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A review of electroencephalogram signal processing methods for brain-controlled robots

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ABSTRACT

Brain-computer interface (BCI) based on electroencephalogram (EEG) signals can provide a way for human to communicate with the outside world. This approach is independent of the body's peripheral nerves and muscle tissue. The brain-controlled robot is a new technology based on the brain-computer interface technology and the robot control technology. This technology allows the human brain to control a robot to perform a series of actions. The processing of EEG signals plays a vital role in the technology of brain-controlled robots. In this paper, the methods of EEG signal processing in recent years are summarized. In order to better develop the EEG signal processing methods in brain-controlled robots, this paper elaborate on three parts: EEG signal pre-processing, feature extraction and feature classification. At the same time, the correlation analysis methods and research contents are introduced. The advantages and disadvantages of these methods are analyzed and compared in this paper. Finally, this article looks forward to the EEG signal processing methods in the process of brain-controlled robots.

Introduction

Since the world's first industrial robot was invented in 1959, robotics has developed rapidly in various fields. It has gradually replaced various jobs in production and life. People in today's society are increasingly inseparable from the assistance of robots [1,2]. In order to control robots, people must rely on keyboards, mice, joysticks. However, these operating methods are not suitable for the elderly or the disabled. Therefore, some auxiliary devices for particular groups of people gradually appear in people's lives, such as single switch systems, eye tracking systems [3].

The BCI technology is a diversified emerging discipline that integrates neural networks, computer science, system recognition and pattern recognition. At the same time, it is a new technology that people can communicate with the outside world without relying on the central nervous circuit of the brain and the human muscle [4,5]. Brain-controlled robots are based on the technology of BCI. It reads the action instructions by analyzing the EEG signals. Thus, it can directly replace the brain nerves and human muscles and establish a unique connection channel with external equipment. The technology of brain-controlled robots combines the robots control technology to achieve the goal that controls robots through the human brain. With the rapid development of computer technology, the BCI technology provides a broader application space for the brain electrical signals in robots' control. As the critical technology of BCI, EEG signal processing plays a vital role in its application to robots and other control equipment. The process of using EEG signals can generally be divided into five stages [6–10]. The application of EEG signals is generally divided into: signal acquisition, pre-processing, feature extraction, feature classification and use of classification results to control external equipment. The process of using EEG signals is shown in Fig. 1.

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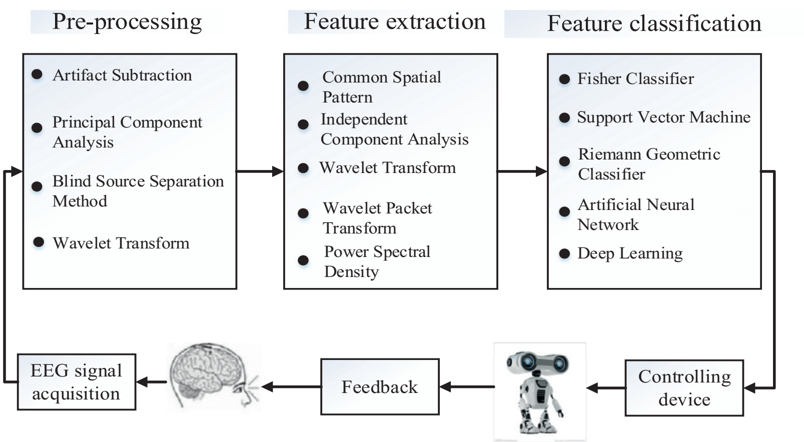

Fig. 1. BCI system structure diagram

Although brain-controlled robots have extremely broad research prospects, there are still many challenges and difficulties that need to be resolved. These current challenges are the main reasons why brain-computer interface technology can only be used in laboratories and cannot be widely used in daily life. The current challenges faced by brain-controlled robotics technology are mainly as follows.

(1) Many current EEG patterns still have problems, such as discomfort and fatigue, and low information transmission rate when used. Therefore, better characteristic EEG signals should be selected through testing.
(2) The question of whether the signal can be processed online in real time. If the online signal processing cannot be processed in real time, the robot cannot guarantee its real-time control accuracy.
(3) How to give feedback when the system is running in real time. If the tactile, visual or auditory feedback cannot be real-time and reliable, it will be detrimental to the system loop composition and correction of deviations in the control process.
(4) The BCI system will have different operating effects due to individual differences. It is also very challenging to study how to modify the parameters so that individual differences will not affect the system.
(5) Obviously, the cumbersome and cumbersome operating system cannot meet the requirements under practical requirements. There are also more urgent needs for wireless transmission to achieve portability and the use of microprocessors to replace computers to achieve miniaturization.
(6) The problem of synchronous and asynchronous modes. That is to solve the wrong control command sent during the non-control time period and eliminate the interference of the spontaneous EEG non-control signal.
(7) To facilitate the control and maintenance, the robot should realize the control precision, humanity and dexterous mechanism design. Service robots should adapt to a broader application field and activity space, and then have a stronger ability to adapt to the external environment.

The structure of this article is as follows: The section 2 introduces the relevant knowledge of EEG signals. The section 3 introduces and compares the pre-processing methods of EEG signal data. The section 4 introduces and compares the feature extraction methods of EEG signals. The section 5 summarizes the feature classification methods of EEG signals. The section 6 summarizes and looks forward to the EEG signal processing methods in the process of brain-controlled robots.

EEG signals

The EEG signal results from the interaction of the central nervous modules of the various functional systems of the human body and the neuronal cells in each area, and its composition mechanism is very complicated. EEG will also show different signal characteristics in different mental states, and the more obvious is the change of frequency-domain signal. BCI is a technology that extracts and recognizes the characteristics of signals through the specificity of human emotions and feelings in different states. In modern medicine, the different frequencies of EEG signals are often used to classify. The variation range of EEG rhythm is between 0.5 and 40 Hz, which can be divided into δ wave, θ wave, α wave, β wave, as shown in Fig. 2. The EEG signal characteristics of different bands are shown in Table 1.

