Optimizing the Classification of SSVEP Signals in Brain-Computer Interfaces: A Novel Sliding Window Data Segmentation Method Based on Weighted Voting Mechanism

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Abstract. This study leverages Steady-State Visual Evoked Potentials (SSVEP) and Brain-Computer Interface (BCI) technology to classify responses to different visual stimuli among various subjects. Real-time collected SSVEP data was utilized, and based on a sliding window data collection method, a new classification optimization method based on a weighted voting mechanism was designed and proposed. By comparing the accuracy and Information Transfer Rate (ITR) between the traditional and new methods, the new method significantly improved performance metrics, with accuracy increasing from an average of 77.2% to 94.5%, and ITR from 107.61 bits/min to 180.60 bits/min. Additionally, through Monte Carlo simulation experiments, this study explored the optimal weighting ratio, ultimately determining the best weight distribution based on the distribution of experimental accuracy rates.

Keywords: SSVEP · BCI · Classification

1 Introduction

The various neural networks distributed in the brain have their own inherent resonant frequencies. Under normal conditions, the spontaneous EEG signals generated by these neural networks are out of sync with each other and are disorganized and irregular [1]. When an external visual stimulus is applied at a constant frequency, the neural network consistent with the stimulus frequency or harmonic frequency will generate resonance, resulting in significant changes in the potential activity of the brain at the stimulus frequency or harmonic frequency, resulting in a steady-state visual stimulus signal (SSVEP). SSVEP signal will be included in the electroencephalogram (EEG) signal, when stimulated, through the analysis of the frequency corresponding to the detection spectrum peak, that is, the stimulus source of the subject's visual fixation can

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be detected, so as to identify the subject's intention. For the SSVEP classification of 40 stimulus targets, the actual classification accuracy has been achieved [2]. Christoph Guger et al. made a study on the visual stimulation of SSVEP subjects under different conditions, and the results showed that the stimulation of subjects by SSVEP was not accidental. Even if the accuracy was reduced in the case of movement, it was still proved that SSVEP could stimulate EEG signals [3].

When neurons are activated, bioelectrical phenomena are generated, and these electrical signals can be captured by invasive or non-invasive detection means. The most famous application of these detection methods is brain-computer interface (BCI), which is built on the transmission of signals between the brain and a machine device. BCI can be used as a bridge to communicate between the human brain and the machine, and the EEG information in the human brain can be fed back to the machine. This information can also control the machine to make corresponding feedback and affect the human. Invasive Bcis work through the recording or stimulation of neurons inside the brain and are able to accurately record the activity information of single neurons or clusters of neurons, providing a high degree of spatial and temporal resolution. Invasive BCI has achieved a series of studies on action potentials, synapses, and extracellular field potentials of nerve cells or nerve fibers [4]. However, this method has obvious risks, such as penetrating brain tissue may cause infection, and the immune system may block the electrode reaction, so that the signal quality decreases over time. Moreover, the implantation process may damage the originally healthy brain structure [5]. Non-invasive BCI mainly uses these data for development by detecting weak electrical signals in the cerebral cortex. The possible problem is that the electrical signal is relatively weak, which is easy to be affected by errors such as heartbeat and blinking, and data fluctuations occur, which has certain limitations. In recent years, BCI system based on SSVEP has been recognized as a feasible result for helping disabled patients with limbs to control the movement process or realize the rehabilitation process [6]. Previous studies have confirmed that compared with other BCI systems, SSVEP-based BCI systems can provide higher signal-to-noise ratio, higher information transmission rate [7], higher information throughput, and shorter training time [8].

This study mainly focuses on the subsequent movement process of movement and rehabilitation for patients with the help of intelligent wheelchairs through visual stimulation signals, so this study mainly classifies and studies the real-time collected EEG signals [9]. The real-time EEG signals are mainly divided into supervised and unsupervised methods for classification. Here, considering the specificity of subsequent patients, the unsupervised training method is selected to make the subsequent process more convenient and convenient.

In this study, we focus on the frequency detection method based on FBCCA without training, and carry out the research on the weighted voting mechanism of sliding window based on the real-time collected EEG data. In order to improve the accuracy of SSVEP recognition, many methods related to sliding window and voting have been studied. Cao et al. published a method of signal interception by sliding window based on SSVEP to improve the accuracy and information transmission rate (ITR) of SSVEP signal recognition [10]. Hadi Habibzadeh et al. proposed an algorithm to dynamically adjust the window length to adapt to the target frequency based on the voting results, which significantly improved MEC and MSI effects except FBCCA [11].

