Design of Brain Computer Interface Control System Based on Neural Network

Manfei Lo
BASIS International School PLH, Huizhou, China
manfei.lo40211-biph@basischina.com

Abstract. As an interdisciplinary technology, Brain Computer Interface(BCI) combines the knowledge of neuroscience, biomedical engineering, machine learning and other fields, and is gradually changing peoples life and work style. The purpose of this article is to s tudy the brain wave signal identification method based on convolutional neural network (CNN). Firstly, advanced data processing methods are used to preprocess electroencephalogram (EEG) data, including noise removal and baseline drift correction, so as to improve the signal-to-noise ratio and characteristics of the data. Then, the CNN model is constructed, and by optimizing the model structure and parameters, it can better adapt to the processing of EEG data. Finally, compared with other neural network algorithms, the results show that the accuracy of CNN algorithm adopted in this article is higher than other algorithms in training set and test set, and the performance is the best. This algorithm can improve the recognition accuracy of EEG signals, thus achieving a more efficient and accurate BCI control system. The research provides new ideas and methods for EEG signal processing based on neural network, and can provide technical support for the design and implementation of BCI control system.

Keywords: Convolutional neural network; Brain Computer Interface; EEG signal; control system.

1. Introduction

Due to the continuous progress of science and technology, the growth of artificial intelligence is changing with each passing day. Among them, BCI, as an interdisciplinary technology, combines the knowledge of neuroscience, biomedical engineering, machine learning and other fields, and is gradually changing peoples life and work style [1]. BCI is a technology that directly establishes communication between the brain and external devices, which allows users to control machines through thinking without language or action [2]. The emergence of this technology has undoubtedly brought new hope to those who have lost their athletic ability due to illness or injury.

There are two main control modes of BCI: encoding and decoding. Coded BCI provides users with artificially expected sensory information by interfering with the sensory input of the brain [3]. This information is not perceived by the human bodys own sensory system, but is input by the outside world. For example, through the visual information provided by BCI, users can "see" the contents displayed on the computer screen [4]. This kind of intervention can induce the brain to produce the expected motor output, thus controlling the behavior of people or animals. For example, users can control external devices such as wheelchairs or artificial limbs through the movement direction and intention information provided by BCI [5]. Decoding BCI is to intervene in the motor output of the brain. By detecting and decoding the motor output information of the brain, it is used to control non-muscle tissues, such as virtual keyboards, mice, wheelchairs and nerve prostheses [6]. The advantage of this control method is that it does not require the user to carry out specific training or conscious control, but directly decodes the motor instructions of the brain.

With the growth of deep learning and neural network, the design of BCI control system based on neural network has made remarkable progress [7]. This article will study the EEG signal detection method based on CNN and apply it to the construction of BCI control system. The research goal is to use CNNs high efficiency and feature extraction ability to improve the recognition accuracy of EEG signals, so as to realize a more efficient and accurate BCI control system. It is hoped that the work in this article can provide useful reference and enlightenment for researchers in related fields and promote the further growth of BCI technology.

The structure of this article is as follows: Firstly, the basic concepts and application fields of BCI are introduced. Then, the basic structure and characteristics of CNN and its application in EEG signal detection are discussed. Finally, the experimental results are analyzed and discussed to verify the feasibility and effectiveness of the proposed method.

2. Theoretical basis

2.1 CNN

CNN is a network structure of deep learning, and its design is inspired by the structure of biological visual nervous system. The basic structure of CNN includes convolution layer (CL), pool layer (PL) and fully connected layer (FCL) [8]. CL is responsible for learning local features from input data, while PL is responsible for reducing the dimension of data to reduce computational complexity. The FCL integrates the previously learned features and outputs the final classification or regression results.

CNN can automatically extract features from input data, which makes it very efficient when dealing with complex data. Because of its special structure, CNN can effectively deal with the spatial locality in images or signals, which is very important for processing data with spatial structure such as EEG signals.

2.2 EEG signal detection

EEG signal is an important biological signal, which is produced by the discharge of brain neurons. EEG detection technology captures and records the electrical activity of the brain by placing electrodes on the scalp. Because of its high temporal resolution, EEG can be used to study the function and cognitive process of the brain.

In EEG detection, there are usually two types of signals to be processed: spontaneous EEG signals and evoked EEG signals. Spontaneous EEG is the electrical activity produced by the brain without external stimulus, while evoked EEG is the response of the brain to external stimulus. Both types of signals can be used to construct BCI control system.