(1) Signal non-linearity: EEG signal has non-linearity, activeness, and time-varying causality. It is a very complex, time-varying, nonlinear dynamic system.
(2) Weakness of signal: Normal EEG signals are feeble. The spontaneous EEG potential of the human body is generally between 2uV and 75uV. The EEG generated by mental, thinking, feeling. It is weaker, about 2 to 10uV, usually mixed in spontaneous EEG and is not easy to detect.
(3) Small frequency range: The frequency of human brain electricity is generally 0.5–40 Hz.

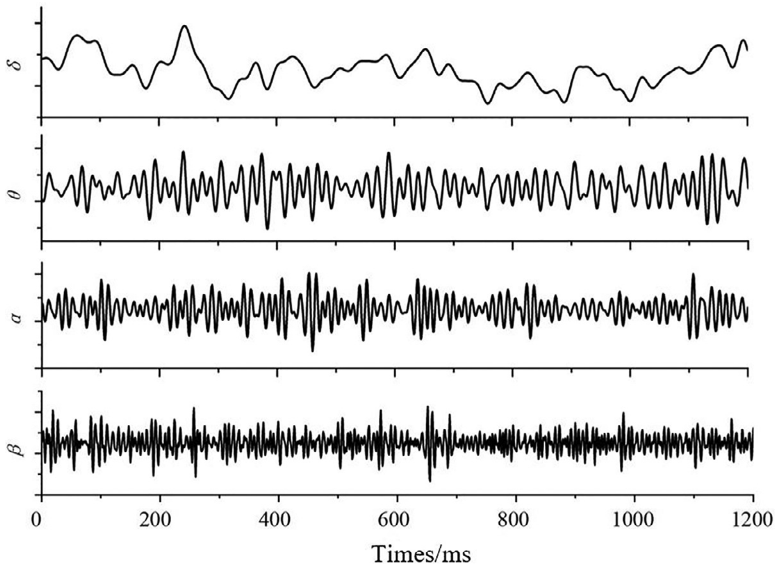

Fig. 2. EEG signals waveform and frequency under different rhythms

Table 1
EEG characteristics of different bands.

Types	Characters
Delta band (0.5–4 Hz)	Delta band appears in the temporal lobe and parietal lobe. This waveband has a significant amplitude. It usually occurs when adults are in a deep sleep or when the brain is suffering from hypoxia. It is the main waveband of the brain in infants.
Theta band (4–8 Hz)	Theta band mainly appears in people's adolescence and is related to people's emotions and mental state. This wave is most apparent when adults have negative emotions.
Alpha band (8–14 Hz)	Alpha band is the wave with the highest frequency in EEG signals. It appears in the back of the brain and on both sides. It often occurs when the brain is awake or resting with closed eyes. This waveband is the basic waveband of EEG signals.
Beta band (14–30 Hz)	Beta band mainly occurs on both sides of the brain. At this time, the cerebral cortex is more excited, and people are in the process of high mental stress. Beta waves are often used to express the excited state of neurons in the cerebral cortex.
Gamma band (>30 Hz)	Gamma band appears in the sensory cortex of the body.

At the same time, EEG signals have the following characteristics:

(4) Strong noise: Because the source of signal mixed noise is complicated, it often contains much noise. Common noises include power frequency interference, white noise, and spikes. In addition, there are usually EMG artifacts and ECG artifacts.
(5) Strong randomness and non-stationary. Due to the influence of various complex factors, they have been changing continuously, but there is no apparent law.
(6) Outstanding frequency domain characteristics. The characteristics of EEG signals in the frequency domain are more prominent.

Signal data pre-processing

The EEG is a kind of bioelectric signal that reflects brain activity. Because of the high time-varying sensitivity, it is susceptible to external interference during the collection. For example, eye movement, blinking, ECG, and EMG will add noise to the accurate EEG signals. These interference noises are often called artifact. Noises bring great difficulties to the analysis of EEG signals [11,12]. In addition, artifact mixed in EEG signals will affect the analysis of the EEG signals. Thus, it has a significant impact on the feature extraction and classification of the EEG signals.

Due to the instability and irregularity of the EEG signals, the processing of the EEG signals is more complicated. Furthermore, it is difficult to analyze the internal connections from them directly. Therefore, under normal circumstances, a certain amount of pre-processing is performed on the signal. Through the pre-processing, a signal with a specific law can be obtained. Therefore, in the feature extraction algorithm of the EEG signals, the collected EEG signals must be processed first. The primary purpose is to remove artifacts and noise in the signals, which is convenient for the latter processing and using [13].

The pre-processing of the EEG signals mainly needs to be considered in two aspects. Part of the noise comes from the interference of the device itself and the line. On the other hand, it considers whether the signal quality has ocular artifacts and ECG artifacts [14,15]. In general, the interference from the equipment itself and the line can be filtered out by removing the limit drift or removing the power frequency interference and band-pass filtering. For the filtering of various artifacts, such as EOG and ECG doped in the obtained EEG signal, adaptive filtering, spatial filtering, and blind source analysis can be used to filter out noise. The EEG signal pre-processing methods are shown in Fig. 3.

