. Medical rehabilitation robots can not only effectively alleviate the problem of insufficient rehabilitation therapists, but also greatly reduce the labor intensity of therapists, and provide patients with accurate rehabilitation training actions and reasonable rehabilitation plans.

In recent years, the development of rehabilitation robots has been very rapid. Many research groups have developed robotic-assisted rehabilitation treatment systems such as MIME [3], BiManuTrack [4], and HIT [5]. Mi Polytechnic's muscles allow unrestricted movement of the shoulder and elbow joints, and MIME allows bilateral exercises of 3 degrees of freedom for shoulder and elbow movements, showing that additional treatment assisted by robotics can improve recovery. Arm guides, which assist in reaching straight trajectories, and double horse tracking, are designed to train distal arm movements by practicing bilateral elbow rotation before and after rotation as well as wrist flexion and extension in a mirror or parallel manner, showing positive results also using simple equipment to make intensive training after stroke patients. Robotic-assisted rehabilitation can provide high-intensity, repetitive, and task-specific treatments for parts of the body damaged by neurological disorders compared to traditional rehabilitation. In addition, it can track the patient's progress and make recommendations to the therapist if necessary.

The upper limb rehabilitation exoskeleton robot based on EEG signals [6] is a wearable bionic robot that integrates mechatronics, sensing technology, automatic control, and biomedicine. Its working principle is to identify the movement intention of the human body through the analysis of the collected human EEG data, and realize the synchronous movement of the rehabilitation robot and the upper limbs of the human body. Kwak et al. [7,8] used bandpass filtering to filter out MYO interference and baseline drift, and power frequency notch to filter out power frequency interference. Since both EEG signal and interspersed noise have obvious spatial distribution characteristics, Chen et al. [9] filter the EEG signal by using the airspace digital filtering method according to the different spatial characteristics of the EEG signal and noise. Jiang et al. [10] used a Laplace spatial filter to filter the EEG signal, which improved the signal-to-noise ratio of the motion-related cortical potential, and the filtering effect was significantly improved.

In pattern recognition, the number and quantity of input data is reduced by feature extraction techniques. When an algorithm's input data too large and cannot be processed, the input data can be converted into a simplified feature vector, a process called feature extraction. By selecting the features to be extracted, you can extract the required information from the input data to simplify the task. Analysis using a large number of variables usually requires a lot of memory and time [11]. It has been found that each person has different characteristics of the brain controlling movement to obtain EEG signals, that is, there is a certain difference between individuals and individuals. Due to the small number of experimental participants, this paper ignores the differences between individuals in the research process and conducts feature extraction and classification identification studies.

There are four main types of EEG feature extraction methods: (1) time domain or frequency domain analysis, such as the use of signals in the time domain Values, peaks and variances, power spectral density in the frequency domain, etc., such methods are simple and small in calculation, but contain little information, so the identification accuracy is not high [12]; (2) Traditional time-frequency analysis, the time-domain mean, peak, variance and frequency domain power spectrum combined to form a characteristic vector, relative to the time domain or frequency domain analysis can provide more information, suitable for processing and analyzing stationary signals, but EEG signal is a typical time-varying non-stationary signal [13]; (3) wavelet transformation coefficient method, Selecting the wavelet coefficients of a specific frequency band to form a eigenvector, but the complex mechanism of EEG signal generation is usually difficult to obtain accurate prior knowledge, so it is not flexible enough [14]; (4) cospatial mode algorithm (CSP), by finding the optimal spatial projection matrix, so that the variance result of the two types of signals is maximized at a distance after projection, so as to obtain a more distinguished feature vector, and the signal feature extraction method based on CSP technology has achieved good results.

However, due to the fact that the EEG signal has the characteristics of time-varying non-stationary, it is difficult for the traditional feature extraction and pattern recognition methods to achieve good classification effects, which greatly limits the application range of the EEG signal as a control input signal. In order to optimize the recognition accuracy and real-time performance of EEG signal control, this paper mainly studies the EEG signal characteristics and pattern recognition methods that find the best classification effect, establishes an exoskeleton robot model for upper limb rehabilitation, and detects the overall time delay of the system through the overall experimental simulation of the system.

In this paper, three types of motor EEG signals are used as research objects to carry out feature extraction and classification recognition experimental studies. In the method part, the first part is the structural design of the lower limb rehabilitation exoskeleton robot. Then the EEG signal is collected. Next, the EEG preprocessing, feature extraction, and model classifier are introduced. The results of the feature evaluation are described in the Results section. The analysis is carried out in the final discussion section.

