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# Research on Signal Preprocessing Methods based on Brain-computer Interface

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**Abstract:**

With the rapid advancement of neuroscience and engineering technology, Brain-Computer Interface (BCI) technology has garnered widespread attention and research interest as an innovative means of directly connecting the human brain to external devices. BCI has emerged as a promising technology for facilitating direct communication between the brain and external devices. However, the quality of EEG signals recorded by BCI systems is often affected by various artifacts, such as eye movements, muscle activities, and powerline interference. Therefore, signal preprocessing plays a crucial role in improving the performance of BCI systems. In this paper, brain-computer interface (BCI) signal preprocessing methods are reviewed. The principles, advantages, and disadvantages of these methods are summarized, and the future development direction of BCI signal preprocessing is discussed. Overall, with these preprocessing methods, the BCI system is able to recognize and interpret EEG signals more accurately and reliably, providing better support for brain-computer interaction. The potential applications of deep learning in EEG signal preprocessing, especially in the recognition and removal of complex artifacts, are of great significance.

**Keywords:** Signal preprocessing; BCI; EEG; Filter; Artifact.

## 1. Introduction

With the rapid advancement of neuroscience and engineering technology, Brain-Computer Interface (BCI) technology has garnered widespread attention and research interest as an innovative means of directly connecting the human brain to external devices. At present, the technology is mainly used in physical, psychological, speech, and other aspects of treatment, but it can also be used in education, art, military, and other aspects where there is great value. However, many technical problems are difficult to overcome, and there are also some ethical problems at the social level.

The exploration of electroencephalography (EEG) for capturing and identifying human brain activity, as well as its potential application in controlling external devices, was initiated by researchers in the 1960s. But at this point, the experiment also focused on distinguishing and classifying EEG waveforms, known as α waves, β waves, and so on.

Fast-forward to the late 1980s, a pivotal moment emerged as researchers began to bridge the gap between theoretical exploration and practical application by integrating BCI technology into clinical practice. This transition marked BCI systems demonstrated their potential to empower individuals with disabilities by enabling direct communication and control of external devices through neural signals. It can be seen that the development of brain-computer interfaces is very rapid.

With the advancement of computer science and technology in the 21st century, machine learning algorithms and enhanced signal processing techniques have been incorporated into the research domain, which has revolutionized the analysis and interpretation of EEG signals, with computer science and neuroscience intersecting to drive the evolution of BCI technology to unprecedented heights. BCI systems can extract meaningful information from complex neural data with higher accuracy and efficiency, ushering in a novel stage of investigation for brain-computer interfaces.

Brain-machine interfaces (BMIs) have emerged as groundbreaking technologies that take signals from the brain, process them (including signal preprocessing, feature extraction, and feature classification ), and then use those signals to control the device, and at the same time, the device signals are fed back to the brain. In this way, a closed-loop framework of the BCI system, which enables seamless interaction and adaptation based on user intent and environmental cues, is formed. When analyzing and processing the measured biomedical signals, useful signals are often overlapped with useless noise, so signal preprocessing technology is crucial to the effectiveness of the BCI system.

Despite the remarkable progress achieved in BCI technology, signal preprocessing remains a cornerstone of system efficacy. However, the inherent noise and artifacts present in EEG signals pose challenges to signal analysis.

This paper aims to focus on the research of signal preprocessing methods based on brain-computer interface technology, with the goal of improving the system's ability to accurately recognize and process electroencephalography (EEG) signals, thereby further expanding the application scope of BCI technology. First of all, this study will give a brief introduction to the brain-computer interface system and explain each module. Secondly, this work will expand on the challenges faced in signal preprocessing and provide explanations for each. Subsequently, we will introduce the mainstream signal preprocessing methods and analyze their advantages, limitations, and applicability.

It is hoped that this study will provide theoretical guidance and practical references for the development and application of BCI technology, thereby facilitating its widespread adoption and advancement in medical care, rehabilitation, human-computer interaction, and other related fields. Ultimately, this research endeavors to contribute significantly to the progress and development of human society.

