Review article: *the key technologies of brain-computer interface*

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**Abstract:** As an important branch of intelligent robots, brain-computer interface (BCI) technology has great application prospects in the fields of neurological rehabilitation, functional prosthesis assistance and neurological monitoring. Many breakthroughs have been made in the research of brain-computer interface. Based on the existing research literature, this paper has done the following work: outlined the research significance and development status of brain-computer interface technology; introduced the working principle and structure of brain-machine interface system; compared EEG signals of different frequencies, and classified their application fields; analyzed five preprocessing methods, and listed their advantages and disadvantages; summarized the theories and algorithms involved in feature extraction and pattern classifier. Finally, after a detailed introduction of the non-intrusive brain-computer interface components, the paper summarized the current technical challenges faced by the brain-computer interface system.

1. **Introduction:**
Brain-Computer Interface (BCI) is a communication method that does not rely on peripheral nerves and muscles, but the brain completes control command output. It has been extensively researched and applied in the fields of neuroprosthesis, neural feedback training, emotion classification, military, entertainment, etc. [1-2]. By processing and transforming brain signals in a certain way, the user's movement or intention is converted into instructions, and assistive devices such as wheelchairs and robotic arms are controlled so that users can directly interact with the outside world through the brain, which can solve the problem of patients with damaged muscles or nerve endings to communicate with the environment to a certain extent [3]. Feature extraction of neural signals from the motor cortex of the brain, analysis of electrical stimulation parameters corresponding to the function, stimulation of peripheral nerves or muscle tissues, can enable paralyzed patients to regain limb movement ability [4]. The use of BCI can increase the skills of special operating and control professional equipment for personnel in special working environments such as pilots and astronauts. In addition, applying BCI technology to games can also provide a new interactive interface.

2. **Research Status of BCI**
Since Jacques Vida first coined the term BCI [5], research on BCI systems has achieved significant results. The Naveen R S team used the BCI system based on motor imagination to realize the motion control of the wheelchair [6]. F Guo demonstrated the feasibility of inducing both P300 and SSVEP characteristic potentials, and introduced SSVEP characteristics into the P300 speller, and proposed a
new hybrid BCI method. The online spelling accuracy reached 93.85% and the spelling speed reached 53.06 bits/min [7]. The BCI system developed by Hochberg et al. enabled two patients with long-term quadriplegia to control the robotic arm to achieve three-dimensional stretching and grasping movements by using motor cortical neuron signals [8-9]. M Gomez-Rodriguez et al. proposed a combination of BCI and robot-assisted neuro-rehabilitation therapy. The BCI-based control interface is used to drive a 7-degree-of-freedom robotic arm to guide the subject's arm for rehabilitation training [10].

The laboratory of Zhejiang University has carried out systematic research on brain-computer fusion, and has established several system examples: the idea of controlling a quadrotor unmanned aerial vehicle through the analysis of scalp EEG signals, three different types of motor imagination and two different emoticons to control the movement of the aircraft in 3D space [11]. Brain-controlling rat robot: the user wears an EEG acquisition cap, and views the action path of the rat robot through an interactive interface, and can control the travel direction of the rat robot through EEG signals [12]. The BCI spelling machine system developed by Tsinghua University used frequency-phase joint modulation to encode 40 characters in a 0.5-second visually induced signal, and then realizes character reading through steady state visual evoked potential (SSVEP), and system information transmission. The rate is as high as 5.32 bit/s [13]. In July 2019, Musk and his team revealed that they have developed ultra-thin "threads" that can be woven into human’s brain to listen to their neurons, and Neuralink has also manufactured them that can be supervised by neurosurgeons robot performing precision surgery [14].