2. Methods

2.1. Overview of the rehabilitation robot

Figure 1 shows the structure of the rehabilitation robot, which is a 6 degrees of freedom upper limb rehabilitation robot, of which 5 degrees of freedom are fully driven, three degrees of freedom of the shoulder joint and one degree of freedom of the elbow joint are the motion mode of the motor series, one degree of freedom of the forearm is the movement mode of gear meshing, the wrist part is the degree of freedom driven by no power, and the movement of each joint is driven by the motor and the reducer, and under the control of the single-chip microcomputer, the individual or compound movement training of each joint can be realized.

Each motor is controlled by the control command, which can drive the arm for rehabilitation training, and the No. 1 disc motor can drive the rail holder to rotate 180 degrees clockwise through the command control, while other joints make corresponding rotations, which can be switched to the training mode of the left upper limb. Through the intelligent interactive screen to send instructions, so that each motor rotation to drive the movement of each part, and then drive the upper limbs of the human body to make a series of basic human body movements to complete the rehabilitation training needs, while the components of each joint can limit their rotation angle through instructions and physical limits to ensure the safety of training.

Figure 1. Mechanical structure of the rehabilitation robot.

2.2. Experimental apparatus

The robot-assisted upper limb rehabilitation system manly includes the functions of online motor imagery EEG signal acquisition, online pattern recognition algorithm, and rehabilitation robot control. The hardware of the system consists of EEG amplifier with universal serial bus (USB) interface, PC, and rehabilitation robot (**Figure 2**).

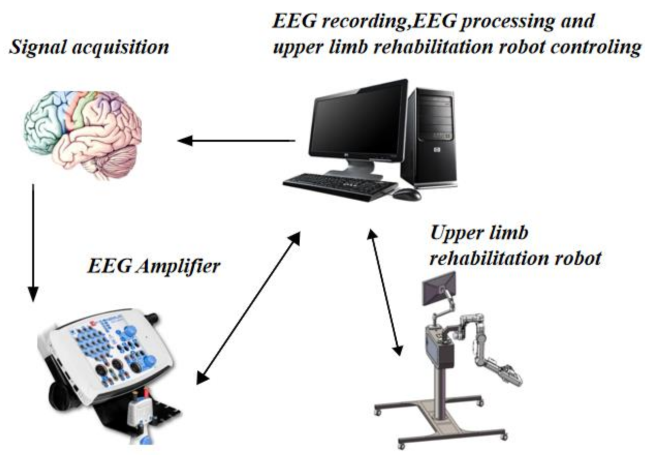


Figure 2. Robot-assisted upper limb rehabilitation system based on EEG.

The EEG acquisition system in this paper is a TeamE-001 EEG signal acquisition device produced by Nanjing Changxiang Technology. The electrode has a large input impedance and a high common mode rejection ratio, and the EEG signal is transmitted wirelessly, removing the shackles of a large number of data lines and making the human body more comfortable to wear. One subject was recruited and EEG collection caps adopted 10–20 national standards. This experiment was approved by the Ethics Committee. Signal analysis and processing are carried out in Matlab.

2.3. EEG signature extraction

2.3.1. Wavelet denoising method based on Gaussian mixture model (GMM)

In this study, we introduce a novel wavelet denoising approach founded on the Gaussian mixture model (GMM). Initially, the observed signal is decomposed into various scales of wavelet coefficients. Subsequently, these coefficients are modeled under the assumption of GMM, aiming to capture both signal and noise characteristics. By modeling the signal and noise separately, we can effectively separate noise from the signal and identify the underlying structure of the signal. Parameter estimation of the GMM is then performed using the maximum a posteriori (MAP) criterion, enabling a more accurate reconstruction of the signal. Finally, the reconstructed signal is obtained by synthesizing the estimated parameters and applying the inverse wavelet transform to restore it to the original domain. Experimental evaluations demonstrate the efficacy of our proposed method in noise reduction while preserving essential signal features. This approach holds promise for various applications in signal processing, offering a robust solution for denoising tasks in diverse domains.