2.3 Application of CNN in EEG signal detection

Because EEG signal is a complex biological signal, traditional signal processing methods often cant effectively extract its features. As a deep learning method, CNN can automatically learn the characteristics of EEG signals, thus improving the accuracy and efficiency of EEG signal detection.

In the detection of EEG signals based on CNN, EEG signals are usually used as the input of the network, and then the features in the signals are extracted through CL and PL [9]. Finally, the extracted features are used for classification or regression tasks through the FCL. The advantage of this method is that it can automatically extract features and avoid the problem of manual design of features in traditional methods. At the same time, because of CNNs powerful feature extraction ability, it can effectively process complex EEG signals, thus improving the accuracy and efficiency of EEG signal detection.

3. EEG signal detection algorithm

BCI system has various forms and is applied to different fields according to different controlled equipment. The BCI system mainly consists of five parts: stimulator, EEG collector, EEG processing equipment, transmission equipment and control equipment, as shown in Figure 1. Firstly, the data is preprocessed to remove noise and baseline drift, so as to improve the quality and reliability of data. Then the EEG data is divided into multiple samples, and each sample contains data within a certain time window. Each sample is labeled to indicate its corresponding cognitive state or action intention for subsequent training and testing.

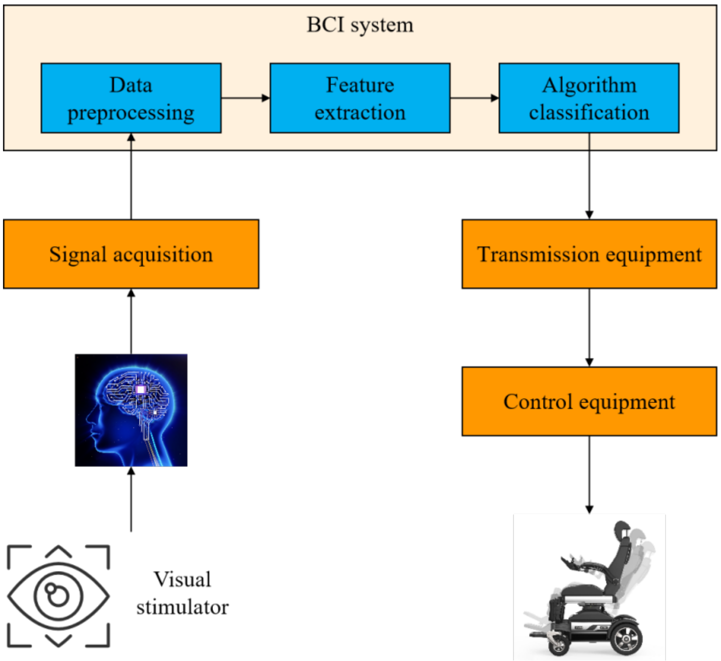

Figure 1 Basic composition of BCI system

The size of the input layer depends on the data dimension of the EEG signal, that is, the number of electrode points per sample multiplied by the time step of each electrode point [10]. Input EEG data to the input layer. CL is the core part of CNN, which can automatically extract local features from input data. Define the size and number of CLs to gradually extract more advanced features [11]. In each CL, multiple convolution kernels are used to convolution the input data to extract different features. The role of PL is to reduce the dimension of data while retaining the most important features. The maximum pooling method is adopted to replace each 2×2 pixel block with the largest pixel value, thus reducing the dimension of data. The operation of PL can effectively reduce the dimension of data while retaining the most important features. The function of the FCL is to integrate the previously learned features and output the final classification or regression results.

Through the signal detection model based on CNN, the data is processed and analyzed, and the algorithm model is shown in Figure 2.