3. Brain-computer interface system

The BCI system framework is shown in Figure 1. The system is generally composed of signal acquisition, processing, and control equipment. The signal processing includes preprocessing, feature extraction, and pattern classifier. As shown in the figure, the working process of the BCI system starts when the subject is stimulated by external stimuli or spontaneous psychological activities, and the brain neurons excite to generate potential changes. The electrodes obtain EEG signals from the scalp or the skull, and then the signal collector transformed into digital signals that can be processed and processed. The digital EEG signals are filtered by the pre-processing algorithm to remove interference, and then feature extraction is used to obtain those feature vectors that reflect the user's intention. Finally, the extracted features are mapped to the user through pattern classification. The control commands are output to the control device, so that the human brain can control and communicate externally. The control objects commonly used in research include wheelchairs, robotic arms, robots and other physical devices. In addition, brain-machine interfaces can also be used for virtual interface operations. At the same time, the subject can adjust the activity of the brain according to the response of the external device to achieve good human-computer interaction.

4. Key technologies of brain-computer interface

The core of BCI technology is a conversion algorithm that converts EEG signals into control instructions. In order to enable the BCI system to convert EEG signals into commands that can be recognized by the control object in real time, quickly and accurately, it is possible to collect signals from Optimized design
in four aspects: processing, feature extraction and pattern classification. This article will review the methods in the literature from the aspects of EEG signals, preprocessing methods, feature extraction, and classifiers for the design of non-invasive brain-computer interface systems.

4.1 Types of EEG signals
Normal human EEG signal is a rhythmic activity affected by ideology and motor behavior. The amplitude is 5 ~ 200μV and the frequency is 0.2 ~ 50Hz. It can be divided into four distinct bands, δ (0.5 ~ 3 Hz), θ (4 ~ 7 Hz), α (8 ~ 12 Hz), β (12 ~ 30 Hz) each wave has its own characteristics, which are affected by different consciousness and behavior. The core content of BCI is the analysis and processing of these EEG signals. According to the causes of the EEG signals, the signals can be divided into evoked potentials and self-generating potentials. Commonly used EEG input signals include P300, steady-state visual evoked potential (SSVEP), cortical slow potential (SCP), and μ or β rhythm.

4.1.1 Evoked potential
Evoked potential is the local potential change produced by nerve cells after the brain is subjected to certain external electrical, light, and acoustic stimuli.

(1) P300 event-related potential
P300 is an event-related potential (ERP), which refers to a potential that produces a positive peak within 300ms after being stimulated by a visual stimulus. The smaller the probability of a visual stimulus event, the more significant the P300 that is triggered. The Wadsworth Research Center has developed a 16-channel BCI system based on the principle of P300. The P300-evoked display contains a 6x6 menu option matrix, randomly highlighting rows or columns, and observing the moment when the P300 potential appears to mark the subject’s choice [15]. C Holzner et al. Used P300 as the input signal of BCI to realize the switching of TV channels and the opening of windows and doors in virtual reality smart homes, and the control success rate was as high as 89% [16]. A.F-R et al. explored how the spatial overlap between visual stimuli affects the performance of P300-based BCI control, and explained the regulation of visual performance caused by overlapping stimuli [17]. Onishi Akinari researched and examined the impact of emotional sounds in BCI based on P300. Experiments show that the late components of P300 show significantly higher point-double correlation coefficients when responding to very positive and very negative sounds than to other sounds [18].

(2) Steady-state visual evoked potential
Steady-state Visual Evoked Potential (SSVEP) is a type of visual evoked potential obtained by applying repeated excitation to the vision at equal intervals greater than 6 Hz. The spectral components of SSVEP are concentrated at the stimulus frequency and its harmonic frequency, so the signal-to-noise ratio is relatively high and it is easier to detect [19]. The brain-computer interface based on SSVEP is the brain-computer interface with the highest information transmission rate at present. Each instruction in the system corresponds to a specific visual code, and target recognition is achieved by interpreting the specific EEG response induced by the code [20]. M A Azom and others designed an automatic dialing system based on SSVEP. The 16 dial buttons flicker at different frequencies. When a participant looks at a dialing key, SSVEP mainly contains multiples of the frequency. The BCI system uses this frequency to select the data on the keyboard to realize the dialing function [21]. Maye et al. Proposed an SSVEP brain-computer interface system based on spatial information coding. According to the principle of visual cortical retinal mapping, when attention is paid to different spatial orientations of visual stimuli, the induced spatial pattern of the EEG response is different, so only one steady-state vision is used. The stimulus can realize the identification of multiple attention targets. This new paradigm is based on the principle of visual cortex retinal mapping. When the user pays attention to different spatial orientations of the visual stimulus, the spatial pattern of the induced EEG response is different, and the classification of the offline 9 orientations is correct. The rate reached about 95% [22].