2.3.2. Wavelet packet decomposition and ERD/ERS theory

Wavelet analysis and wavelet packet analysis are often used in engineering applications to analyze some non-stationary signals, and wavelet packet decomposition Wavelet Packet Decomposition (WPD) is a more comprehensive result of Wavelet Decomposition (WD). It uses multiple iterations of the wavelet transform to analyze the details of the input signal, compensating for the disadvantages of fixed time-frequency decomposition in wavelet decomposition. WD decomposes the original signal into low-frequency parts and high-frequency parts, WD only further decomposes the low-frequency part, but does not decompose the high-frequency part, so the wavelet transform can be a good representation of the signal with low-frequency information, and contains a lot of details The signal is very good, but the WPD can decompose both the low-frequency part of the signal and the high-frequency part, because the WPD has multiple orthogonal bases, so different classification performance can be obtained, and the complete wavelet packet tree can be obtained. In this paper, WPD is used to decompose the original signal to obtain 8 frequency bands such as 1–4 Hz, 4–8 Hz, ..., 24–28 Hz, and 28–30 Hz for different frequency bands.

2.3.3. Random forest

A random forest is a classifier consisting of decision trees with multiple different input samples, and its output is determined by each decision tree. The category with the highest percentage of output results is determined. The input sample of each decision tree is selected by random sampling, because the input samples are different and there is no correlation between each decision tree, then for a test sample, N trees will have N classification results, and the random forest determines the most numerous categories of all decision tree output results as the final output results. The advantage is that the N subsamples are randomly selected in a way that has been put back, and the N subsamples are used to train N base learners, and when each base learner is trained, K features are randomly selected, and the optimal features are selected from them to split the nodes, which further reduces the risk of overfitting the model.

Decision trees are the basic building blocks of a random forest. A decision tree is a tree-shaped prediction model in which each internal node table is listed. Each fork path represents the result of the attribute test, and each leaf node corresponds to a category.

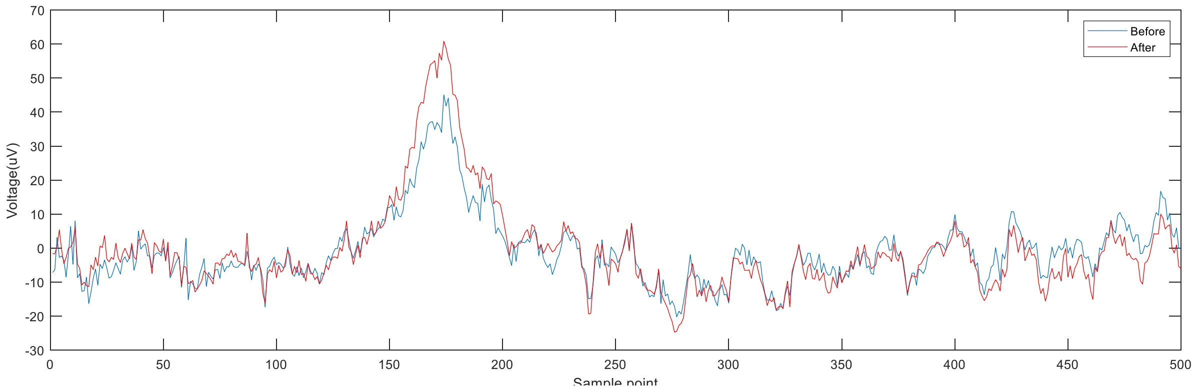
2.3.4. Characteristic performance index

Due to the randomness of the clustering effect, there is no direct judgment criterion for the quality of the clustering performance of the feature vector. Influenced by Davidson Inspired by the Bauding index [15], this paper proposes a feature index based on martens and Pap distances. Performance Index, or FPI for short). In 1936, the Indian statistician Mahalanobis proposed a generalized distance called the Mahalanobis distance. The Martens distance can effectively calculate the closest distance between a sample and the "center of gravity" of the sample set [16]. Martens distances take into account the connections between various features. The Martens distance can easily measure the distance between the test sample and the same type of sample set, and the smaller the mean of the Markov distance for all samples in the sample set, the better the feature clustering effect of the sample set, so it is suitable for use in classification recognition. Bhattacharyya distance is commonly used in classifications to measure the separability between classes. The greater the distance between the centroid of the mass of the class i and the sample set of category j indicates that the better the separation between classes, that is, the classification recognition effect will be better.