2 Method

2.1 Data Collection Prosess

Dataset. In this study, in order to study the classification of real-time visual stimulation signals, and to help patients achieve the effect of rehabilitation treatment with the help of intelligent exercise wheelchairs, this experiment uses its own real-time collection of visual stimulation signal data for research. The code for visual stimulus signal flashing was developed based on matlab language. Visual stimuli were displayed on a 27-inch LCD screen (P27QBA-RA) with a refresh rate of 60HZ and a resolution of 2560×1440 pixels. The visual stimuli in the experiment are shown in Fig. 1. The stimulation consisted of six targets, and repeated flicker stimulation was performed at 7, 8, 9, 10, 11, and 12 HZ.

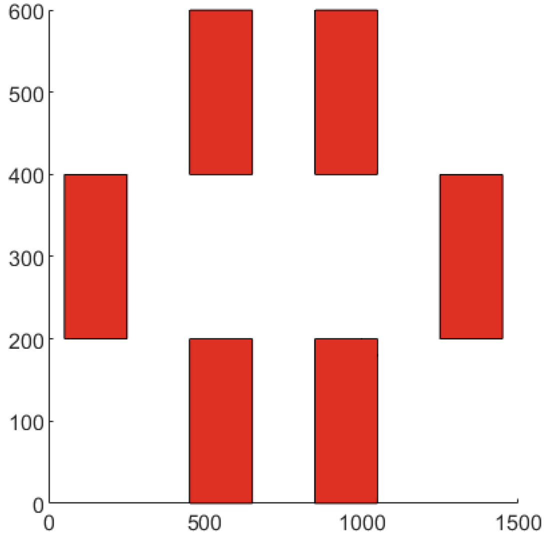

Fig. 1. Example of visual stimuli

Data Acquisition Process. During the experiment, subjects were asked to fixate on one of six targets according to the tester command. The stimuli lasted for a total of 7 s. After the stimulation, the subject was prompted for a rest period, which lasted for 3 s. The subjects then continued to look at one of the six targets on command, in a loop back and forth. After cycling the rest process for 4 times, a long rest period was entered, which lasted for 10 s in total, and then the experiment and data collection were continued.

Signal Channel Selection The data acquisition of SSVEP signal was carried out by UnicornHybridBlack data acquisition device, which has a total of 8 acquisition channels (FZ, C3, CZ, C4, PZ, O1, OZ, O2). SSVEP signals mainly stimulate the occipital region of the brain, so PZ, O1, OZ, O2 four groups of channels were selected for the study of SSVEP signal classification and processing.

2.2 SSVEP Recognition Methods

Standard CCA. Canonical correlation analysis (CCA) is a multivariate statistical method to study the correlation between two groups of variables. Based on the concept of correlation coefficient in univariate analysis, it is a statistical analysis method for the correlation between two groups of variables.

In the operation of SSVEP recognition using CCA in this experiment, the multi-channel array generated by one set of collected EEG data and another set of sinusoidal and cosine functions generated according to frequency are used for CCA operation. By calculating the correlation degree of sine function and cosine function of different frequencies for EEG signals at a given frequency, the magnitude difference between the values was compared to find the group with the highest correlation degree to complete the frequency identification. The reference signal Y_{i} is shown in Eq. 1

$$Y_i = \begin{bmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \vdots \\ \sin(2\pi N_h f t) \\ \cos(2\pi N_h f t) \end{bmatrix}, \quad t = \frac{1}{f_s}, \frac{2}{f_s}, \ldots, \frac{N_s}{f_s} \tag{1}$$

where N_{h} is the number of harmonics, and f_{s} is the sampling rate.

Filter Bank CCA (FBCCA). SSVEP signals are composed of fundamental and harmonic frequency components. Both fundamental and harmonic components contain the characteristic information of SSVEP, while only fundamental information is used in CCA [12]. Therefore, the characteristic part of SSVEP information in harmonic components is added to enhance the frequency detection quality of CCA. This method is called filter bank based CCA method (FBCCA).