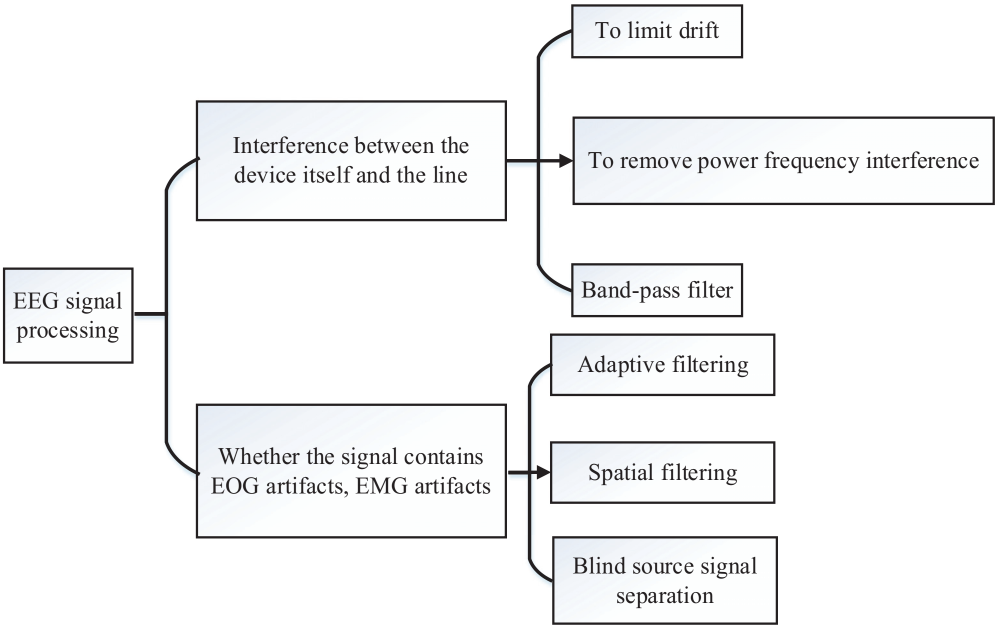

Fig. 3. EEG signal pre-processing methods

Artifact subtraction

Artifact subtraction (AS) is an earlier method of noise removal. This method is easy to understand. Also, the physical meaning is clear. Therefore, we can apply it to the removal of eye movement. It is the subtraction of artifacts. This method is set up under the conditions that the observed EEG and EOG are in line with a linear combination and not correlated. Also, the eye movements can be estimated from the recorded EOG. However, due to the EEG and artifacts influence each other, this subtraction method, like regression-based methods, will mistakenly exclude certain EEG components [16,17]. In order to use this method, the following three conditions must be met.

(1) It is assumed that the collected EEG signals and artifact signals of the subjects are linearly added.
(2) Ocular artifacts can be measured.
(3) There is no correlation between EEG signals and artifact signals.

It usually uses the least square methods to determine the value. Because the amplitude difference between electrooculogram artifacts and EEG signals is noticeable, it can be obtained directly by measurement. Therefore, the way of artifact subtraction can be used to remove electrooculogram artifacts. Huang et al. [18] proposes a better adaptive filter to remove the eye movement and determine parameters in real-time. Zamanian and Farsi [19] put forward a good "multiple-source EOG" program to remove the electrooculogram components in the EEG, which are not affected by the EEG. However, it is difficult to model and compare the propagation path of the EEG signal on the scalp. Rao and Reddy [20] uses nonlinear recursive least squares methods to train the filter. Rao developed a system that can remove electrooculogram artifacts in a current time. However, this method must use a suitable electrooculogram reference model for training. Furthermore, it still depends on the experience of the analyst.

Principal component analysis

At present, principal component analysis (PCA) is the most commonly used denoising processing method. In the EEG signal processing process, the noise interference of the ocular electricity has a more significant interference to the EEG signals [21,22]. The principal component analysis method is used to decompose the collected data. Then the separated ocular electrical components are subtracted from the collected data. In this way, we can obtain the EEG data without eye electrical interference. The basic theory of the PCA algorithm for removing ocular artifacts is: assuming that the EEG signals and the visual signals are orthogonal. The original n-dimensional feature data is mapped to the orthogonal k-dimensional feature space to achieve the feature separation of the original signal. Based on the distribution of the EEG leads, the PCA algorithm decomposes the signals into independent components. It removes the unnecessary components and reconstructs the EEG to wide of the noise.

Cao et al. [23] proposes the algorithm of PCA and Fisher scoring to eliminate the background noise. The apparent distinguishing features are used for supervising fatigue driving. Compared with the results obtained from the other algorithm, the classification results of the PCA algorithm have higher accuracy in the bands. Furthermore, the results show that using a component analysis algorithm for data dimensionality reduction and noise removal is excellent.

Chang et al. [24,25] propose the ways of PCA to remove electrooculogram artifacts. The EEG and EOG signals are recorded when the subjects completed the task of eye movement and blinking. Then the principal components of these signals are calculated as the principal components of eye movement and blinking artifacts. This component is removed from the mixed-signal in order to obtain a corrected signal. Turnip's research shows that PCA is significantly better than the regression method and dipole method in noise filtering effect. However, this arithmetic cannot wholly separate the noise of potential similar to its waveform. The component analysis method can find substitute variables under the premise of minimum information loss to achieve dimensionality reduction. However, for some classification problems, it is hard to get a good classification effect.

Lin and Hsieh [26] uses the principal component analysis as an auxiliary method to reduce the dimension of the feature space in the EEG classification. This algorithm is used for the left and right-hand motion imagination. Results show it can get a better result of classification. According to the research [27], the component analysis method can extract the artifact components in the EEG signals and reconstruct the EEG signals after removing the artifact components.

Blind source separation method

Blind source separation (BSS) is a powerful signal processing method, which developed rapidly in recent years. As a better method, blind source separation combines artificial neural networks, statistical signal processing, information theory and computer systems. The method has become an important research and development topic in many fields, especially in image processing, remote sensing, radar and communication systems. Science data mining have made outstanding contributions [28–30]. EEG signals are weak electrical signals generated by the biological movement of brain nerve cells. The most important source of interference is the non-stationary characteristics and weak electrical signals in the acquisition of EEG signals.

Because the EEG signals and the electrooculogram artifacts are independent, the blind source separation algorithm can be used to eliminate the electrooculogram artifact and solve the problems. The most common method of blind source separation is independent component analysis (ICA) [31,32]. It has achieved sound application effects in biomedical signal processing, mixed speech signal separation, image denoising. The idea of ICA comes from the central limit theorem: the result of a set of random variables whose mean and variance are the same order of magnitude must be close to Gaussian distribution. The separation result of mixed signals produced by a linear combination of statistically independent sources. When these signals reach the maximum, these mixed signals can be considered to achieve separation.

Liu et al. [33] performs artifact removal on the EEG of a lying child with eyes closed. He determines whether it is an artifact by observing the independent components analyzed. However, this method lacks the quantitative analysis of the denoising effect of ICA. Gao et al. [34] uses the same method to perform ICA denoising on the three experimental data sets. They compared the results with the PCA and the regression algorithm analysis through graphs, but they did not perform quantitative analysis.

