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Novel Real-Time EEG Signal Decoding Algorithm based on Deep Learning

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***Abstract*— This study proposes the novel real-time electroencephalogram (EEG) signal decoding algorithm based on deep learning from the theoretical modeling level. The original intention of the design of this algorithm is to optimize the decoding accuracy and timeliness of EEG signals in the brain-computer interface (BCI) system. Considering the low efficiency of feature extraction and data processing in traditional EEG signal decoding methods, this study adopted a multi-core collaborative signal transmission architecture and deep learning model for overall optimization. First, the study used multi-core parallel computing mode to increase data processing speed. This operation can reduce system latency and achieve efficient decoding of real-time EEG signals. In terms of core architecture, convolutional neural network (CNN) is used to extract and classify EEG signals. This operation can further improve the accuracy of signal decoding. In addition, in order to solve the problem of artifacts in EEG signals, independent component analysis (ICA) is used to pre-process the original signal to remove the interference of noise actions such as eye movement, electromyography and the other noise on data. The experimental results show that the proposed deep learning algorithm can accurately analyze the characteristics of EEG signals in the different frequency bands, thereby significantly improving the decoding accuracy.**

Keywords*— *Real-time EEG decoding; Deep learning algorithms; Neural signal processing; Brain-computer interface

I. INTRODUCTION

There are generally three main schemes for multi-brain EEG signal decoding [1]-[4]: signal layer fusion, feature layer fusion and decision layer fusion. Signal layer fusion is mainly aimed at original signals or preprocessed signals. After simple processing of the EEG signals of the multiple subjects, EEG signals of multiple brains are obtained, thereby extracting multi-brain motor imagery features. In the current research, various traditional methods are generally used to extract features. Feature layer fusion is aimed at the extracted features. After obtaining the characteristics of each individual, various feature interaction methods are used to extract multi-brain motor imagery coupling information to improve the decoding effect. Decision layer fusion is aimed at classification results. By analyzing the recognition effects of multiple classifiers, all classification results are integrated into the results of group collaboration using corresponding fusion methods. In the Figure 1, as the example, the EEG signal decoding is shown.

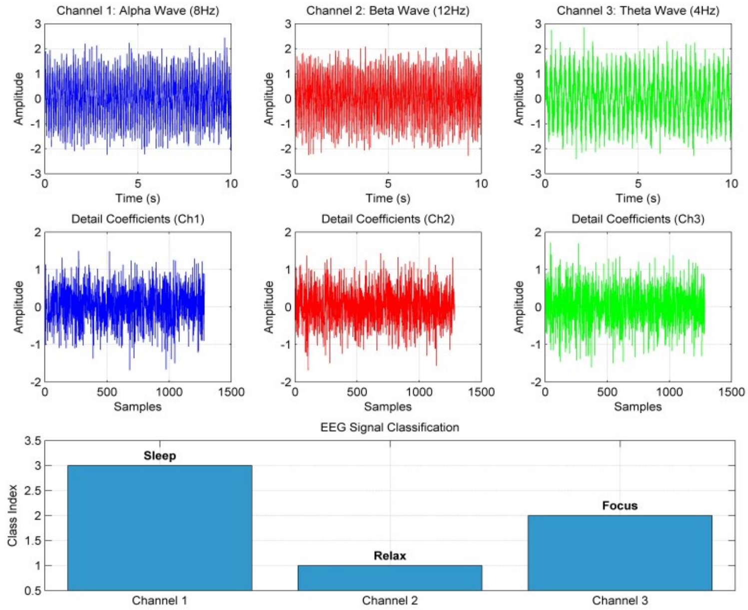


Fig. 1. The EEG Signal Decoding (An Example)

At present, the research basis of EEG is brain-computer interface technology. The Brain-Computer Interface (BCI) technology collects and processes EEG signals to identify changes in the brain activity, thereby achieving the direct communication and control between the human brain and external devices. The BCI system mainly analyzes the characteristics of the EEG signals generated by the wearer in different thinking states in real time, decodes the core information in the brain, and thus realizes the control of external devices. Its core has two points: one is the accurate decoding of brain information, and the other is the control accuracy of external physical devices. To optimize the existing algorithm, this study proposes the novel real-time EEG signal decoding algorithm based on deep learning.

II. RELATED WORK OF EEG SIGNAL PROCESSING

Due to its uniqueness, EEG signal processing can be widely used in computer-assisted medical scenarios. In recent years, the EEG analysis framework based on signal processing has been continuously optimized.