## 2. BMI System Framework

Brain-computer interfaces can be divided into two types, invasive and non-invasive, and researchers use these two types of technology to collect EEG signals to design BCI systems. Non-invasive BCI involves surgically implanting electrodes into the brain's cortical tissue, which produces high-quality signals but carries risks. Therefore, most of the research focuses on non-invasive BCIs, such as electroencephalography (EEG), magnetic resonance imaging (MRI), and magnetoencephalography (MEG), especially EEG [1].

### 2.1 Acquisition Module

From a physiological point of view, the brain uses peak potential to communicate. When neurons receive incoming current through synaptic connections, they produce a huge electrical impulse, which is also the most intuitive brain signal. Nerve signals (like EEG) can be received by detecting changes in nerve potential. As technology developed, scientists discovered the relationship between nerve signals and changes in blood flow and magnetic fields, resulting in techniques such as nuclear magnetic resonance(MRI) and functional infrared imaging(fNIR) [2].

### 2.2 Processing Module

Data is usually preprocessed in EEGLAB [3]. The collected EEG signals may contain various noises and artifacts, so preprocessing is needed to extract useful information and reduce the effect of noise. Features are extracted from the preprocessed EEG signals to represent the user's brain activity. According to the pattern recognition results, the corresponding control instructions are generated.

### 2.3 Control and Interaction Module

Firstly, the processed signals should be converted into corresponding control commands, and the information should be transmitted to the machine in the appropriate machine language to operate.

At the same time, the state of the controlled object is transmitted to the brain through the body's perceptual system. Based on the different types of physiological electrical signals, it can be divided into three categories: motor imagery, P300, and steady-state visual evoked potential (SSVEP) brain-computer interface [1].

## 3. Electroencephalography (EEG)

At present, the most common signal acquisition methods are implantable electrode acquisition and scalp acquisition, and the implantable electrode has a high resolution, high signal noise, and stability, so the research direction of this paper will focus on scalp electrodes.

### 3.1 How EEG work

Neurons in the brain generate electrical signals through an electrochemical process. When a neuron excites, it releases chemicals (neurotransmitters) that cause electrical potential changes inside and outside the neuron. This change in potential creates an electric field around the neurons and travels to the surface of the cerebral cortex. Metal electrodes are placed on the surface of the scalp to record the electrical activity of the brain, usually in a specific location layout (such as the International 10-20 system). These electrodes come into contact with the skin via a conductive adhesive or cap and are connected to physiological signals.

Finally, the signal is amplified, processed, recorded, and presented [4].

### 3.2 Electrode placement

The collection of EEG electrical signals is placed on the scalp surface of the brain in accordance with 10-20 international standards [5] and recorded by the EEG collection system.

There are several important reference points in the international 10-20 system for determining the position and orientation of the electrodes. These reference points include Natal (Nz), the crown of the head (Cz), earlobes (A1 and A2), etc., which provide a baseline for electrode placement.

It provides a standardized way to place EEG electrodes so that data can be compared and shared between different laboratories and researchers.

## 4. The challenge of signal preprocessing

EEG signal is very weak and easily polluted and affected, so preprocessing is very important for it. These noise signals that interfere with normal EEG signals are collectively referred to as EEG artifacts [6].

### 4.1 Introduction to artifacts

EEG artifacts are also a general term for noisy signals that interfere with electrical brain signals. The frequency range of EEG signals is 0.01Hz to 100Hz, and depending on the frequency range, EEG signals can be divided into five different types: Beta (12-30Hz), Alpha (8-12Hz), Theta (5-7Hz), Delta (1-4Hz), and Gamma (>30Hz) [7]. Often, we can clearly see the signal beyond the range, but the trouble is that these artifacts are mixed with EEG signals; it is difficult to observe the correct signal, so it is necessary to pre-process the EEG signals.