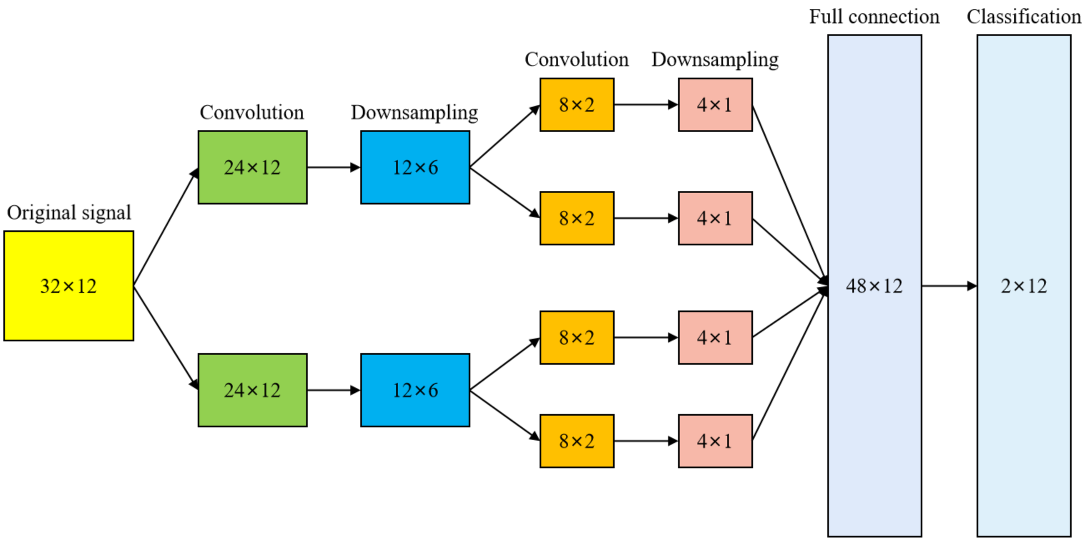

Figure 2 Signal detection model based on CNN

Let X_i^k represent the sum of inputs of k layer neurons i, Y_i^k is the output, and the weights of $k-1$ layer neurons j to k layer neurons i are W_{ij}, then there is the following functional relationship:

$$Y_i^k = f\left(X_i^k\right) \tag{1}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{2}$$

Generally, f A is an asymmetric Sigmoid function:

$$f\left(x_i^k\right) = \frac{1}{1+\exp\left(-X_i^k\right)} \tag{3}$$

If the output layer is the m layer, the actual output of the i neuron in the output layer is Y_i^m. Let the corresponding human body signal be Y_i, and define the error function e as:

$$e = \frac{1}{2}\sum_i \left(Y_i^m - Y_i\right)^2 \tag{4}$$

In order to increase the training sample size of the model and improve the generalization ability of the model, data enhancement technology is adopted to randomly transform and expand the original data to obtain new data samples. This can increase the training sample size of the model without increasing the actual data size [12]. Regularization is a technique used to control the complexity of the model, which limits the complexity of the model by punishing the model parameters. Perform equal weight superposition and average processing on the data. Assume that the sample signal is expressed as:

$$s(k) = x(k) + n(k) \tag{5}$$

Where $s(k)$ is the acquired sample signal, $x(k)$ is the standard brainwave signal, and $n(k)$ is the noise signal. Let N original sample signals:

$$s_i(k) = x(k) + n_i(k) \tag{6}$$

$n_i(k)$ is independent white noise, and after equal weight superposition average filtering:

$$\hat{x}(k) = \frac{1}{N}\sum_{i=1}^{N} s_i(k) = x(k) + \frac{1}{N}\sum_{i=1}^{N} n_i(k) \tag{7}$$

Through the observation of the above formula, it can be seen that the noise signal is reduced to the original $\frac{1}{N}$, the brainwave signal is unchanged, and the sample signal-to-noise ratio is effectively increased.

Cross entropy loss function is usually used to calculate the loss in classification problems. Input the training set data into the model, calculate the prediction result through forward propagation, and then calculate the value of the loss function. This process is repeated until the performance of the model reaches the preset stop condition.

4. Algorithm testing and analysis

The study collected a set of EEG data, including data in different cognitive states, such as attention, relaxation and thinking. Then, the data are preprocessed, including noise removal and baseline drift correction, to improve the signal-to-noise ratio and characteristics of the data. In the training process, random gradient descent optimization and regularization techniques are used to prevent the occurrence of over-fitting. Then, the test set is used to test the model and calculate its accuracy and error. In order to verify the advantages of CNN model, a comparative experiment was conducted to compare CNN model with other neural network algorithms, including long-term memory network (LSTM), recurrent neural network (RNN) and back propagation neural network (BPNN). Figure 3 shows the errors of different algorithms on the training set. Figure 4 shows the errors of different algorithms on the test set.