EEG signal processing for Alzheimer's disease was studied as a topic by [5]. This study used discrete wavelet transform and combined with multiple machine learning methods to develop a new computer-aided diagnosis system. This system was used to diagnose Alzheimer's disease based on EEG data. EEG signal processing for epileptic seizure detection was studied by [6]. This study innovatively proposed a feature extraction paradigm based on a combination of five-level Db4 wavelet transform and genetic algorithm. This paradigm can effectively analyze the EEG signals of epileptic patients. Experimental results show that the proposed classification scheme using ANN and SVM can make accurate predictions. EEG signal processing for automatic sleep stage scoring was studied by [7]. This study proposed a method using separable convolutional neural network. This method can be effectively used to automatically score the sleep stages of EEG signals. This study reduced the number of trainable parameters and thus reduced the risk of overfitting. This innovation directly enhanced the feature extraction capability. EEG signal-based emotion recognition system was studied by [8]. This study proposed a new automatic model for emotion recognition. The model combines the empirical mode decomposition (EMD) and variational mode decomposition (VMD) for the signal processing stage. Furthermore, in the feature extraction stage, technologies such as entropy and Higuchi fractal dimension are used to greatly improve the recognition accuracy.

The automatic detection of EEG abnormal signals is the research focus of [9]. The authors designed an automatic analysis architecture based on wavelet packet decomposition (WPD) and gradient boosted decision tree (GBDT). Gaijiaguo is cleverly applied to binary classification of brain signals. At the same time, a new dimensionality reduction method is proposed to maintain feature quality and significantly improve classification efficiency. EEG signal processing for movement intention decoding is the research focus of [10]. This study proposes a brain-computer interface system based on motor imagery. Classifying EEG signals via CNN, the system achieved an average accuracy of 85.64% in 30 independent experiments. EEG signal processing for the schizophrenia detection is the research focus of [11]. This study proposes a new algorithm based on multi-variable iterative filtering. This model is used to separate intrinsic modal functions from EEG signals and extract features such as Hjorth parameters. Psychological task-related EEG signal processing is the research focus of [12]. This study summarizes common processing methods for task-related EEG signals. These methods specifically include the extraction and visualization of time-domain event-related potentials and time-frequency domain oscillatory responses. At the same time, scholars explored the potential applications of single-test analysis and source analysis.

III. The Proposed Methodology

A. The Theoretical Basis of Real-time Signal Processing for EEG Signals

The essence of real-time signal processing is real-time signal transmission [13]-[15]. How to determine transmission method and algorithm is of utmost importance.

In this study, the multi-core task collaborative signal transmission architecture is adopted. Since EEG has extremely high requirements for real-time signal processing, and DSP is a serial processing structure, in order to speed up data processing, the multiple CPUs [16]-[18] must share the work simultaneously, that is, multi-core parallel computing. The data flow mode is selected as the core architecture. In the data flow mode, there is no control core, and each core has equal status. After the task starts, each core directly starts processing data according to the set address range, and all cores exit the task after completing the task processing. In the data flow mode, tasks generally have a sequence, and the output of the previous task is used as the input of the next task, and there may be communication and data interaction between the cores. In the Figure 2, the multi-core task data flow coordination mode is shown.

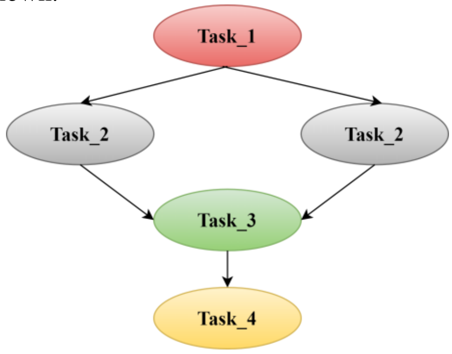
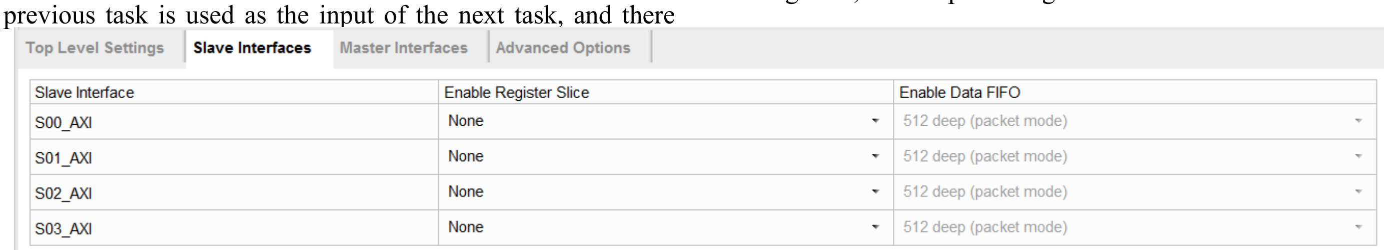