The FBCCA operation requires the establishment of a filter bank suitable for multi-channel EEG signal filtering. We used an IIR filter in this experiment. The IIR filter has the characteristics of short processing time and large amount of data, and it has a good filtering effect on EEG signals. At the same time, we need to design the filter range of each filter of the filter bank, which is highly related to the results of FBCCA operation. Different EEG signals have different applicability to different filter banks, so we need to design the filter bank with the highest applicability to experimental EEG signals. FBCCA coefficients can be obtained by calculating a weighted summation of the squares of the correlation coefficients from all N sub-band components as follows:

$$\hat{\rho}_f = \sum_{n=1}^{N} w(n) \cdot (\rho_f^n)^2, \quad f = f_1, f_2, \ldots, f_{N_f} \tag{2}$$

2.3 Performance Evaluation

Information Transmission Rate Calculation Process. In this study, ITR was used to evaluate and calculate the amount of data information transmitted per unit time. ITR was originally used to measure the communication and computation rate of the system in the communication field, and was introduced into the BCI field by Wolpaw [13]. In the BCI field, ITR is used to calculate the amount of information transmitted per unit time, and the larger ITR value represents the faster information transmission rate. It needs to be clear that the amount of information transmitted by a single target selection is the spot rate (B)

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left(\frac{1 - P}{N - 1} \right) \tag{3}$$

where P is the target recognition accuracy and N is the number of optional targets.

The multiplication of the number of decisions made per unit time (C) and the replacement rate (B) is the ITR, so the value of C needs to be calculated

$$C = \left(\frac{60}{T} \right), T = t_s + t_b \tag{4}$$

where t_{s} is the model identification time, t_{b} is the sliding window step time, and T is the response time. According to the size of B and C, the ITR size values in a set of experiments can be obtained.

$$ITR = B * C \tag{5}$$

Classification Accuracy Calculation Procedure. In this study, the performance of different algorithms in terms of accuracy is analyzed, and the formula is given as follows.

$$Accuracy = \frac{C}{N} \tag{6}$$

where C is the number of correct data and N is the total number of data.

3 Result And Analysis

3.1 Comparison Between Weighted Voting Mechanism and Traditional Non-voting Mechanism

Acquisition Design of Experimental Data Duration. The goal of this experiment is to use the classification of real-time visual stimulation signals to help patients achieve the effect of rehabilitation therapy with the aid of intelligent exercise wheelchairs. In the design of intelligent wheelchair control, on the one hand, the controllability of wheelchair should be considered, and the recognition time should not be too long, which leads to the wheelchair not performing movement operation for a long time or the same movement operation, which is a very dangerous operation behavior. At the same time, in order to ensure the accuracy of recognition, the duration of visual stimulation should not be too short [14]. On the other hand, the patient's comfort level should be considered, and short rest and long rest should be added during the operation to ensure that the patient's signal collection is comfortable and effective.

Based on this practical application concept, specific acquisition steps of signal stimulation, short rest and long rest were included in the experimental acquisition process, and data were collected in accordance with the details of data acquisition standards described in the previous section.

Data Processing Procedure for Experimental Data. The SSVEP frequency detection method introduced in the previous article is based on the classification calculation method with the same weighting without voting. In this study, we propose a novel voting classification method, which adopts the way of voting weighted classification, and applies Monte Carlo simulation to obtain the best correct rate distribution according to the distribution of correct rates at different times. In this experiment, the weight distribution of 0.05, 0.05, 0.3, 0.3, 0.3 was used to process the weighted voting of the data.

3.2 Experimental Result

The weighted voting mechanism and the traditional non-voting mechanism were used to classify the real-time collected EEG signals, respectively, and the specific effects are shown in the Table 1. The average ITR and the classification accuracy of visual stimuli at different frequencies were used to measure the performance of the two mechanisms. In the experiment, the window length of both voting mechanisms was chosen to be 4.5 s, and the step size was 0.5 s. When the two mechanisms were compared, the average accuracy was improved from 77.2% to 94.5%. ITR also increased significantly from 107.61 bits/min to 180.60 bits/min. Therefore, it was confirmed that the weighted voting mechanism method applied to the classification of visual stimuli could improve the performance of real-time EEG signals.

Table 1. Comparison of methods.

Method selection	Accuracy	ITR
Traditional method	77.2%	107.61
New method	94.5%	180.60

4 Discussion

4.1 Monte Carlo Simulation Used to Simulate the Weight Distribution Under the Best Correct Rate

Before processing weighted voting data, it is necessary to record and simulate the correct rates of different window periods under the condition of unweighted weighting. As mentioned above, the window length of this paper is 4.5 s, the step size is 0.5 s, and the stimulus duration is 7 s, so a total of 5 window times are recorded. The accuracy rates of recording 1000 times of 5 Windows were 0.64, 0.64, 0.86, 0.86 and 0.86, respectively. The matlab tool was used for Monte Carlo simulation in this study.