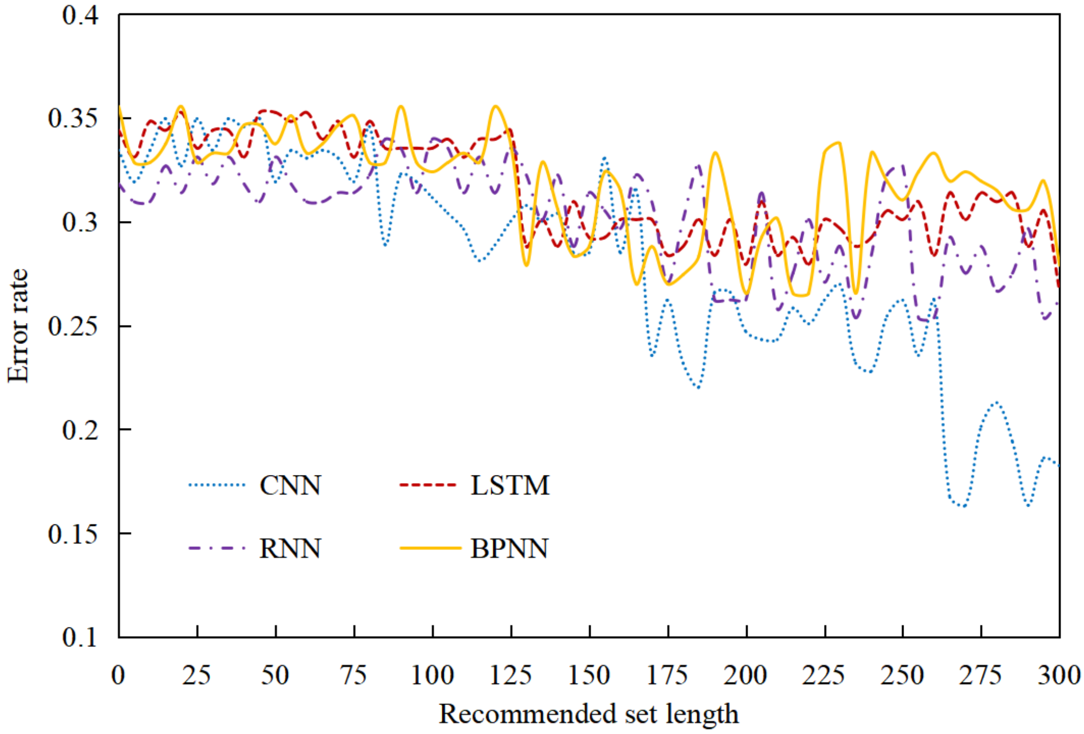

Figure 3 Error of algorithm on training set

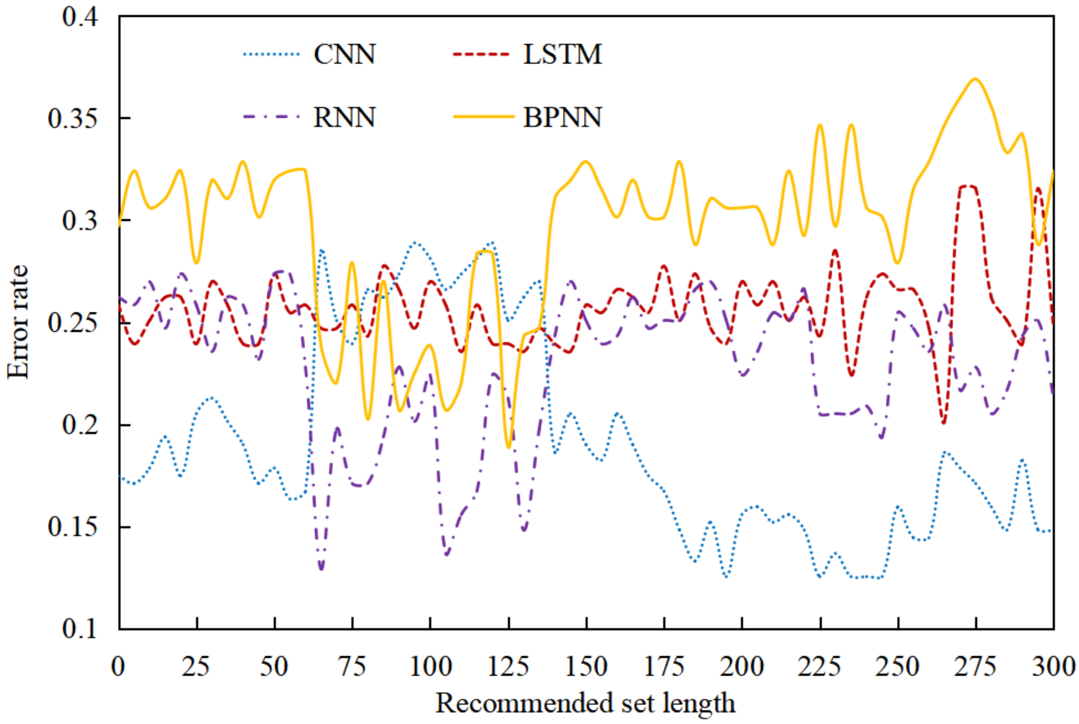

Figure 4 Error of algorithm on test set

EEG data has high spatio-temporal characteristics, similar to image data. CNN can better capture this feature, and thus get lower error on the test set. CNN has CL and PL, which can automatically extract local features from input data and keep the most important features while reducing the data dimension. This makes it possible for CNN to be more effective in processing EEG data. Several other neural network algorithms have higher errors on the test set, which may be due to over-fitting. These algorithms may perform well on the training set, but there is over-fitting phenomenon on the test set, which leads to high error. In contrast, CNN algorithm may have better generalization ability, thus obtaining lower error on the test set.

As can be seen from Figure 5, the CNN algorithm adopted in this article has the best performance in brain wave signal identification task, and its accuracy is obviously higher than other algorithms. This shows that CNN algorithm has advantages in processing EEG data, which can better capture the characteristics of EEG signals and improve the accuracy of identification.