### 4.2 Artifact classification

EEG artifacts mainly come from two parts: physiological artifacts and non-physiological artifacts.

Physiological artifacts include electrical potentials generated by biological activity near the subject's head or subject's movements, such as head and neck muscle activity, blinking, heartbeat, etc.

Non-physiological artifacts mainly include artifacts generated from electrode contact with the scalp to the device itself or the environment (the environment around the device or the device in the subject's body) [8].

## 5. Method of signal preprocessing

The purpose of preprocessing is to preserve the original appearance of the data; although there is no way to guarantee to get absolutely clean data, we can still make a lot of attempts on the original data.

In Rajesh's introduction to BCI, the artifact processing methods are summarized as threshold method, band-stop and notch filtering, linear model, principal component analysis, and independent component analysis. In 2023, Luo Ruipeng and other scholars summarized the preprocessing methods as digital filtering method, independent component analysis method, wavelet transform method, empirical mode decomposition method, hybrid optimization method, and deep learning method [9]. The latter has methods that the former does not have, and they also have the same methods but with different expressions and research directions. The following will understand, analyze, and elaborate on the methods they talked about and add new perspectives and details.

### 5.1 Digital Filter (DF)

Digital filtering is the simplest and fastest method among several methods. Its principle is to effectively extract signals of a specific frequency and perform specific processing on the extracted part (such as gain, attenuation, and filtering). It can also be understood as a frequency selection device, which allows signals of a specific frequency to pass through and retains signals of the required frequency band. And other frequency band attenuation operations. It is divided into "infinite impulse response digital filter (IIR)" and "finite impulse response digital filter (FIR)" [10].

Classification from the required frequency can be divided into:

1) Low-pass filter: allows the low-frequency or DC components of the signal to pass through, suppressing the high-frequency components or interference and noise;

2) High-pass filter: allows the high-frequency component of the signal to pass through, suppressing the low-frequency or DC component;

3) Bandpass filter: allows the signal of a certain frequency band to pass through and inhibits the signal, interference, and noise below or above the frequency band;

4) Band resistance filter (Notch filter): suppresses the signal within a certain frequency band and allows the signal outside the frequency band to pass through;

5) All Pass Filter: means that in the full band, the amplitude of the signal does not change; that is, the amplitude gain in the full band is identical to 1. General all-pass filters are used for phase shifting, that is, to change the phase of the input signal, and ideally, the phase shift is proportional to the frequency, equivalent to a time delay system.

Rajesh's book does not outline the larger concept of digital filtering, only describes the band-stop filtering (notch filtering) method, such as the band-stop set to 59-61HZ; in the United States, this method can be used to deal with 60HZ power frequency interference, of course, EEG signal as a biological rhythm of low-frequency signal, can use a low-pass filter. But it also risks losing useful information. High-pass filtering at 0.1Hz can be used to attenuate skin potentials and other slow voltages. Still, if the cutoff frequency is not chosen properly when used, it may lead to distortion of the waveform and may produce spurious peaks in the waveform. The analysis of the digital filter is shown in Table 1.

**Table 1. Analysis of Digital Filter (DF)**

| | |
|---|---|
| Range of application | Non-physiological artifacts and partial myoelectric artifacts. |
| Advantage | Simple and fast |

| | |
|---|---|
| Disadvantage | The ideal filter is difficult to implement, and the real filter has the possibility of losing useful information when removing artifacts. ( The frequency bands of the artifact signal and the normal EEG signal were not aliased ) |

## 5.2 Spatial Filter (SF)

Different from digital filtering, spatial filtering processes brain signals from different channels through some methods. The methods applied to BCI signal preprocessing include independent component analysis (ICA), principal component analysis (PCA), bipolar filtering, and Laplace filtering.