Sadleir et al. [35] proposes a method to automatically extract and remove the eye movement artifacts after ICA analysis. This result is equivalent to the manual ICA denoising effect, which has far-reaching significance for further promoting ICA arithmetic. The blind source separation method does not require reference electrodes for artifacts in pre-processing of EEG signals. It can be used for the separation of various artifacts with high accuracy in removing artifacts. ICA arithmetic denoising also has some problems that need to be solved and discussed. For example, most EEG signals are the result of the joint activity of multiple neurons. When the number of sources is greater than the number of sensors, it is a question to separate the source signals.

Wavelet transform

The wavelet transform (WT) was put by geophysicist when analyzing and processing geophysical exploration data. It has a good effect on the processing and analysis of non-stationary signals. WT is a development of Fourier transform. Compared with Fourier-transform, wavelet transform has good time-frequency characteristics [36,37]. It adopts the method of changing the window shape in the time and frequency domain. That is, it has higher frequency resolution and lower time in the part of low frequency. Also, WT is known as the "mathematical microscope" [38]. Wavelet threshold method denoising is a method based on the wavelet transform multi-resolution analysis. The noisy signals undergo the multi-resolution stepwise decomposition of the wavelet transform. The amplitude of the noise discrete detail signal decreases with the increase of the wavelet transform scale.

Nevertheless, the relationship between the wavelet transform coefficient and the scale of the valuable signals are reversed. By the characteristic of wavelet transform of noisy signals, we can select the appropriate threshold and process the discrete details of each scale after wavelet transform of the signal. Finally, the approximation signals and the processed discrete details are reconstructed by wavelet inverse transform to reconstruct the signal. According to these steps, the purpose of denoising is achieved.

Ramanan et al. [39,40] adopts the Haar wavelet to detect eye movement artifacts in patients with epilepsy. Experiments show that when the human eye is opened to closed and closed to open, a falling edge and a rising edge with a slight delay are obtained. Ramanan uses this feature to detect the moment when the electrooculogram artifact occurs accurately. Then he uses it to control the wavelet filters and buffers to ensure that the wavelet filters only denoising when the eye movement occurs. This discovery solves the clinical problem that epilepsy wave is indistinguishable from blinking artifacts.

Advantages and disadvantages of EEG signal pre-processing methods

Among the EEG signal pre-processing methods, the filtering method is a classic method, which is usually used to filter the power frequency interference and electromagnetic interference doped in the EEG signals. Moreover, it is required that the target signal and

Table 2
Comparison of advantages and disadvantages of EEG signal pre-processing methods.

Pre-processing methods	Advantages	Disadvantages	References
AS	Effectively estimate artifacts	Part of the EEG signals will be lost	[18–20]
PCA	Reducing data dimensions	Poor filtering	[23,34,25–27]
BSS	High computational efficiency	Too much calculation	[33–35]
WT	Realizing data reconstruction at different scales with good processing effect	Higher requirements for the choice of wavelet base	[39,40]

the artifact signal spectrum do not overlap. On the other hand, regression and artifact subtraction are commonly used to remove eye movement interference. The former assumes that the transmission frequency of the visual potential is independent, and there is no delay. The latter assumes that the target signal and the artifact signal are linearly superimposed to estimate the artifact. The shortcomings of the two ways are inevitably losing part of the EEG signal while removing artifacts.

Furthermore, principal component analysis is usually used to reduce the dimensionality of the collected multi-channel data. It is beneficial to the subsequent analysis and data processing. The method of independent component analysis uses an optimization algorithm to decompose the multi-channel observation signal into several independent components according to statistical independence. The focus of the application is on the selection of the objective function and the optimization algorithm. Wavelet transforms way is a multi-scale time-frequency analysis tool. It can extract and reconstruct the wavelet coefficients of EEG signals at different scales. It can remove the artifacts effectively. When used in the application environments, the appropriate wavelet base must be selected according to the specific situation. The advantages and the disadvantages of the EEG signal pre-processing methods are shown in Table 2 below.

There are many methods for pre-processing EEG signals. Each method has its advantages and limitations. The specific user needs to be selected according to the specific conditions. Because of the multi-channel characteristics of the EEG signals, principal component analysis is commonly used in research to reduce dimensionality. The ways of the independent component analysis extract independent components. It also can extract data of interest while removing interference information.

In conclusion, the primary purpose of the EEG signal pre-processing is to remove the interference while retaining the practical components. According to the methods, we will extract the feature information with a higher recognition rate subsequently. In order to meet the requirement of higher accuracy, the current artifact methods usually combine two or more methods. These hybrid methods are better at removing noise from the EEG signals.

EEG signal feature extraction

The original EEG signals become a relatively pure EEG signal after pre-processing. However, due to a large amount of EEG signal data, the direct processing is too complicated. Moreover, feature extraction is required to reduce the data dimension [41,42]. The characteristics and extraction of EEG signals are mainly based on the three aspects of time-domain, frequency-domain and the spatial space domain [43,44]. The time-domain method of EEG signal feature extraction has strong intuitiveness. Specific wave is easy to identify and have obvious characteristic significance.

In the time domain feature extraction method, the focus is to extract features based on the shape and intensity of the wave, such as the maximum and minimum amplitude, zero crossings, mean and mean square error. The frequency-domain feature analysis method mainly observes the frequency spectrum of the EEG signal of a certain length, which can obtain the distribution and change of each rhythm in the EEG signal. Its main indicators are frequency mean, frequency variance, frequency standard deviation. The spatial domain analysis method mainly reduces the dimensionality through spatial projection, converts multiple variables into a small number of principal components. Moreover, it realizes the extraction of the characteristic information of the EEG signal. The EEG feature extraction methods in the time domain and frequency domain mainly include Fourier transform, WT and auto-regressive algorithms. Feature extraction algorithms in the airspace mainly include Common spatial pattern, principal component analysis, common average reference and other algorithms [45–47].

Common spatial pattern

Common spatial pattern (CSP) is a spatial filtering feature extraction algorithm for two classification tasks. First, it can extract the spatial distribution components of each category from multi-channel brain-computer interface data. The basic principle of the CSP algorithm is to use the diagonalizable matrix to find a set of optimal spatial filters for projection. Second, to maximize the variance of the two types of signals, thereby obtaining a feature vector with a higher degree of discrimination [48–50]. CSP is mainly used to process BCI motor imagination EEG data. The basic idea is to design a spatial filter to process EEG signals to obtain a new time series so that one type of signal has the most significant variance.