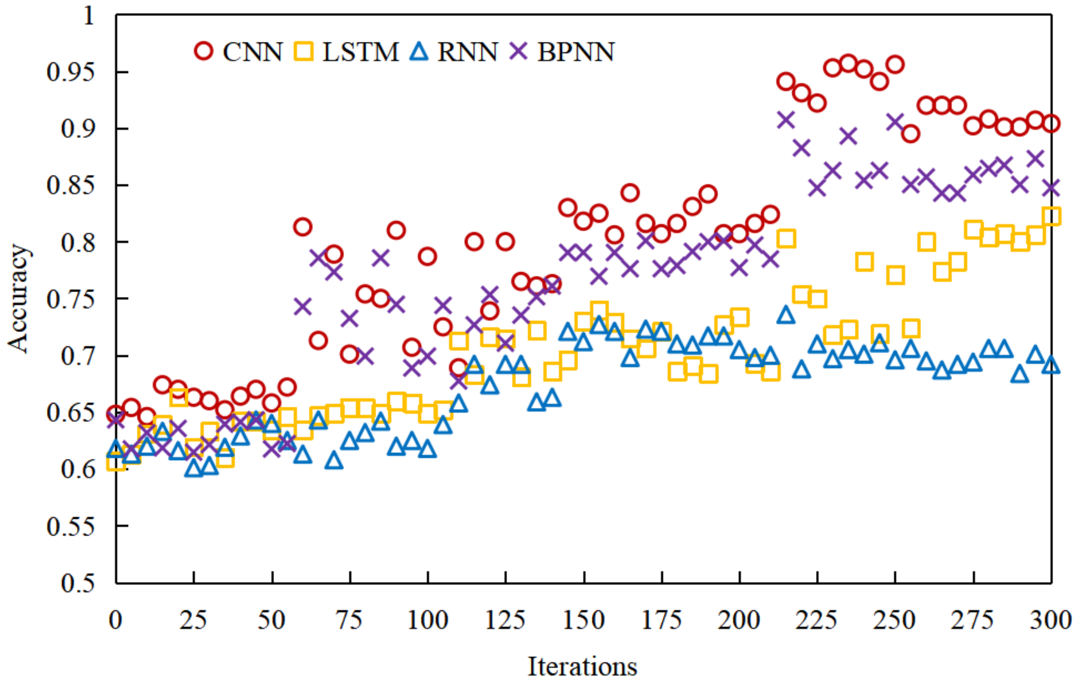

Figure 5 Accuracy of EEG signal identification using different methods

This article focuses on the classification and recognition of brain wave signals, so the adaptability of the model is very important. In this article, advanced data processing methods are used to preprocess EEG data, including noise removal and baseline drift correction. These processing methods can effectively improve the signal-to-noise ratio of data and enhance the characteristics of signals, thus improving the training effect and test accuracy of CNN model. In order to improve the performance of CNN model, many optimization strategies are adopted, including random gradient descent optimization and regularization. These optimization strategies help to prevent the occurrence of over-fitting, improve the generalization ability of the model, and thus obtain higher accuracy on the test set. Compared with other neural network algorithms, CNN algorithm performs best in brainwave signal identification. This further verifies the advantages of CNN model in processing EEG data.