### 5.2.1 Bipolar filtering

Bipolar filtering improves the signal-to-noise ratio of EEG signals by calculating the difference between the two electrodes to eliminate common mode noise (such as EMG or power line interference). This method takes advantage of the spatial locality between the signal source and the reference electrode.

It can improve the clarity and reliability of signals and help more accurately analyze activity in specific brain regions.

### 5.2.2 Laplace filtering

Local noise is eliminated by calculating the weighted average of multiple surrounding electrodes, highlighting the details of brain activity. It calculates the new signal by taking the difference between each electrode signal and the average of the signals from the surrounding electrodes. It can highlight specific activity in brain regions and reduce interference in neighboring brain regions or distant brain regions so that specific brain activity regions can be more accurately located and analyzed.

### 5.2.3 Principal component analysis (PCA)

The goal of PCA is to find r ($r < n$) new variables, make them reflect the main features of things, compress the size of the original data matrix, reduce the dimension of the feature vector, and select the least dimension to summarize the most important features. Each new variable is a linear combination of the original variables, reflecting the comprehensive effect of the original variables, and has a certain practical meaning. These new variables are called "principal components", and they can largely reflect the influence of the original n variables, and these new variables are unrelated and orthogonal. Through principal component analysis, the data space is compressed, and the features of multivariate data are expressed intuitively in the low-dimensional space.

Through this process, PCA can extract the most representative feature components, reduce redundant information, retain the main variability, and help simplify the complexity of data analysis and model building.

However, PCA assumes that the data is linearly correlated, but EEG signals may contain nonlinear dynamics and interactions. Therefore, in some cases, PCA may fail to capture the nonlinear structure of the signal, resulting in inaccurate analysis results. If there are also outliers or noise in the data, it may affect the performance of PCA and the stability of the results.

### 5.2.4 Independent component analysis (ICA)

ICA focuses on the independence of data rather than the correlation in the above methods, which makes spatial filtering a breakthrough in the field of brain-computer interface. The independence of ICA is also its first feature, aiming to decompose the mixed signal into independent components, where each component represents an independent generation process in the source signal.

Secondly, ICA is a blind source separation method that does not require prior knowledge to decompose mixed signals. This means that in artifact removal, it is not necessary to know the specific features or time points of the artifact accurately but to automatically separate the artifact components from the mixed signal through the algorithm (including FastICA and Informatica).

Last is nonlinear; ICA can process signals with non-Gaussian distributions and does not require the signal to satisfy the assumption of linear mixing. This allows ICA to better deal with complex signal mixing situations, including possible nonlinear relationships between EEG signals and artifact signals.

The commonly used algorithms are FastICA and InfomaxICA, and Table 2 shows the analysis of independent components analysis.

**Table 2. Analysis of Independent Components Analysis (ICA)**

| Range of application | Electroophthalmogram, electromyogram, electrocardiogram, etc |
|---|---|
| Advantage | Since it was proposed in 1996, it has gradually matured through continuous improvement, reducing the possible errors caused by human identification. Many tools have been developed to apply the technique, such as EEGLAB, SPM, and so on [11]. |

| | |
|---|---|
| Disadvantage | It requires human observation and identification of artifact components to remove, which is time-consuming and labor-intensive, and the results are not necessarily accurate. The effectiveness of the algorithm depends on the size of the data. |

## 5.3 Wavelet Transform (WT)

Wavelet transform is a frequency-domain analysis method. To understand WT [12], this work must first understand Fourier analysis. The basic idea of Fourier analysis is to decompose a signal into a weighting of sine and cosine waves of non-stationarity. Even if short-time Fourier analysis (STET) can solve this problem, there is a contradiction between time resolution and frequency resolution in the window width, which can be overcome in WT.

Wavelet transform is an analysis method that can obtain the local characteristics of signals in the time domain and frequency domain. The change of signal in time and frequency can be analyzed more accurately, and the transient and time-frequency characteristics of the signal can be captured [13].

Wavelet transform will process data from three directions, namely, maximum denoising, correlation denoising, and threshold denoising [14].