Moreover, the other has a minor variance. The advantage is that there is no need to select a specific frequency band in advance. The disadvantage is that it is sensitive to noise and relies on multi-channel analysis. In order to solve the problem, the traditional EEG signal feature extraction method based on frequency features only extracts the energy features of each channel. It ignores the related information between each channel.

Feng et al. [51] proposes a new method based on the wavelet packet and CSP to obtain better feature extraction results. First, based on analyzing the channels and frequency bands closely related to the event, the EEG signal is decomposed by a wavelet packet. Then the activity of the EEG signals are extracted, and the cooperative rhythms are imagined. Next, the CSP algorithm is used for spatial filtering to extract features, and relevant nodes are selected to calculate the wavelet packet energy. Combining the advantages of the wavelet packet method and the CSP method, the relevant information between different channels can be fully utilized. The classification results show that the proposed feature extraction method based on wavelet packet decomposition and CSP can extract valuable features of moving image EEG signals and obtain high classification accuracy.

Saha et al. [52] proposes a new method to realize CSP in the frequency domain of EEG signals. It can realize feature extraction of the EEG signals. Moreover, it can achieve a feature extraction method of random variables based on frequency domain CSP. The algorithm extracts feature with a higher sampling rate in the time domain from the frequency domain information of the EEG signals. In order to realize this idea, it first collects EEG data of several healthy subjects. These data are related to the motion stimulation of the left and right images. Then, these signals are processed appropriately. Furthermore, the data is separated according to different stimulus categories. Finally, the results indicate that the classification accuracy rate can be improved by 10% based on the CSP method.

Park and Chung [53] puts forward a new global CSP feature extraction and classification method based on EEG. Comparing the significant difference between the local features and the global features of the CSP feature extraction method, the classification performance is improved compared with the conventional method. In addition, it can achieve higher accuracy. This globally optimized CSP feature extraction method is especially suitable for small sample data.

Independent component analysis

Independent component analysis (ICA) is used to find hidden factors or components in statistical data. ICA is also a widely used blind edge separation method to reveal information hidden in random variables or signals [54,55]. The way is used to extract independent signal information from mixed signals [56,57]. It was proposed in the 1980s. According to the ICA algorithm theory, the eye movement artifacts, ECG artifacts and power frequency interference are all generated by independent signal sources, which are statistically independent. Separate it to extract helpful EEG signals. ICA algorithm provides an effective method to separate and remove eye movement artifacts in EEG signals. Independent components should be independent of each other. It is the basic principle on which ICA is established. At the same time, it can be said that we can estimate this model only with this principle. The independent components must be non-Gaussian. The high-order cumulant of the Gaussian distribution is 0, but high-order information is necessary to estimate the ICA model.

Pontifex et al. [58] discusses the automatic separation method of ICA components of eye movement artifacts, which can avoid the error separation of the signal components similar to the distribution of the eye movement artifacts in the scalp EEG. It also reduces the errors that may be caused by human confirmation of artifacts. Paradeshi et al. [59] uses the independent component analysis technology for artifact suppression. Using Haar wavelet, the EEG signal is statically segmented. Compared with the earlier methods, the results of the existing methods are more satisfactory. The wavelet-enhanced ICA algorithm is suitable for removing eye artifacts.

Samadi and Cooke [60] proposes a feature extraction method based on independent component analysis to apply steady-state visual evoked (SSVEP) experiments. The experimental results show that the original EEG is compared with the features extracted from the "clean" EEG reconstructed by ICA. SSVEP response detection with frequency features extracted from ICA components has higher SSVEP response detection accuracy and lower human-to-human difference. This work highlights that ICA performs well in source separation and can better meet the robustness requirements of EEG signals. Subasi and Gursoy [61] proposes an independent component reference analysis method. This approach is a constrained paradigm that incorporates a priori information about the required source as a reference signal into the comparison function of the ICA. The reference signal makes the search more inclined to separate the target source, which is more efficient and accurate than the traditional ICA.

Wavelet transform and wavelet packet transform

Wavelet transform (WT) is a time-scale analysis method used for non-stationary signals. It can characterize local characteristics of signals in both time and frequency domains. Wavelet transform stresses the signal characteristics, and it refines the signal in multiple scales through the expansion and translation operation. Thus, the time resolution at the signal's high frequency and the frequency resolution at the low frequency are improved.

The signal time-frequency analysis requirements are automatically adapted. In the process of wavelet transform decomposition, only the low-frequency part of the signal is decomposed. The high-frequency part is not decomposed. Therefore, as the signal frequency increases, the frequency resolution decreases [62,63]. The frequency resolution of wavelet packet transform (WPT) for high-frequency signals is higher than that of WT. Therefore, an excellent wavelet packet basis function, with strong signal analysis ability, is widely used. WT is generally divided into continuous wavelet transform and discrete wavelet transform. Although the emergence of the continuous WT significantly improves the Fourier transform, it also brings a significant degree of information redundancy.

Cárdenas-Barrera et al. [64] proposes a WPT EEG data compression algorithm based on Shannon entropy. The algorithm can compress data well, and it can maintain the signal integrity with an excellent linear frequency modulation signal modulation and MAE. It can be used to analyze and detect WPT of the epileptic events in EEG signals. Zhou et al. [65] introduces a sleep spindle detection algorithm based on SVM and wavelet transform to detect the sleep spindle in the EEG signals accurately. This method takes advantage of the high resolution of the wavelet transform, and it has high precision in the extraction of features in harmonic analysis.

Hu et al. [66] introduces a short-term EEG feature extraction algorithm based on wavelet transform. Firstly, perform wavelet decomposition of the EEG signal on a specific lead, and reconstruct the frequency synchronization function, including event-related, to remove redundant information. Then the short-time Fourier transform is used to extract the features of the moving image and visualize these features. Finally, the convolutional neural network is used for classification. This method is applied to two kinds of BCI competition sports imaging EEG data sets. The experimental results show that the classification recognition rate can reach 96.67%.