Fig. 2. The Multi-core Task Data Flow Coordination Mode

The next issue is the data flow distribution. Specifically, considering the data cache at the interface, the design will enable Data FIFO and select packet mode to set its depth to a maximum of 512. Since the maximum performance mode was selected before, these parameters will be configured by default. In addition, the parameters at the Master interface can be configured by default and will not be described in detail. In the Figure 3, the sample configuration interface is shown.



Slave Interface	Enable Register Slice	Enable Data FIFO
S00_AXI	None	512 deep (packet mode)
S01_AXI	None	512 deep (packet mode)
S02_AXI	None	512 deep (packet mode)
S03_AXI	None	512 deep (packet mode)

Fig. 3. The Sample Configuration Interface

In terms of specific real-time data simulation, it includes the following four steps:

1) Set up 4 master devices and one slave device;

2) The master device data width is 32 bits, the burst length is set to 32, and the slave data width is 256 bits;

3) Simulation stimulus sets the 4 master devices to initiate read operations at the same time;

4) Check the read data timing of the slave device through the simulation timing diagram, and check whether the 4 master devices can read in parallel and make the data flow.

Furthermore, for the optimization of the real-time signal processing core, in order to enable the core to achieve high-speed data transmission normally, a state machine is used to manage configuration and error restart operations. The state machine structure is shown below:

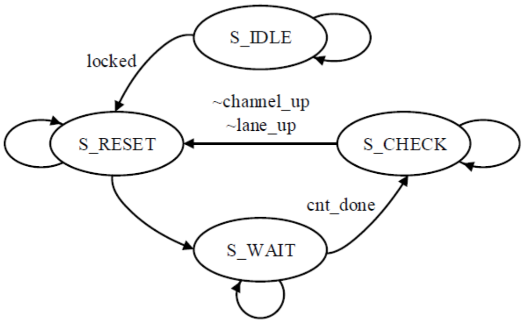


Fig. 4. Core Module State Machine Structure Diagram

S_IDLE is the initial state. This state will wait for the two main clocks Refclk and INIT clk required by the core to be locked before jumping to the S_RESET state, otherwise it will stay in the original state. Refclk is introduced by the differential clock pin of GTH and connected to the core, and is judged by the mmcm_not_locked_out signal; INIT clk uses the clock frequency generated by the clocking wizard to set the system clock, and is judged by the locked signal of the clocking wizard. S_RESET is the core reset state. Set pma_init and reset_pb to reset the entire high-speed serial transceiver and core. After maintaining the set state for a period of time, release the reset signal and enter the S_WAIT state at the same time, and jump to the S_CHECK state after waiting for a certain period of time. In this way, the stable real-time transmission module of the model is built through such a self-check system.

B. The EEG Signal Decoding Algorithm based on Deep Learning

Neurons are an important part of the human brain [19]-[20], accounting for one tenth of the approximately 10 trillion cells. Neurons have the function of receiving, processing and also transmitting information in real time. A single neuron usually consists of one or more dendrites and an axon. Dendrites are important information receivers that receive and transmit excited signals from neighboring nervous systems. Neuron cell structure is shown in the Figure 5.

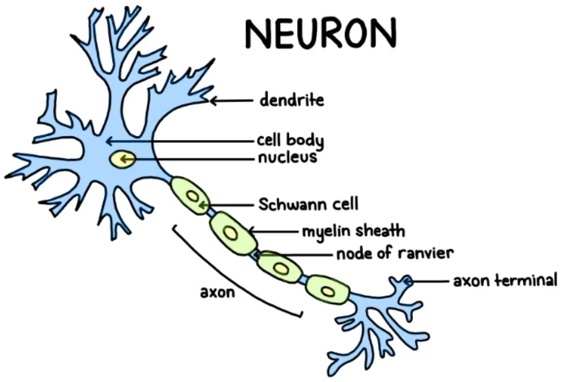


Fig. 5. The Neuron Cell Structure (**Image Source: https://www.simplypsychology.org/neuron.html**)

The EEG signal can accurately identify the characteristics of the brain electrical signal. EEG expresses the synchronous potential difference of a group of nerve cells within a certain range in the cerebral cortex. It has the general characteristics of electrical signals: such as frequency, amplitude, phase, etc. The frequency of the brain electrical signal is generally below 50 Hz, and is generally divided into five frequency bands, each of which has different characteristics.