4.1.2 Self-generating position
Spontaneous power generation refers to the electrical signals generated by the cerebral cortex nerve cells
spontaneously without any artificial stimulation from the outside world. The spontaneous EEG signals currently widely used are as follows:

(1) Motor imaging related potentials

Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) are closely related to subjective motor imagination, and are accompanied by an increase or decrease in synchronization of Mu rhythm and Beta rhythm in EEG. The results of the research by H G Yeom et al. Show that when imagining right-hand movement, the ERD appears at the C3 position during the Mu wave, and ERS appears during the Beta wave; while when imagining left-hand movement, the ERD appears at the C4 position during the Mu wave, ERS appears during Beta waves [23]. The BCI system uses different classification algorithms to identify the ERS / ERD patterns related to a certain movement, so as to distinguish the corresponding movement imagination. T.M. realizes the classification and recognition of four types of movements by imagining the combined movements of fingers, hands, and feet, and proposes a movement imagination mode that imagines Chinese characters with different degrees of difficulty in writing with left and right hands. Javier et al. successfully constructed a three-dimensional information graphic related to ERS / ERD to distinguish between jumping, moving to the left, and moving to the right to realize the control of the online game interface [24].

(2) Alpha wave of spontaneous EEG signal

Among the spontaneous EEG signals, α wave is the most obvious wave in rhythmic EEG with a frequency of 8 ~ 13Hz. In BCI systems, the blocking phenomenon of Alpha waves is often used as a control input. Zhao et al. used the alpha wave to build a BCI system, which completed the system's arbitrary start and accurate output of given commands. And by real-time detection of the state of the alpha wave in the case of eyes open and closed, the on-off control of external equipment is realized [25]. Denis et al. Used a linear discriminant function-based method to measure the alpha wave on the 2s segment from the occipital lobe, detect events related to eye opening and closing, and used to control the switching of the BCI system [26]. The above two experimental results show that the BCI system based on alpha wave has higher sensitivity, stability and classification accuracy.

(3) Slow Cortical Potentials (SCPs)

SCPs are parts of EEG signals with frequencies below 1 Hz and can last between 500ms and a few seconds. In normal brain function, positive SCPs reflect a decrease in cerebral cortex activity. Negative SCPs are often accompanied by an increase in neuron excitement. After training, they can artificially control the positive and negative of SCPs, and shift the direction of SCPs to different target stimuli. Correspondence can achieve some simple control tasks. The TID system designed by Neumann et al. enabled patients with ALS to control the positive and negative shifts of SCPs to complete the movement of the screen cursor to the basic communication purpose [27]. S R et al. demonstrated that model performance is positively correlated with motion speed and negatively correlated with position variance [28]. The results of this study demonstrate the feasibility of predicting 3D imaginary trajectories of all arm joints from the scalp EEG, and suggest the existence of motor-related neurological factors in slow cortical potentials.

Summarizing the above literature, EEG signals can be roughly divided into five categories, and the corresponding typical applications are shown in Table 1.

| EEG Signal Type | Occurrence Time/Frequency | Typical Application |
|-----------------|---------------------------|---------------------|
| P300            | 300ms                     | TV channel switching, sound discrimination |
| SSVEP           | 6~60HZ                    | Automatic dialing, spatial positioning, visual mapping, speller |
| ERD/ERS         | μRhythm 8-12Hz            | Cursor control, motion recognition, game interface |
|                 | βRhythm 18-26Hz           |                     |
| Alpha           | 8~13HZ                    | Switch control, command output |
| SCPS            | 500ms                     | Motion prediction, screen cursor communication |

The above EEG signals can be used as input signals of the BCI system, each with its own characteristics and limitations. Evoked potentials do not require training, are easy to detect and handle, but depend on human perception and need to provide stimulation devices. Spontaneous signals are not
dependent on external stimuli, but require a lot of special training.