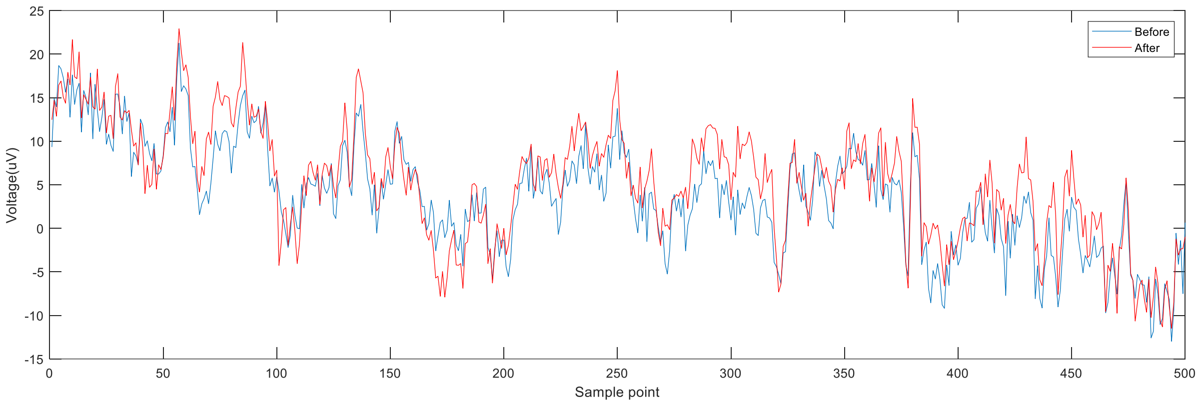
3. Results

Based on the Gaussian hybrid model, the wavelet noise reduction method filters the waveform pairs of the eight channels before and after, as shown in the **Figure 3**, and the original signal uses 500 data point signals after the limbs begin to move. In the spectrum map, the horizontal coordinate is the number of sampling points, the vertical coordinate is the amplitude, the red curve is the waveform diagram of the EEG signal before filtering, and the blue curve is the waveform plot of the EEG signal after wavelet reconstruction, (a)~(h) corresponds to the eight acquisition channels of FP1, FP2, F3, F4, C3, C4, P3, and P4, respectively. The wavelet base of the wavelet transform adopts the sym8 wavelet base, and the 4-layer wavelet decomposition was used in this paper.

These figures shows that the wavelet denoising method based on Gaussian mixture model closely fits the original signal, and the signal is smoother. It is confirmed that the wavelet noise reduction method based on gaussian hybrid model achieves a good filtering effect.


Before
After
Voltage(uV)
Sample point

(a)


Before
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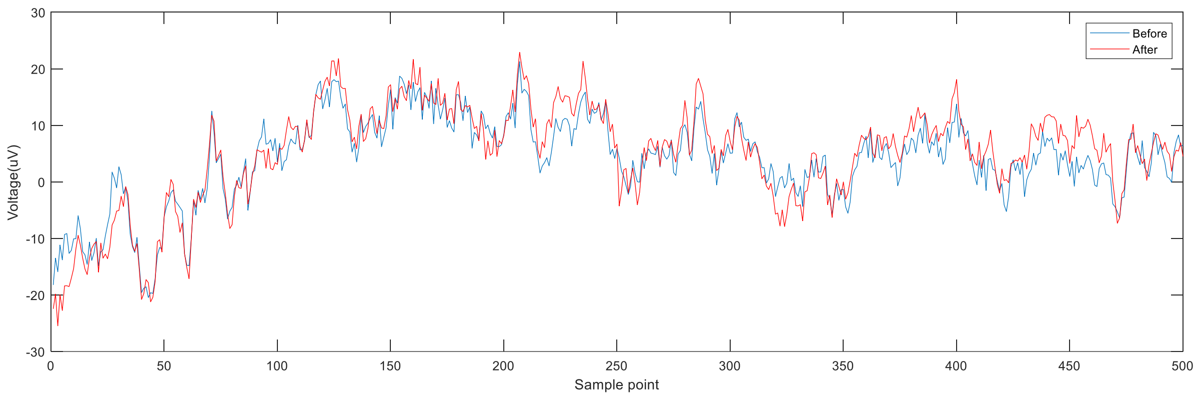
(b)