Maximum denoising: This method is suitable for signal denoising with low SNR. Although the calculation is simple and fast, it will lead to the loss of some important local features of the processed signal.

Correlation denoising: The principle is that the wavelet coefficients on each scale of the signal after the wavelet transform have a strong correlation so that they can be distinguished from the noise components. This method has a good denoising effect, but it will bring an uncertain denoising effect.

Threshold denoising: The wavelet transform threshold denoising method was first proposed by professors Johnstone and Donoho in 1992. It is a nonlinear denoising method, which can reach the approximate optimal in the sense of the minimum mean square error and has the characteristics of the simplest implementation and the smallest computation. The basic principle is that orthogonal wavelet decomposition has the ability of time-frequency local decomposition. In signal processing, the amplitude of the wavelet component is large, which is in obvious contrast with the uniform realization of the noise in the high-frequency part. After wavelet decomposition, most of the wavelet coefficients with larger amplitude are useful signals, while the coefficients with smaller amplitude are generally noise; that is, the wavelet transform coefficient of the useful signal can be considered to be greater than the wavelet transform coefficient of noise. The threshold denoising method is to find a suitable threshold value, retain the wavelet coefficients greater than the threshold value, do corresponding processing of the wavelet coefficients less than the threshold value, and then restore the useful signal according to the processed wavelet coefficients.

The key to the success of denoising is how to select and quantize the threshold value. There are two kinds of threshold functions commonly used: the hard threshold function and the soft threshold function.

In summary, wavelet transform is a valuable method in EEG preprocessing, which can provide multi-scale, time-frequency localization of signal analysis, help to remove noise and artifacts, and retain the local features of the signal. However, attention needs to be paid to selecting the appropriate wavelet basis function and parameter tuning, as well as considering factors such as computational complexity. The analysis of the Wavelet transform is shown in Table 3.

**Table 3. Analysis of Wavelet Transform (WT)**

| | |
|---|---|
| Range of application | Eye movement, electrocardiogram |
| Advantage | Compared with the Fourier transform, the wavelet transform is more helpful in describing the characteristics of unstable signals accurately. |
| Disadvantage | The effect is affected by the wavelet basis function chosen, and different wavelet basis functions are suitable for different types of signals. Moreover, the computational complexity is high. In decomposition, there may be a problem of modal overlap. |

## 5.4 Empirical Mode Decomposition (EMD)

In order to solve the problem of nonlinear and non-stationary signal analysis, Norden et al. proposed Empirical Mode Decomposition(EMD) in 1998. This approach is based on the following assumptions: Any signal is composed of the Intrinsic Mode Function (IMF), where the components can be linear or nonlinear, and a signal can be composed of many components of the intrinsic mode if each component overlaps with each other, then the formation of a composite signal [15].

The ensemble empirical mode decomposition (EEMD) and the complementary ensemble empirical mode decomposition (CEEMD) have appeared successively, which makes the EMD improve continuously. It effectively suppresses the boundary flying wing phenomenon in EMD, and by adding pairs of white noise with opposite signs to the source signal, the source signal decomposition has a real physical meaning, reduces the reconstruction error, and eliminates the residual noise introduced by multiple noise-adding in EEMD. Still, it also increases the amount of calculation.

Compared with wavelet transform, EMD is data-driven, so it has good data adaptability and does not need to select basis functions; it can reduce the distortion of EEG signal after removing artifacts. At the same time, it gets rid of the constraint of the Fourier transform and absorbs the advantage of the multi-resolution of the wavelet transform. Table 4 shows the analysis of Empirical mode decomposition.