4.2 Preprocessing methods of EEG signals
EEG signal is a kind of non-stationary and non-linear weak signal, which is very susceptible to noise, such as spontaneous EEG signal, eye movement, myoelectricity, and line interference that are not related to control consciousness. The purpose of signal preprocessing is to remove the interference that is not related to the control signal in the EEG signal and improve the signal-to-noise ratio. Commonly used EEG signal preprocessing algorithms include linear filtering, artifact reduction, wavelet threshold filtering, principal component analysis, and independent component analysis.

4.2.1 Linear filtering
Linear filtering uses the frequency distribution characteristics of each component signal to remove components. If the EEG signal is mainly distributed at 0.2-50Hz, a low-pass filter can be used for EMG (higher than 50Hz) distributed at high frequencies, and for low-frequency eyes High-pass filters can be used for dynamic interference, but this method cannot effectively separate noise interference that overlaps with EEG signals.

4.2.2 Artifact Subtraction
Directly subtracting artifact components from the contaminated EEG wave to offset noise pollution. This method is intuitive and easy to implement, but the subtraction program needs to model the propagation path of the EEG signal reasonably, and requires the model to be a linear system. At the same time, the artifacts are not linear with the desired signal, which makes this method difficult to apply to complex biological systems.

4.2.3 Wavelet Transform
Wavelet threshold is a filtering method based on the time-frequency characteristics of wavelet transform. Signals containing artifacts are decomposed into a series of decomposition coefficients by wavelet transform, and then threshold shrinkage is performed on the wavelet coefficients at different scales to achieve the purpose of noise reduction [29-30]. For example, for 5 ~ 200Hz EMG interference, high-frequency interference can be directly filtered by wavelet analysis multi-resolution analysis method. For interference with EEG (main frequency component below 30Hz), it can be eliminated by wavelet threshold [31-32]. However, the traditional wavelet threshold denoising assumes that the different wavelet coefficients are independent of each other, ignoring the relationship between the parent wavelet coefficients and the child wavelet coefficients, which causes the original related information to be repeatedly processed, thereby losing some important details. For this shortcoming, CHEN et al. [33] proposed an improved bivariate shrinkage function model to achieve the local adaptive shrinkage processing of the wavelet coefficient threshold and avoid repeated processing due to the assumption of independence. In addition, some studies have tried to combine wavelet with other filtering methods. Chen Jun [34] et al. Used ICA to decompose the multi-channel EEG signal into several independent components, and then used the wavelet threshold to denoise the independent components. Chao Liu [35] and others proposed an EEG signal preprocessing algorithm combining wavelet transform and Fast ICA. The high-frequency signal in the target signal was filtered by wavelet transform, and the signal was reconstructed into the input signal of the ICA algorithm to overcome Disadvantages of the independent component analysis method that cannot distinguish noise. The correlation analysis of the output components shows that the number of correlations between the components is approximately 0, which has a good denoising effect.