1. δ rhythm. The rhythm is 1 Hz to 3 Hz, which is a slow wave, and its amplitude ranges from about 200 micro-volts.

2. θ rhythm. The rhythm is 4 Hz to 7 Hz, with an amplitude of around 100 micro-volts to 150 micro-volts.

3. α rhythm. The rhythm is 8 Hz to 13 Hz, with an amplitude of 20 micro-volts to 100 micro-volts.

4. β rhythm. The rhythm was 14 Hz to 30 Hz, with amplitude values ranging from 5 μV to 22 μV.

5. γ rhythm. The rhythm is 31 Hz to 50 Hz, which is the highest frequency among brain waves.

Before decoding, it is very important to choose a suitable EEG signal feature extraction algorithm. Choosing a suitable EEG signal feature extraction algorithm has a great impact on the design performance and application of brain-computer interface. After feature extraction, EEG signals can better identify the corresponding EEG features, thereby obtaining better experimental application effects. In order to improve the design performance of the BCI [21]-[22], a higher feature extraction accuracy and information transmission rate can be obtained by improving the feature extraction algorithm and integrating multiple EEG signal features.

The induced brain-computer interface system needs external stimulation to generate EEG signals. The following introduces the design paradigm of the steady-state evoked potential. In the experiment based on SSVEP [23]-[24], the subject is required to identify the target with sight, the user's attention is fixed on the target, and the target is accurately identified through feature extraction and analysis. Based on the BCI system of the SSVEP signal, the stimulation display interface is stimulated by flickering stimulation at different frequencies, forming the research direction of SSVEP BCI. In the experiment, the subject needs to look at the flickering stimulation module, and the subject's brain will induce a unique SSVEP signal. The induced signal extracts the signal features through a series of signal processing methods, thereby obtaining the target that the subject is concerned about. Then initial step for he processing is the signal pre-processing. The collected EEG signals are mixed with interference from other components. If these interference are not eliminated in time, the performance of the brain-computer interface system will be seriously affected. Therefore, the collected EEG signals must first be filtered and pre-processed. The power frequency interference and myoelectric interference can be eliminated by filtering. In EEG research, it is a common and important problem to detect artifacts generated in EEG data through muscle activity, blinking and electrical noise. Eye artifacts are the main component of EEG signals and an important part of SSVEP signal pre-processing.

To achieve this goal, the independent component analysis (ICA) [25]-[26] is considered. The ICA method is chosen to remove artifacts and pre-process the EEG model mainly because that ICA does not require the specific location of the source signal, nor does it require the source signals to be orthogonal to each other. The Figure 6 shows the diagram.

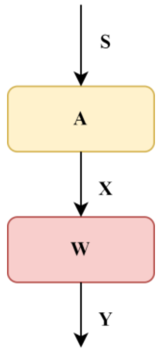


Fig. 6. The ICA Block Diagram

In the diagram, the S is the N source signals defined as:

$$S = [s_1, s_2, s_3, \ldots, s_N]^T \quad (1)$$

After S passes through the mixing system A, the following information is obtained:

$$X = [x_1, x_2, x_3, \ldots, x_N]^T \quad (2)$$

X is M observation signals, Y is the estimate of the N pairs of signal sources obtained after separation system W as:

$$Y = [y_1, y_2, y_3, \ldots, y_N]^T \tag{3}$$

The purpose of ICA separation is to recover the source signal S using only the observed signal X.