The study first designed a sequence to simulate the correct rate of five Windows. Initialize five empty arrays of 1000 lengths and fill them with random numbers between 0 and 1 generated by the random function. For a window with an accuracy rate of 0.64, those with a random number lower than 0.64 are required to be correct and set to 1, and those with a random number higher than 0.64 are required to be wrong and set to 0. For a window with an accuracy rate of 0.86, those with a random number lower than 0.86 are required to be correct and set to 1, and those with a random number higher than 0.86 are required to be wrong and set to 0. For these 5 0 and 1 sequences with length of 1000, they are merged into a 5×1000 two-dimensional array, and 5 numbers in each row are recorded as whether the vote is correct or not. After normalization, when the initial weight is the same, the weight size of each window needs the record value of the correct or not of the window. At this point, all the numbers in each row are added according to the weight size. If it is greater than 0.5, it means that the voting is valid, and if it is less than or equal to 0.5, it means that it is wrong. For example, if 10010 appears in a row, it will be regarded as $0.2\times1+0.2\times0+0.2\times0+0.2\times1+0.2\times0=0.4$¡0.5, that is, the voting result of this row is wrong. At this time, if each row of the two-dimensional array is calculated incorrectly or not, the correct rate of 1000 simulation results can be obtained with the same weight.

After completing the Monte Carlo simulation design with the same weight of different correct rate Windows, the weight ratio of each window was dynamically adjusted. Here, because the accuracy rate of the first two Windows is approximately equal, and the accuracy rate of the last three Windows is approximately equal, it is stipulated that the weight of the first two Windows decreases by 0.0006 each time, and the weight of the last three Windows increases by 0.0004 each time. In addition to changing the weight size of different Windows in each cycle process, it is also necessary to calculate the corresponding voting result value according to the weight value of the change, and compare it with 0.5 to determine whether the voting result is correct or wrong, and calculate the correct rate of the result based on 1000 sites. Before the start of the cycle, the position with the highest correct rate was defined as the correct rate when the weights were equal, and the weight distribution at this time was recorded. In the future, the accuracy rate of each update should be compared with the highest accuracy rate. If it is greater than the highest accuracy rate, the size of the highest accuracy rate and the weight distribution at this time should be updated and recorded (Table 2).

Table 2. Monte Carlo simulation results.

Correct rate with equal weights	Optimal weights	Correct rate with optimal weights
93.05%	0.05 0.05 0.3 0.3 0.3	94.45%
92.62%	0.05 0.05 0.3 0.3 0.3	94.32%
92.78%	0.05 0.05 0.3 0.3 0.3	94.73%
92.57%	0.05 0.05 0.3 0.3 0.3	94.65%
93.03%	0.05 0.05 0.3 0.3 0.3	94.71%
92.70%	0.05 0.05 0.3 0.3 0.3	94.45%
92.61%	0.05 0.05 0.3 0.3 0.3	94.67%
92.92%	0.05 0.05 0.3 0.3 0.3	94.58%
92.76%	0.05 0.05 0.3 0.3 0.3	94.57%
92.73%	0.05 0.05 0.3 0.3 0.3	94.62%

4.2 Future Works

In the following work, we can try and improve in the following directions. First of all, this study uses online BCI experimental data, and can try to add offline public data sets to try to observe the accuracy and the improvement effect of ITR. Secondly, according to different parameters such as window length and step size, different weight distribution sizes are given, and the general law of weight distribution under the universal problem is summarized. Finally, we hope to design an intelligent rehabilitation wheelchair based on this visual stimulation signal in the future, and plan to use the classification of SSVEP to realize the control of the direction and speed of the wheelchair [15], and assist patients with limb inconvenience to control the wheelchair through visual stimulation to achieve mobility and rehabilitation treatment.

4.3 Conclusion

In this study, we propose a new method for sliding window data segmentation based on weighted voting mechanism. Based on the weighted voting mechanism, the best weight size is used for real-time SSVEP classification. Compared with the sliding window method, the accuracy and ITR are greatly improved, and the acquisition experiment effect is improved. In this study, Monte Carlo simulation was used to simulate the optimal weight distribution under the condition of given window accuracy distribution, fixed window length and moving step size. We plan to continue to improve this method, and strive to adaptively adjust the weight ratio between different Windows according to the real-time situation, so as to be applied to intelligent rehabilitation wheelchairs in the future.

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