4.2.4 Principal Component Analysis (PCA)
The principle of principal component analysis (PCA) noise reduction is: according to the principle of variance maximization, orthogonal variables are used to represent multiple variables with a few unrelated and orthogonal components. This group of uncorrelated orthogonal bases (principal
components) is similar to the largest unrelated group of the original data array, and the original data represented by the principal components can be regarded as the projection of the original data under the new orthogonal basis. When PCA is used to remove EEG artifacts, the multi-lead EEG can be decomposed into unrelated components, the main components are extracted, the unwanted artifact components (such as the electrooculogram) are removed, and then the EEG can be reconstructed and compared. Clean EEG signals. Berg et al. proposed a method of using PCA to eliminate electrooculum artifacts. First, record the electroencephalogram and electroencephalogram signals of the subjects when they completed the blinking motion, calculate the main components of the electroencephalogram, and then subtract them from the electroencephalogram signals. The main components of the electrooculogram artifacts are corrected EEG signals. Experimental results show that the PCA method can achieve a better effect of eliminating electroencephalogram artifacts [36]. However, PCA has some limitations for the removal of artifacts: when the signal and noise have similar potentials, it is difficult to remove it by the PCA method; because the PCA algorithm can only analyze the covariance of the signal (second-order statistical characteristics), cannot decompose the high-order related signals, so the information of high-order statistical characteristics in the signals will be lost. Despite the limitations of artifact processing, the PCA algorithm is often used for dimensionality reduction optimization of the extracted feature set [37].

4.2.5 Independent Component Analysis (ICA)

Independent component analysis (ICA) is a blind source separation method used to separate or approximately separate the original signal when only the mixed signal is known, but the source, noise, and mixing mechanism are not known [38]. An important assumption for the application of the ICA method is that the source statistics are independent. Therefore, when ICA is used to separate the EEG noise, it is assumed that brain activity and other signals (electrooculogram, myoelectricity, etc.) come from different physiological processes. Infomax ICA was used to decompose the EEG signals, and then the P300 component IC was automatically found using 6 superposition averages, and finally the P300 component was reconstructed to obtain the P300 component [39]. Zhang Yu et al. Used the Fast ICA algorithm to process the EEG signal, and then averaged it with fewer times to achieve the purpose of extracting P300 [40]. Liu Long et al. Used the Fast ICA algorithm to process the original EEG signals collected by the Mindset headset, and the results show that the Fast ICA algorithm has a better effect of removing 50HZ power frequency interference and ECG artifacts with the wavelet transform [41]. Hu Pan et al. combined the characteristics of ICA unsupervised learning and the phenomenon of motion-related desynchronization (ERD), constructed a simple and practical ICA airspace filter design method and three types of motion imagination discrimination criteria. The results of the three-class motion imagination recognition in offline and online experiments reached 89.78% and 89.89%, respectively, indicating that the ICA algorithm has a small time overhead and has the potential for cross-platform transplantation [42].

In summary, the advantages and disadvantages of the pretreatment methods mentioned in the literature are shown in the following table:

| Pretreatment method       | Advantages                              | Disadvantages                                         |
|---------------------------|-----------------------------------------|-------------------------------------------------------|
| Linear filtering          | Filtering based on frequency            | Ineffective separation of noise                       |
| Artifact Subtraction      | Intuitive and easy to implement         | Hard to apply complex biological systems             |
| Wavelet threshold filtering | Good denoising effect                   | Lost details                                          |
| PCA                       | Good low order artifact removal         | Poor higher-order statistical properties              |
| ICA                       | Blind source separation, higher-order statistical characteristics | Outliers in the data have a greater impact on the estimation effect |

In summary, the advantages and disadvantages of the pretreatment methods mentioned in the literature are shown in the following table:
4.3 Feature extraction

Feature extraction is to extract as few feature vectors as possible from the pre-processed signal that can characterize the characteristics of the information as input for subsequent pattern classification. The feature extraction method is divided into two angles of filtering: time domain and space domain.

4.3.1 Time domain filtering analysis method

The extraction of time-domain features is mainly a statistical analysis of amplitude values, such as the mean, standard deviation, variance, and slope. The time-domain feature extraction method is simple, intuitive, and easy to implement, but for unstable and complex EEG waveforms, the excellent evaluation of feature values often depends on the operator's experience. Alternatively, the time-domain signal can be transformed into the frequency domain, and the relevant features can be extracted from the frequency. This frequency-domain filtering method converts the EEG whose amplitude changes with time into a map whose power varies with frequency, so that the distribution and transformation of EEG rhythm can be observed intuitively.