Before decoding, understanding the key procedure of the encoding is essential. A stimulation type that can induce high-quality SSVEP signals in the subject's brain is crucial to the BCI system. In existing SSVEP studies, there are the following stimulation methods: cathode ray tube flashing, light-emitting diode flashing, and liquid crystal display flashing. These three stimulation methods have their own advantages and disadvantages, and need to be selected according to the actual situation of the research. The frequency encoding of the SSVEP-BCI system needs to be carefully designed. The value of the set stimulation frequency is related to the effectiveness of the decoding algorithm in extracting features from the signal. Therefore, the selection of frequency cannot be arbitrary, and various factors need to be considered. The higher the frequency of SSVEP-induced stimulation, the fewer frames of the stimulation target will be presented in one second. This can alleviate the subject's fatigue to a certain extent, but the induced SSVEP signal will be very unclear, and there are certain requirements for the recognition algorithm. Since the number of frames presented in one second in low-frequency band stimulation frequency is large, the SSVEP induced in the subject's brain will be stronger accordingly, and it has the characteristics of a high signal-to-noise ratio, and it is relatively easy for the algorithm to identify the correct frequency.

The implementation of the flicker stimulus program is an important step in the encoding. In the Figure 7, the stimulus interface is visually illustrated.

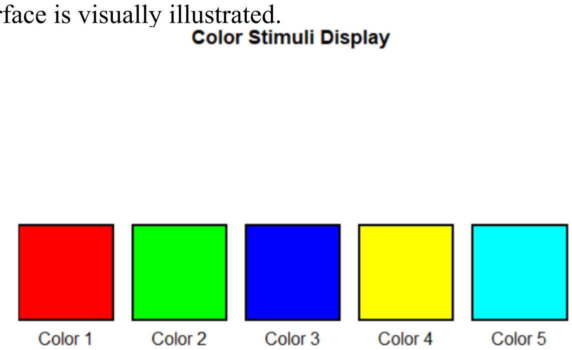


Fig. 7. The Stimulus Interface

At the same time, the corresponding values of frequency and phase are calculated according to the following formula:

$$f(i, j) = f_0 + \Delta f \times [10(i-1) + j - 1] \tag{4}$$

$$\vartheta(i, j) = \vartheta_0 + \Delta\vartheta \times [10(i-1) + j - 1] \tag{5}$$

Where i and j represent the horizontal and vertical coordinates of the character in the stimulus interface, respectively. Stimuli are presented on an LCD display using sampled sine coding. By adjusting the brightness of the screen, stimulus sequences are generated at specific frequencies and phases as:

$$seq(f, \vartheta, i) = \frac{1 + \vartheta + \sin\left[2\pi f\left(\frac{i}{freshrate}\right) + \vartheta\right]}{2} \tag{6}$$

Then, the deep learning based decoding can be studied. For the deep neural network, this module uses F_2 one-dimensional convolution kernels with size (1, 1) and $2F_2$ one-dimensional convolution kernels with size $\left(1, \frac{f}{8k}\right)$ to construct a densely connected convolution operator. The convolution kernel of size (1, 1) is used to fuse cross-channel features. This operator superimposes the input and output features together, which provides a shortcut for transmission of network gradients during back propagation, thereby alleviating the problem of the gradient disappearance during training. The classifier is a fully connected layer with a Softmax activation function, the loss function is:

$$Loss(\vartheta_F, \vartheta_C) = \Re_{(x,y)\sim source} Loss_{initial} \tag{7}$$

Hyper-parameter setting principles are:

1.The hyper-parameter k controls the kernel size of the dimensionality reduction operators (convolution and pooling). The maximum kernel size of the operators in the time dimension should cover the known frequency range of spontaneous EEG tasks.

2.The hyper-parameter F1 controls the number of the convolution kernels. The empirical value of F1 is two times the task rhythm range.

3.The hyper-parameter D is the depth multiplier of the depth-wise convolution in spatial module, which determines the number of convolution kernels acting as spatial filters in each channel.

Subsequently, a deep network-dimensional filtering model is designed to achieve more accurate decoding results. CSP is selected as the target method. It is a two-class spatial filtering feature extraction algorithm that can extract the spatial distribution of one class from multi-channel SEEG data. The basic principle of CSP is to use the diagonalization of the matrix to find a set of optimal spatial filters to project the signal, so as to maximize the variance difference of the two types of signals, thereby obtaining a feature vector with high discrimination. The two types of EEG signals are represented as two-dimensional Channel-Time matrices X1 and X2, the normalized covariance matrix is defined as:

$$r_i = \frac{X_i X_i^T}{trace(X_i X_i^T)}, i = 1 or 2 \tag{8}$$

The trace(X) means summing the elements on the diagonal of matrix X. Then solve the covariance matrix of the mixed space as:

$$r = \overline{r_1} + \overline{r_2} \tag{9}$$

Since the mixed space covariance matrix r is a positive definite matrix, it can be characteristically decomposed by the singular value decomposition theorem as:

$$r = U\kappa U^T \tag{10}$$

Where the U is the eigenvector matrix, κ is the diagonal matrix corresponding to eigenvalues, where the eigenvalues are arranged in descending order. After CSP filtering, the signal after each frequency band filtering is filtered to obtain feature vector of corresponding frequency band. Then, by reverse training the deep neural network, the decoding result can be accurately obtained.