Before
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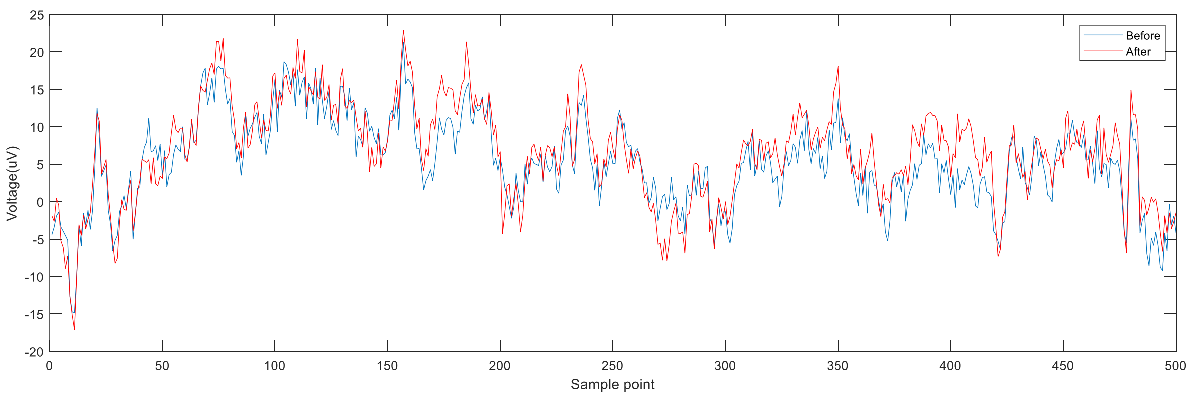
Sample point

(c)


Before
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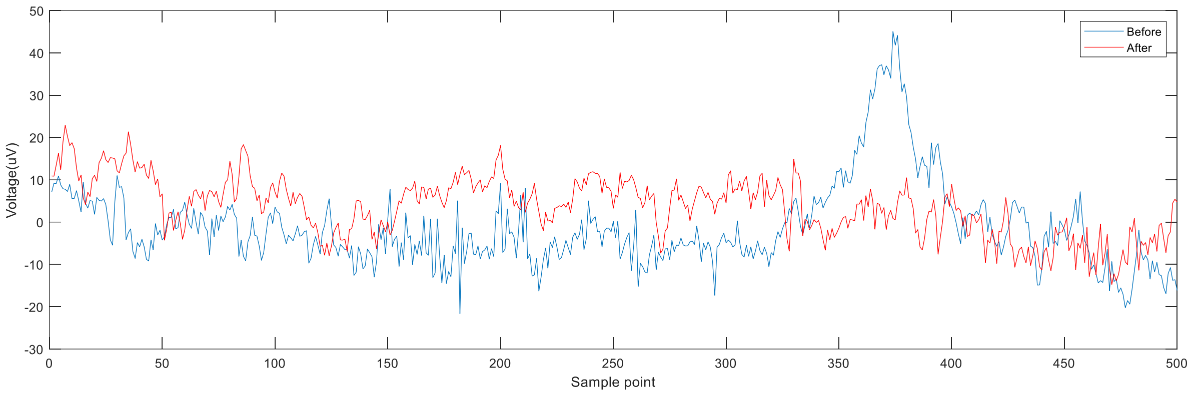
(d)