Power spectral density

The EEG signals are non-stationary random signal. Generally speaking, the duration of the random signal is infinite. Moreover, the total energy of the random signal is infinite. Any sample function of the random process does not satisfy the absolute condition. Its Fourier transform does not exist [67]. However, the total energy of a random signal is infinite. The average power is limited. Therefore, to analyze the frequency domain of a random signal, it is only meant to study from the power spectrum [68–70]. For this reason, power spectral density (PSD) is often used in research to analyze the frequency domain characteristics of the EEG signals. The power spectral density is a measure of the mean square value of a random variable, which is the average power dimension per unit frequency.

Kocak [71] established a mouse sleep staging method based on power spectral spectrum analysis. The EEG signals of the cerebral cortex and neck were collected by placing *in vivo* electrodes in mice and using the multi-channel EEG recording system. Then the data analysis software is used to establish the power spectral density spectrum diagram of the original EEG signals. Finally, according to combine the physiological characteristics and videos of mice sleep, the time interval of each sleeping period of mice is determined from the power spectral density spectrum. The results show that compared with the sleep staging results of artificial visual analysis of electrical signal wave, the coincidence rate of mouse sleep staging results based on power spectral density spectrum analysis is more than 91%. Min [72] uses power spectral density and fractal dimension to evaluate the difference between "before", "interval", and "after" in children's sleep spindle period. The results show that there are statistical differences between "interval" and "before" and "after" periods. The numbers are also significantly different. These differences are good for understanding the changes in sleep spindles.

Advantages and disadvantages of feature extraction methods

EEG signals have more prominent frequency domain characteristics such as non-stationary and nonlinear, determining their analysis methods. Therefore, it is more suitable for time-domain analysis and nonlinear methods. In recent years, EEG analysis and processing methods such as waveform feature description, auto-regressive AR model, Fourier transform, power spectral density, wavelet transform, artificial neural network, and nonlinear dynamic analysis have been deeply studied. However, these methods also have their advantages and limitations.

The power spectrum analysis method analyzes the EEG signals from the perspective of the frequency domain, which can well reflect the energy change process of the signal. The traditional power spectrum analysis method is to estimate the power spectrum through Fourier transform directly. Although it is easy to implement, the resolution ability is limited. The commonly used method in modern power spectrum estimation is the AR model. Compared with the traditional power spectrum method of the AR model. The advantage of the method is that only short-range data is needed to obtain high-resolution spectrum estimates.

Furthermore, it can be easily converted into feature vectors. The wavelet transform method performs joint analysis on the signal in the time domain and frequency domain. Wavelet transform has multi-resolution characteristics, which can decompose each frequency band of the signal. Then reconstruct the signal of each frequency band. In addition, wavelet transform can extract the hidden features of the signal in the process of decomposing and reconstructing the signal.

Independent component analysis uses the ICA method to analyze EEG signals, extracting ECG and EOG signals from EEG signals. This method can separate noise signals such as power frequency interference, thereby effectively enhancing the analysis of EEG signals. The basic principle of the CSP algorithm is to design the optimal spatial filter by diagonalizing the two covariance matrices simultaneously. Then it distinguishes the EEG signal characteristics of left-hand motor imagination and right-hand motor imagination. This method is most suitable for motor imagination EEG signal data. In all, Different EEG signal feature extraction methods have their suitable places. At the same time, it has its unique advantages and disadvantages. There is also the possibility of combining the methods in comparison with each other. The specific advantages and disadvantages of the EEG signal feature extraction are shown in the following Table 3.

Feature classification of EEG signals

Different movements or senses can produce different features of the brain's electrical response. Signal classification is based on these characteristics to determine the type of movement or consciousness. This method can determine the relationship between consciousness and signals [73,74]. After the EEG signals are processed and extracted, the extracted feature vector is classified by the classifier to realize the analysis and prediction of the EEG signals. The classifiers commonly used in the feature classification of the EEG signals include the Fisher classifier, support vector machine, Riemann geometric classifier, artificial neural network, and deep learning.

Table 3
Advantages and disadvantages of EEG signal feature extraction algorithm.

Algorithms	Advantages	Disadvantages	References
CSP	Suitable for processing motor imagery data	Need more electrodes	[51–53]
ICA	High computational efficiency, can process large amounts of EEG data	Need a longer data length	[58–61]
WT	It handles time domain and frequency domain signals well, and can be used for feature extraction of unsteady signals	Lacking of response to noise	[64,65]
WPT	It can be used for non-steady state signals with better processing details	Calculation time is too long	[66]
PSD	Has good stability characteristics	Not suitable for non-stationary signals	[71,72]

Fisher classifier

The classifier of linear discriminant analysis is a linear learning method proposed by Fisher in 1936. The main idea of the approach is to find the appropriate projection direction for a given training sample set and project the sample onto a straight line. These similar projection points are concentrated as much as possible. Furthermore, different types of projection points try to stay away. Then, using the same method to classify the new sample, it can determine the new sample category according to the position of the projection point of the new sample on the straight line. Thus, Latent Dirichlet Allocation (LDA) has a small amount of calculation, which is easy to use.

In conclusion, this is a better classification method. The Fisher classifier is a linear classification with the characteristics of a small amount of calculation and can be widely used in BCI brain-computer interface research [75,76]. The application purpose of the Fisher classifier is to convert high-dimensional space data to low-dimensional space. Thus, reducing dimensionality is the key to solving the problem [77,78]. LDA projects the high dimensional sample data to the low dimensional space to ensure that the sample data has the most considerable inter-class distance and the smallest inter-class distance in the space.

Muthong et al. [79] solve the non-stationary problem by capturing all the change points in the EEG signal and dividing it into a set of signals. Then the regularized LDA is applied to each divided signal to form a classifier for feature classification. The experiment was conducted on the BCI Competition IV data set. The experimental results show that the Fisher classifier is very effective for the feature classification of the EEG signals.

Jian-Feng [80] compare three different classifiers based on linear discriminant analysis LDA, artificial neural network (ANN) and support vector machine based on detecting a group of subjects' imagination movement. The results show that the three classifiers have good classification performance. The classification accuracy of these three classifiers is LDA: 88.6%, ANN: 81.9%, SVM: 82.6%, respectively for the moving imagination.