At present, the time-frequency analysis method is the most classic BCI research method, which mainly refers to the wavelet transform, wavelet packet transform, and Hilbert yellow transform based on the short-time Fourier transform. The wavelet transform approximates the original signal through different scales [43]. It has good time-frequency localization characteristics, which is very suitable for analyzing the transient and time-varying characteristics of non-stationary signals. As a supplement, the decomposition algorithm further decomposes the high-frequency signal by a binary filter to further improve the time-frequency resolution. When wavelet transform and wavelet packet transform are used to decompose signals, it is necessary to preset the number of decomposition layers and wavelet functions, and the adaptive decomposition ability of the signal is poor. Decomposed into a limited number of single-component signals with high time-frequency resolution [44]. HHT transform includes empirical mode decomposition (EMD) and Hilbert spectrum analysis [45]. After IMF is obtained through EMD decomposition, Hilbert transform is performed on each IMF component to obtain its instantaneous frequency and amplitude. The Bert spectrum is the distribution of instantaneous amplitudes in the frequency-time plane.

4.3.2 Spatial domain filtering analysis method

Spatial domain filtering analysis refers to different signal weights obtained by different electrodes. Through spatial filtering, the importance of different signal categories is discerned, and the feature vector with the largest discernibility between categories is obtained [46]. Spatial filters are spatial high-pass filters with fixed filtering characteristics. Typical are Laplace spatial filters and common average reference filters.

The common spatial pattern (CSP) algorithm is the most widely used filtering method in the spatial domain. The basic principle is to use the diagonalization of the covariance matrix to find an optimal spatial filter. The variance of the variance is maximized to obtain a feature vector with higher discrimination. This algorithm is mostly used for EEG feature extraction of left and right hand motion imagination [47].

4.4 Pattern classifier

The main task of the classifier is to map the extracted feature vectors to the current activity mode of the user's brain. Commonly used BCI classification methods include linear discrimination, support vector machines, artificial neural networks, and so on. For the classification of a single feature, the linear method is adequate, but linear discriminant analysis (LDA) cannot give satisfactory results for some complex non-linear brain signal data [48].

4.4.1 Support Vector Machine

Support vector machine (SVM) [49] is a machine learning method based on statistical learning. It maps input vectors to high-dimensional feature space through non-linear mapping, and then linearly classifies
vectors in high-dimensional space. The basic idea of SVM is to solve the problem of being able to train the correct partition of the data set and obtain the separated hyperplane with the largest geometric interval, as shown in Figure 2.

![Figure 2. Schematic of support vector machine algorithm](image)

The core of the SVM algorithm is to find the hyperplane, that is, the choice of the kernel function. Commonly used kernel functions include linear kernels, polynomial kernels, and radial basis kernels. Different kernel functions can be used to construct different SVM classifiers. Support vector machines have generalization advantages in small sample, non-linear and high-dimensional pattern recognition, and have better anti-noise capability, but the selection of kernel functions and kernel parameters lacks effective methods. Therefore, the study of multi-core learning and SVM kernel function classifier combined with adaptive genetic algorithm, integrated learning feature selection algorithm, regression feature replacement algorithm, etc. is widely used, which makes feature selection a good compromise in algorithm speed and selection effect [50-51]. Z.X. et al. used a multi-core SVM classifier and a multi-feature weighted fusion method for image classification. The accuracy of image classification is much higher than the single-feature and single-core classifier method, which effectively improves the accuracy of image classification [52].

4.4.2 Artificial Neural Network

Artificial neural network (ANN) is a data processing algorithm established by simulating the characteristics of the neural network of the brain. The artificial neural network has a strong learning ability and adaptive ability. It can obtain the structural characteristics of the network through certain training and learning, avoiding artificial The information loss caused by the design feature extractor is widely used in BCI systems. The artificial neural network is shown in Figure 2. It includes an input layer, a hidden layer, an output layer, and feedback. The hidden layer and the output layer neurons are the calculation nodes.