5. Conclusion

BCI is a technology that directly establishes communication between the brain and external devices. It allows users to control machines through thinking without language or action. With the growth of deep learning and neural network, the design of BCI control system based on neural network has made remarkable progress. The CL and PL of CNN can automatically extract local features from the input EEG data, and reduce the dimension of the data, while retaining the most important features. This enables CNN to better understand the EEG data and improve the accuracy of identification. In this article, the EEG signal identification method based on CNN is studied, and the EEG signal data is classified and identified by constructing CNN model. The experimental results show that the accuracy of CNN algorithm adopted in this article is higher than other neural network algorithms in training set and test set, and the performance is the best. The brain wave signal identification method based on CNN is an effective solution with high accuracy and good generalization ability. This provides strong support for further research on the application of EEG signals. Future research can continue to explore different neural network structures and optimization strategies to further improve the accuracy and reliability of EEG signal identification.

References

[1] Gordleeva S Y, Lukoyanov M V, Mineev S A, et al. Exoskeleton Control System Based on Motor-Imaginary Brain-Computer Interface. Sovremennye Tehnologii v Medicine, vol. 9, no. 3, pp. 31, 2017.

[2] Lee, Hyeonseok, Jiang, et al. A Hybrid Brain-Computer Interface System for Multidimensional Control Using Motor Imagery and Eye Closure. Journal of Medical Imaging and Health Informatics, vol. 7, no. 7, pp. 1580-1588, 2017.

[3] Jochumsen M, Niazi I K, Nedergaard R W, et al. Effect of subject training on a movement-related cortical potential-based brain-computer interface. Biomedical signal processing and control, vol. 41, no. 3, pp. 63-68, 2018.

[4] Martinez-Cagigal V, Santamaria-Vazquez E, Gomez-Pilar J, et al. Towards an accessible use of smartphone-based social networks through brain-computer interfaces. Expert Systems with Applications, vol. 120, no. 4, pp. 155-166, 2019.

[5] Zhuang W, Shen Y, Li L, et al. A brain-computer interface system for smart home control based on single trial motor imagery EEG. International Journal of Sensor Networks, vol. 34, no. 4, pp. 214, 2020.

[6] Chen C, Zhou P, Belkacem A N, et al. Quadcopter Robot Control Based on Hybrid Brain-Computer Interface System. Sensors and Materials, vol. 32, no. 3, pp. 991, 2020.

[7] Korovesis, Kandris, Koulouras, et al. Robot Motion Control via an EEG-Based Brain-Computer Interface by Using Neural Networks and Alpha Brainwaves. Electronics, vol. 8, no. 12, pp. 1387, 2019.

[8] Parashiva P K, Vinod A P. Improving direction decoding accuracy during online motor imagery based brain-computer interface using error-related potentials. Biomedical signal processing and control, vol. 2022, no. 4, pp. 74, 2022.

[9] Uma M, Sheela T. Analysis of Collaborative Brain Computer Interface (BCI) based Personalized GUI for Differently Abled. Intelligent Automation & Soft Computing, vol. 24, no. 4, pp. 747-757, 2018.

[10] Gao Q, Zhao X, Yu X, et al. Controlling of smart home system based on brain-computer interface. Technology and health care: official journal of the European Society for Engineering and Medicine, vol. 26, no. 12, pp. 1-15, 2018.

[11] Lin C T, Chiu C Y, Singh A K, et al. A Wireless Multifunctional SSVEP-Based Brain-Computer Interface Assistive System. IEEE Transactions on Cognitive and Developmental Systems, vol. 11, no. 3, pp. 375-383, 2019.

[12] Zhou B, Wu X, Ruan J, et al. How many channels are suitable for independent component analysis in motor imagery brain-computer interface. Biomedical Signal Processing & Control, vol. 50, no. 4, pp. 103-120, 2019.