Mahanta et al. [81] proposes how using an LDA feature extractor to extract salient features is a necessary step to classify EEG signals. However, the multi-channel EEG is naturally in the form of the matrix variables, while traditional feature extractors such as LDA are designed for vector variable input. Therefore, the LDA feature classifier method requires a priori vectorization of the EEG signal. Furthermore, the inherent matrix variable structure in the data is ignored, which will result in high computational complexity.

Support vector machine

Support vector machine (SVM) is a class of generalized linear classifiers that classifies data binary in a supervised learning method. The basic principle is to find the optimal decision surface in space so that different data types are distributed on both sides of the decision surface. In order to achieve a better classification [82,83], SVM can be divided into linear separable support vector machine and nonlinear support vector machine according to its construction model from simple to complex. Support vector machines are supervised learning models and related learning algorithms that analyze data in classification and regression analysis.

The SVM training algorithm creates a model that assigns a new instance to one of the two categories, making it non-probability two Meta-linear classifiers. The SVM model represents instances as points in space so that the mapping makes individual categories of instances separated by the broadest possible, noticeable interval. Then, mapping the new instances to the same space and predicting their category based on which side of the interval they fall on.

Sani et al. [84] uses support vector machines to classify stress objects based on EEG signals. The support vector machine is used to classify the power spectrum density and energy spectrum density of the EEG alpha-band data and determine whether the subject is in a stress state. The correct classification rate of the data is 83.33%. The results show that the support vector machine method can effectively classify EEG signals.

Hajibabazadeh and Azimirad [85] propose a new method for using SVM feature classification to realize brain-controlled robots. The EEG data related to the left and right moving images are extracted and classified using support vector machines. First, collect the six-channel EEG signal and then use a low-pass filter for filtering. Wavelet transform decomposes the signal into frequency sub-bands as features. In the next step, the support vector machine divides the features into two categories: left and right moving, features extraction and classification of the EEG data related to the left and right moving images. Finally, the SVM divides the sub-band coefficients into two categories (left-hand moving images and right-hand moving images) as features. The output data is used for the control of the Tabriz-Puma robot. The experiment uses 360 training sets and 90 test sets for testing, and the classification accuracy is 75%.

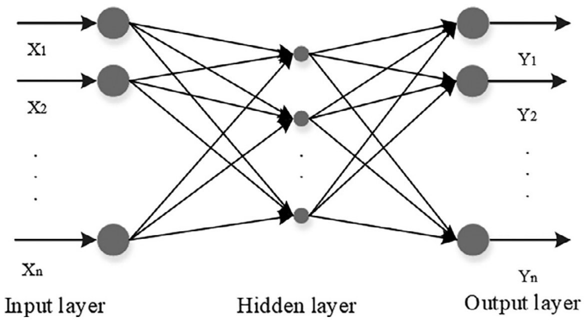

Fig. 4. The Structure Diagram of Artificial Neural Network

Kousarrizi [86] uses five different methods to detect tests that contain artifacts. Finally, two different neural networks and support vector machines classify the features extracted by wavelet transform. Use 70% of the data set for training and the rest for testing the classifier. Compared with neural network classifiers, SVM classifiers have better training accuracy, but neural network classifiers have better test accuracy than SVM. However, due to the unstable nature of the SVM classifier, the test accuracy is low.

Riemann geometric classifier

The classifier based on Riemann Geometry directly maps the data to a geometric space with appropriate metrics instead of estimating spatial filters and selecting features. The mapped geometric space is the flow pattern space. The measurement tool is the external distance (non-Euclidean Reid distance) [87]. Extend the problem of machine learning to flow space. The unique nature of Riemannian geometry makes the classifiers have good generalization ability, which can be used to study conversation transfer and subject transfer problems in BCI. Tensors provide a natural representation for EEG data. These are gradually being used in feature extraction, clustering and classification tasks in BCI. Basic machine learning algorithms can be extended to tensors. Its advantages are the high classification accuracy and the strong generalization ability. Disadvantages: high complexity and high computing power requirements. Also, it is not suitable online.

In EEG signal processing, the matrix is generally operated under smooth constraints. The constrained space can be understood as smoothly curved space. The symmetric positive definite matrix space where the commonly used sample covariance matrix is a Riemannian manifold. Traditional LDA, CSP and other methods all use sample covariance matrices in the Euclidean space without considering the curvature of the symmetric positive definite matrix space to which they belong, which is not conducive to accurately establishing the model literature [88,89].

Algorithms based on Riemann geometry have good generalization ability and robustness literature [90–92]. At present, the methods for BCI decoding EEG signal characteristics based on Riemannian geometry can be divided into two categories:

(1) Synthesize the advantages of Riemann space and Euclidean space and map the Riemannian manifold to its tangent space through logarithmic mapping. The tangent space is Euclidean space, and methods such as LDA, CSP, can be used directly. However, it is worth noting that feature selection still needs to be considered in the Euclidean tangent space to reduce the feature dimension and avoid the disaster of dimensionality.
(2) In the Riemannian manifold, based on the invariance of the Riemann distance, the spatial information in the covariance matrix is used for direct classification. The Riemann mean minimum distance is a typical representative of this type of algorithm.

Artificial neural network

Artificial neural network (ANN) is new popular research that has emerged in artificial intelligence since the 1980s [93]. The ANN abstractly simulates the human brain neuron network from the perspective of information processing, establishes corresponding models, and forms different networks according to different connection methods. Thus, ANN is inspired by the human brain and various biological neural networks. It is mainly used to process massive data, solving classification and regression problems. It belongs to a branch of the machine learning methods [94–96].

The forward neural network is further divided into a single-layered feed-forward neural network (SFNN) and a multilayered feed-forward neural network (MFNN). The SFNN input layer and the output layer are directly connected. The MFNN input layer and the output layer contain a hidden layer. The RNN contains a feedback loop based on MFNN. That is the output layer neurons feedback to their input neurons. A neuron is the basic unit of ANN, which is composed of the input variable, input variable weights, activation functions, deviation values and output variables. The general neural network is composed of the input layer, the hidden layer and the output layer. The structure is shown in Fig. 4.