![Figure 3. Schematic of artificial neural network](image)

The neural network learning algorithm adjusts the weights according to the environmental changes in the calculation nodes to continuously improve the system behavior. Among them, BP neural network
learning (BPNN) learning is an algorithm trained by error backpropagation in a multilayer feedforward network, which can approximate any non-linear mapping relationship, and has good generalization and fault tolerance capabilities [53]. In the application of artificial neural networks, more than 80% of the network models sample the BP network or its deformation. Convolutional neural networks (CNN) are also widely used. Their main feature is that they can automatically learn complex models and use a series of operations such as convolution filtering, local normalization, nonlinear functions, and local downsampling to extract features from the signal. Based on the back-propagation training process and optimization algorithms such as gradient descent. LeCun et al. originally proposed a CNN neural network structure to simplify the processing of pictures as much as possible [54]. Many other new algorithms have emerged. Among them, Extreme Learning Machine (ELM) has begun to be widely used because of its fast learning speed and good generalization performance. This is a simple and effective learning algorithm based on a single hidden layer feedforward neural network. During the execution process, there is no need to adjust the input weight of the network and the hidden layer bias. The calculation process is not based on an iterative calculation method. Song Jia et al. applied the extreme learning machine algorithm to aircraft fault diagnosis, which improved the accuracy of fault diagnosis and also improved the diagnosis efficiency [55].

5. Challenges Facing BCI System

BCI technology is a cross-cutting technology. The construction of its system requires the introduction of multidisciplinary technologies such as cognitive neuroscience, computer science and information science. At present, BCI technology can only realize simple information reading and input. In order to realize the practicality of BCI system, it is urgent to solve the following problems.

(1) Improve the information transmission rate of the BCI system. The Institute of Semiconductors of the Chinese Academy of Sciences uses a task-related component analysis algorithm to increase the communication rate of steady-state visual evoked potential BCI to 5.4 bit / s, and the optimal result reaches 6.3 bit / s [56], but the information speed based on several other EEG signals is still not enough to meet the daily communication needs. In addition, the lag and long response time of online system information transmission seriously affect the user experience.

(2) Improve the accuracy of the BCI system. At present, the average level of the non-intrusive BCI system recognition rate still needs to be improved, and the recognition rate is affected by the test time. How to use a simple and efficient signal classification processing algorithm to achieve system accuracy is a requirement for BCI system researchers. Great challenge.

(3) Improve the parameter adaptive ability of the BCI system. The existing BCI system is affected by the individual differences of test subjects, the accuracy of the control of the equipment varies, and even the optimal parameters of the same BCI system for the same subject will change over time.

(4) Optimize EEG signal acquisition equipment. Due to the cumbersome operation steps of the existing non-intrusive EEG signal acquisition solution and the large volume of the data processing unit, it has greatly hindered BCI from entering the laboratory into real life. Miniaturization and portability of signal acquisition equipment are the key to the practical application of BCI systems. Technology one.

(5) Because the preprocessing methods, feature extraction methods, and classifiers used by different BCI systems are very different, especially in terms of input, output, and classification algorithms, it is necessary to be objective in different BCI systems. Scientific evaluation is very difficult. Establishing a unified performance evaluation standard will also have far-reaching significance for the development of BCI systems.

6. Conclusion

Taking the BCI system framework as the starting point, this paper gives a comprehensive overview of key technologies in each key element of the BCI system. Five types of EEG signals used in the BCI system were compared, with summarizing their frequencies and application fields. Five preprocessing methods were analyzed, with their advantages and disadvantages listed. And the paper summarized the theories and algorithms involved in feature extraction and pattern classifier.
As a new communication and control method of biological-machine intelligent integration, BCI has broad application prospects and research value. However, there are still many problems that need to be solved to make BCI stable and reliable in practice.

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Conflicts of Interest:
The authors declare no conflicts of interest.

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