**Table 4. Analysis of Empirical Mode Decomposition (EMD)**

| | |
|---|---|
| Range of application | Ocular and myoelectric artifacts |
| Advantage | It has good adaptability and does not need to define the basis function |
| Disadvantage | Possible modal confusion (multiple time scale features in one IMF) |

### 5.5 Deep Learning

Deep learning can learn to map neural activity to certain control commands (including supervised and unsupervised learning),

In particular, models based on convolutional neural networks (CNN) and recurrent neural networks (RNN) are widely used for noise reduction of EEG signals. For example, the CNN model can be used to learn the spatiotemporal characteristics of EEG signals and remove the noise component. RNN model can make use of time dependence to model and remove noise from sequential signals.

The most important is the generative adversarial network (GAN), which can generate new samples with similar characteristics by learning the data distribution. In EEG signal denoising, GAN models can be used to learn the distribution of noise and generate estimates of noise components, which are then removed from the original signal. The analysis of deep learning is presented in Table 5.

**Table 5. Analysis of Deep Learning**

| | |
|---|---|
| Range of application | Electrooculogram, myoelectricity, Power line interference, and Motion artifact |
| Advantage | The number of electrodes does not limit it and does not need to remove artifacts from the original EEG signal collected through the corresponding reference channel. |
| Disadvantage | When multiple artifacts exist simultaneously, the stability and reliability of the algorithm model need to be improved. Rely on large amounts of EEG data to train the model. |

## 6. Discussion

In this study, we review the current status and development of brain-computer interface (BCI) signal preprocessing methods. We find that the current preprocessing methods mainly focus on artifact processing, spatial filtering, and frequency domain analysis. These methods have achieved some results in improving the quality and accuracy of EEG signals, but there are still some challenges and room for improvement.

First of all, although independent component analysis (ICA) and other methods have shown good results in artifact processing, there are still some limitations. In particular, the recognition and removal of complex artifacts remains challenging, and future research could explore more efficient and accurate algorithms to deal with different types of artifact interference.

Secondly, the spatial filtering method is of great significance in extracting the spatial features of EEG signals, but there are still some controversies and optimization Spaces. For example, how to select suitable spatial filter parameters and how to deal with boundary effects need to be further studied and improved.

In addition, frequency domain analysis methods also play an important role in preprocessing, but the current methods are still limited to linear transformation and fixed frequency band selection. Future research could explore more flexible and adaptive frequency domain analysis methods to better adapt to the characteristics of different experiments and individuals.

In addition, we discuss the potential applications of deep learning in EEG signal preprocessing. Deep learning models have powerful learning and representation capabilities, which can better capture complex features and patterns of signals. Future research could further explore how to combine deep learning techniques with traditional signal processing methods to achieve a higher level of pre-processing effects.

## 7. Conclusion

This paper reviews the development and application of brain-computer interface (BCI) signal preprocessing methods. When processing artifacts in electroencephalogram (EEG) signals, independent component analysis (ICA), frequency domain analysis, and time domain analysis are widely used to improve signal quality and accuracy. Spatial filtering methods, such as Laplace filtering and bipolar filtering, play an important role in removing artifacts and extracting spatial features of EEG signals. Frequency-domain analysis methods, such as wavelet transform and empirical mode decomposition (EMD), are also used to preprocess EEG signals. In addition, the potential applications of deep learning in EEG signal preprocessing, especially in the recognition and removal of complex artifacts, are of great significance.

Overall, with these preprocessing methods, the BCI system is able to recognize and interpret EEG signals more accurately and reliably, providing better support for brain-computer interaction.

In the future, the development of brain-computer interface (BCI) technology will face more challenges and opportunities. With the continuous advancement of deep learning technology, it can be expected to be applied to the signal preprocessing of brain-computer interfaces. Deep learning models can better learn and understand complex signal patterns and improve the efficiency and accuracy of signal processing. Future research could explore how to combine deep learning and traditional signal processing methods to achieve higher levels of preprocessing. There are many problems to be solved in the field of pre-processing, which also represent opportunities that will better deal with increasingly complex signal characteristics and application scenarios and bring greater breakthroughs and progress for the development and application of brain-computer interaction technology.

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