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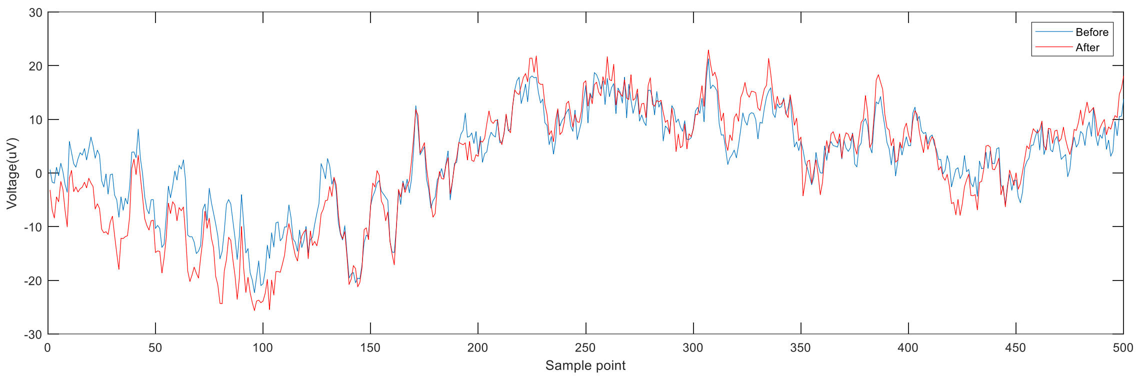
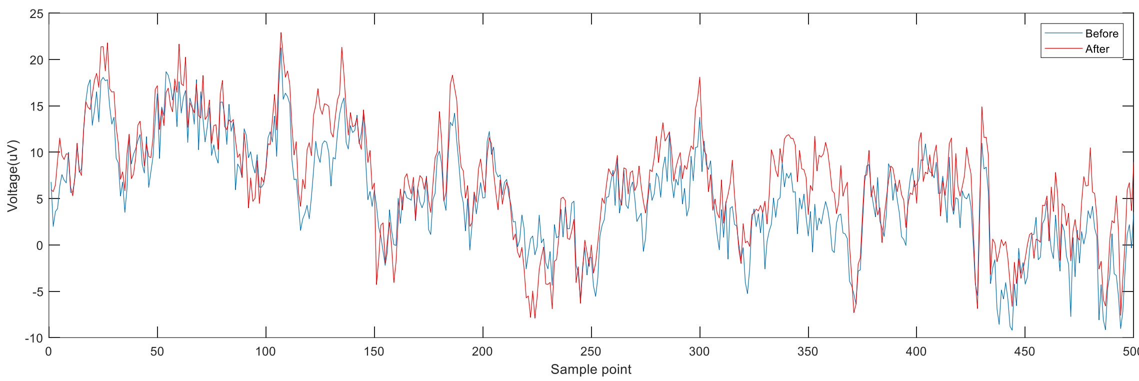
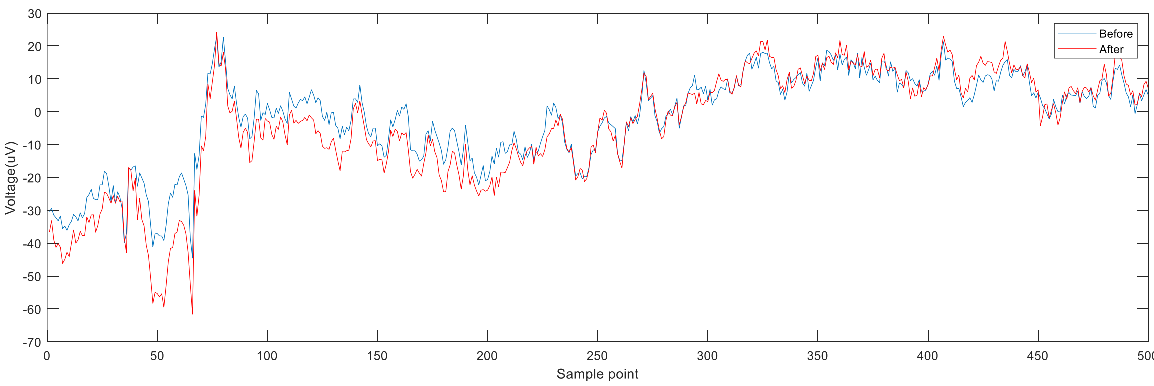


(f)



(g)



(h)

Figure 3. Waveform comparison chart of eight channels before and after the wavelet noise reduction method filtering.

Using wavelet decomposition technology, the 8-channel EEG signal is decomposed by frequency band, **Figure 4** is the relative importance of each feature, the abscissa coordinates are 8 channels 1–30 Hz features, ordinate is the relative importance. For example, the abscissa 1–64 is characteristic of the 8 frequency bands of 1–30 Hz of electrodes FP1, FP2, F3, F4, C3, C4, P3, P4.