IV. SIMULATION

The experiment of the disappearance of EEG potential decoding in preparation for movement is the experimental scenario for verifying the algorithm in this study.

A. The Cued-Movement Experimental Paradigm Design

At the beginning of each experiment, a white "X" will appear in the center of the screen, as shown in Figure 8. In the next 3 seconds, the subject remains still with his hands, forearms and elbows on the armrests of the chair. Next, a prompt arrow pointing left or right appears in the center of the screen and lasts for 0.5 seconds. After the prompt disappears, the subject is ready to perform the corresponding task indicated by the visual prompt. The arrow pointing to the left indicates raising the left hand; the arrow pointing to the right indicates raising the right hand. After a waiting time of about 2 seconds, the subject performs the corresponding hand-raising movement. Then, 5 seconds after the visual prompt, a voice prompt of the end of the trial is played to inform the subject that the current hand-raising task has ended.

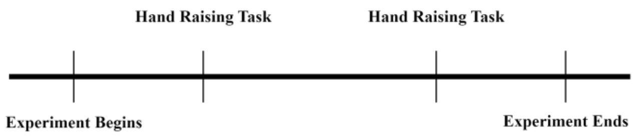


Fig. 8. Experimental Paradigm Design of Cued and Voluntary Movement Tasks

At the beginning of each experiment, the experimenter reminded the subject to remain still and then verbally informed the subject that the experiment had begun. After the experiment began, without visual cues, the subjects voluntarily performed the left and right hand raising tasks, as shown in the Figure 8. The subjects were allowed to perform the hand raising task at any time they wanted to move. Each set of experiments lasted 5 minutes, including approximately 15 left hand raising trials and 15 right hand raising trials, and each subject completed 10 sets of experiments.

B. The Decoding Performance Test

This experiment conducted 5 independent EEG signal decoding performance tests, each using a different public data-set. For the decoding algorithm, the proposed deep learning architecture was used to classify the signals and calculate the decoding accuracy. In the Figure 9, test result is demonstrated.

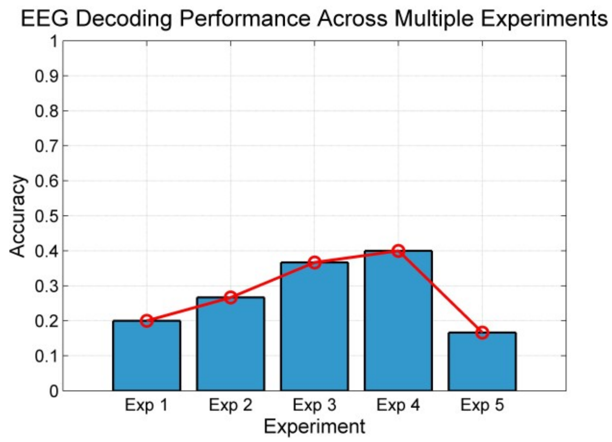


Fig. 9. The Decoding Test Result

In each experiment, the data-set is divided into a training set and a test set at a ratio of 80%. The training set is used to train the classification model, and the test set is used to evaluate the classification effect of the model.

In 5 independent experiments, the classification accuracy rates are:

Experiment 1: 80.00%
Experiment 2: 83.33%
Experiment 3: 76.67%
Experiment 4: 81.67%
Experiment 5: 79.33%

Through the visualization experiment, it is concluded that the decoding performance based on the current data-set and classification model fluctuates less between the different experiments. Although there is a certain degree of randomness, the overall accuracy can still reach a relatively ideal level.

V. CONCLUSION

In the context of brain-computer interface, this study proposes a real-time EEG signal decoding algorithm based on deep learning to improve the traditional model. The proposed algorithm significantly improves the decoding efficiency of EG signals by combining multi-core parallel computing and deep learning algorithms. In order to conduct rational analysis of data, this study effectively removed artifacts through the ICA method and further optimized the quality of the signal. Experimental results show that the proposed decoding algorithm performs well in a variety of EEG signal processing tasks, and has obvious advantages in the classification and control accuracy of real-time EEG signals.

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