ANN has the advantages of high classification accuracy, vital learning and high fault tolerance. It also can fully approximate complex nonlinear relationships. However, a large number of parameters are required, the learning time is long, and the process is not easy to observe, which affects the acceptability of the results. Those are the disadvantages of the way. Nevertheless, ANN can be used for spontaneous EEG analysis. The purpose of the analysis is to detect EEG spikes and seizures. The input methods can use the original signals model and the characteristic parameter model. Some methods combine wavelet transform and artificial neural network to detect spike and spike components in EEG signals. Using wavelet transform to process the input of the ANN-based EEG spike detection system to simplify the input mode of ANN without reducing the information content of the signal and the detection performance.

Belakhdar et al. [97] evaluates the classification of the two classifiers for EEG to select one that can provide higher accuracy. The experiment researched the EEG signals of the polysomnography database. The results show that the ANN classifier is better than the SVM classifier when using the one-person EEG channel. Collet et al. [98] uses artificial neural networks to analyze brainwave spectrogram images for robot applications. The time-frequency method or spectrogram image processing technology is used to analyze EEG signals. The GLCM texture feature is extracted from the spectrogram image and passed through principal component analysis to reduce the feature dimension. The experimental results show that the neural network can optimize the training model by changing the neurons, learning rate and momentum in the hidden layer. According to the EEG image, the effect is significantly better than the traditional EEG signal feature classification methods.

Li and Fan [99] describes the two artificial neural network methods (BP and self-organizing competitive ANN). He uses the EEG rhythms to distinguish three subjects. In addition, the two artificial neural networks are compared. The results show that ANN is an effective method to identify these three characteristic samples. In this study, BP neural network has an all-around performance than self-organizing competitive artificial neural network technology.

Deep learning

Deep learning (DL) is a type of machine learning and an extension of the ANN. DL refers to the learning, analysis, and processing of many hidden layer neurons in the ANN. Early ANN were shallow primarily models. The basic structure of the DL was deep neural networks with many hidden layers. It includes a large number of neurons. Many of the parameters should be adjusted. DL is an essential branch of machine learning, and it is a research hot spot in recent years. It has been widely used in the analysis and processing of physiological signals. For researches, this is a suitable method by using the deep learning methods to achieve the classification of the EEG signals. These spots mainly include emotion recognition, mental detection, event-related potential detection and the sleep score.

Borrowing the idea of the Ada-boost algorithm, An et al. [100] proposes a new method about the EEG signal proposing. He combines multiple weak classifiers trained by the deep belief network (DBN) into a robust classifier. The result shows it can achieve a better recognition result of left movement and right hands movement imagination EEG signals. Zheng et al. [101] put forward the DBN model and Hidden Markov model. This model can easily recognize positive and negative emotions based on EEG signals.

Moreover, it can achieve a reasonable recognition rate of 87.62%. Lngkvist et al. [102] summarized a series of deep learning methods. Martin used them in the feature learning of the time series signals such as EEG signals, which solved the difficulty of the feature extraction caused by the change of the time series signals such as mean, variance, frequency. Deep learning provides a new idea for the feature extraction and recognition of EEG signals in the brain-computer interface. Pontifex et al. [103] uses a deep neural network to build a robust and automated system for the classification of MI EEG records by using the entire input data in the process of learning salient features. Compared with other architectures, convolutional neural network (CNN) and Hybrid CNN have high-performance architectures.

Advantages and disadvantages of EEG signal feature classification methods

There are many methods for EEG signal feature classification and EEG signal feature extraction. Each of the methods has its advantages and disadvantages. And the specific application needs to consider the specific situation. The standard EEG signal feature classification methods include SVM, Riemann geometric classifier, artificial neural network, deep learning and Fisher classifier algorithm. SVM is a more traditional classification algorithm. Although it has good robustness, it lacks prior knowledge of the distribution characteristics.

The Fisher classifier can get a high accuracy rate, but it needs to perform a priori vectorization of the EEG signals. At the same time, it ignores the inherent matrix variable structure in the data. Artificial neural networks and deep learning have become the research hot spots in recent years. Deep learning mainly used in the big data processing. It has a high accuracy rate and a flexible network architecture. Thus, it can be applied to a variety of scenarios. However, the disadvantage is obvious. It requires a large amount of data for training. Furthermore, the performance also depends on the construction of the network structure. The advantages and disadvantages of the various classification algorithms are shown in Table 4 below.

Conclusion and future directions

This article mainly reviews the researches of EEG signal processing in the process of brain-controlled robots. The content includes three parts which are the EEG signal pre-processing, the EEG feature extraction and the classification. The BCI system relies on EEG signals. It determines the instructions issued by the human brain. The collection of the EEG signals, the data processing and the classification determine the performance of the BCI system. Data processing affects the speed and the accuracy of the subsequent pattern classification. The choice of the classifier determines the result of the pattern classification.

At present, DL methods are a research hot spot. DL proposes a method for the computer to learn the pattern features automatically. It integrates feature learning into building the model, thereby reducing the incompleteness caused by human design features. DL uses the original EEG data as input without feature extraction and selection to preserve the original EEG information as much as possible.

Table 4
Advantages and disadvantages of EEG signal feature classification algorithm.

EEG signal feature classifier	Advantages	Disadvantages	References
SVM	Good robustness	Lacking of certain prior knowledge of the distribution characteristics of the signal	[79–81]
RGC	Strong generalization ability High accuracy and flexible structure	Complicated calculation	[84–86]
ANN	High accuracy and flexible structure	Depending on the number of neurons in the hidden layer	[88,89]
Fisher	Effectively improve calculation efficiency and classification accuracy	Matrix variable structure inherent in the data is ignored	[97–99]
DL	Flexible structure and high accuracy	Depending on the construction of the network structure	[100–103]

At present, EEG signal processing with deep learning as the core has achieved recognition or classification capabilities that surpass existing algorithms in application scenarios that meet specific conditions. Using DL to carry out EEG signal classification research mainly includes emotion recognition, motor image recognition, mental load detection, epilepsy detection, event-related potential detection and sleep score in the future. One limitation of current deep learning applications is the large amount of data required. Moreover, this problem will be solved in the future. Therefore, DL in the feature extraction and classification of EEG processing is bound to be a research trend in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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