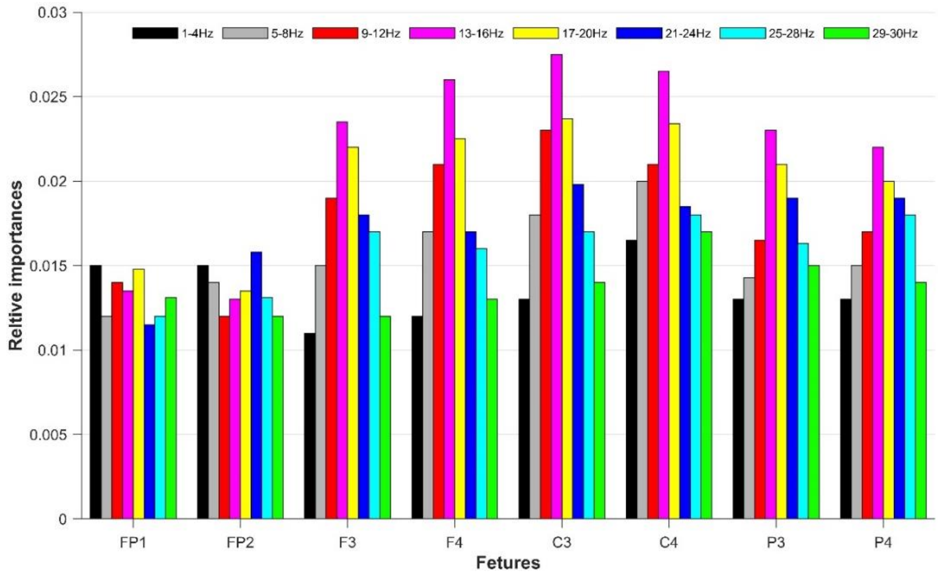


Figure 4. The relative importance of individual features after wavelet decomposition.

From the **Figure 4**, it can be seen that the relative importance values of the different frequency bands of channels FP1 and FP2 do not have particularly prominent values, while channels F3, F4, C3, C4, P3, P4 each frequency band has common characteristics, in the middle band will appear very high relative importance value, the relative importance value of both sides of the frequency band are relatively low, so the histogram will show an arch, which is in line with the theory of ERD/ERS, that is, imagine the left limb or right limb movement, the brain on the opposite side of the relevant motor area a rhythm and b rhythm energy decrease (event correlation to synchronize ERD), and the ipsilateral related movement area a rhythm and b rhythm energy increase (event-related synchronous ERS), when moving , a rhythm and b rhythm contain the most movement information, so the relative importance of the image will appear arched.

4. Discussion

According to the generation mechanism of EEG signal, the waveform characteristics of different frequency bands of EEG signal and the distribution characteristics of each frequency band in the head area, eight channel EEG signal acquisition equipment is selected and EEG signal acquisition is completed. The calculation results of the signal-to-noise ratio of EEG signal processed by the wavelet denoising method based on Gaussian mixture model show that the signal-to-noise ratio of each channel is more than doubled, which means that the noise contained in the signal of each channel is significantly reduced after the wavelet denoising based on

Gaussian mixture model.

Based on ERD/ERS theory and wavelet packet decomposition method, the 1–30 Hz frequency band is decomposed and the input data matrix of motion signal is established. The relative importance of all features is sorted by calculating the importance of each feature. The 0–4 Hz and 28–32 Hz frequency bands of each channel have the lowest relative importance, which means that their classification effect is the worst. The value of the relative importance of the 8–20 Hz frequency band characteristics of each channel is very high, indicating that the 8–20 Hz frequency band contains the most information and its clustering performance is the best. The features with higher relative importance are retained and the features with lower relative importance are discarded to form the final feature vector of the input classifier. From the perspective of feature performance index, it is obvious that the feature vector formed by relative importance ranking and elimination has better classification performance.

In the future, flexible structured rehabilitation robots could be considered, as well as more advanced signal processing and pattern recognition methods. At the same time, the EEG characteristics of stroke patients were studied to better adapt to clinical application.

5. Conclusions

Upper limb rehabilitation exoskeleton robot, as a new type of robot, provides help or rehabilitation treatment for patients with upper limb dyskinesia. Brain-computer interface technology is widely used in rehabilitation training, using EEG signals to realize the communication and control between human brain and rehabilitation auxiliary equipment.

1) Optimize the structural design of upper limb rehabilitation robot. The system can realize the individual or compound exercise training of each joint, and the multiple limit design ensures that the patient will not have secondary injury.
2) A wavelet denoising method based on Gaussian mixture model is used to remove baseline drift and background noise. The signal curve is smoother after filtering, which proves the effectiveness of the filter.
3) In terms of the classification performance of the relative importance of features, the relative importance value of each feature is calculated, which contains more motion information, which makes CSP features have higher accuracy, improves the real-time performance of signal feature extraction, and achieves a higher level of overall system accuracy and real-time performance.

Ethical approval: Ethical review and approval were waived for this study due to the collection of scalp EEG from only a single subject. Informed consent was obtained from all subjects involved in the study.

Conflict of interest: The authors declare no conflict of interest.

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