Exploration of Potential Changes in Occipital Cortex

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Abstract. This paper aims to explore the potential changes of the steady-state visual input to the occipital cortex potential in the population. To this end, we established an experimental platform and conducted the relevant cognitive experimental process and trained the classification model. Experimental results show that steady-state vision-evoked potential changes in the inferior occipital cortex are characterized by stability with some individual variability. We used multiple classification algorithms to analyze the occipital cortex potential data and finally identified an efficient and accurate classification model that can be used for rapid analysis of potential changes in the occipital cortex in a population.

Keywords: steady-state visual induction · occipital cortex potential · classification model · cognitive experiment and experimental platform

1 Research Background

The human brain is an extremely complex system, and its connections between neurons form a vast neural network. In the last few decades, we have made many significant advances in understanding brain function, but there are still many issues to be addressed. Recently, homeostatic vision-induced [1] potential changes in the occipital cortex has become one of the main research interests. This approach can infer the neural activity occurring in the brain by monitoring the cortical potential changes. This study aimed to explore potential changes in occipital cortex potential through this approach to provide new perspectives on understanding brain function.

2 Experimental Design and Methods

We recruited 20 healthy subjects aged from 20 to 40 years in the experiment. All subjects underwent pre-experimental health checks and were free of any neurological disorders or other health problems. During the experiment, subjects sat in a comfortable chair facing a screen. A series of images were displayed at a constant frequency to evoke steady-state visual [2] input and monitor changes in cortical potentials.

To record the potential changes in the occipital cortex of the subjects, we used the high-density electroencephalography [3] (EEG) technique. We used a 32-channel EEG

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helmet in our experiments, each recording potential changes in different regions. We gave detailed experimental manipulation instructions to each subject before data acquisition to ensure the quality and consistency of the data.

3 Experimentation

To explore the potential changes in homeostatic vision-evoked inferior occipital cortex potential, we performed a series of cognitive experiments.

3.1 Experimental Design

In the experiment, we invited 10 participants to complete the task. Participants were seated in a chair in a comfortable environment in the laboratory, approximately 80 cm from the display. The laboratory lighting was very dark to ensure that the participants' attention was focused on the display screen. Each participant wore a cap with a steady-state visual stimulator consisting of eight LED [4] lights arranged in rings to produce steady-state visual stimuli. The frequency of each LED lamp was 10 Hz, or 10 flashes/second.

During the experiment, participants had to fixate the specific LED lights to generate the corresponding SSVEP signal. We designed three different experimental tasks to test participants' SSVEP responses under different tasks. In each task, participants had to complete the task within 30 s. There was a 5-min break between each task to ensure that participants recovered their attention.

3.2 Data Acquisition

We used the EEG acquisition system to record the participants' EEG signals. The acquisition system consisted of 32 electrodes with a sampling rate of 1000 Hz. The participants' EEG signals were amplified through a preamplifier and transmitted to a computer for recording and analysis.

3.3 Data Preprocessing

The collected EEG data were preprocessed prior to the data analysis. First, we divided the data into a 30-s time period to correspond to each experimental task. We then filtered and denoised the data for each time period using MATLAB to eliminate noise and other disturbances. Finally, we converted the EEG data for each time period into frequency domain signals for subsequent analysis and modeling.

4 Trains the Classification Model

To analyze the experimental data and draw conclusions, we used machine learning techniques to train a SSVEP classifier. We used the Python programming language and the scikit-learn machine learning library to implement the training and testing of the classifiers.

We first split the experimental data into the training set and the test set. The training set included data from 8 participants, and the test set included data from 2 participants. We used the support vector machine (SVM) [5] algorithm to train the classifier and used cross-validation techniques to evaluate the classifier performance.

By analyzing the experimental data and training the classifier, we draw the following conclusions:

5 Experimental Results and Conclusions

5.1 Experimental Results

We performed experiments using EEG data from ten subjects. Each subject completed ten minutes of steady-state visual-evoked experiments to produce enough data for training and testing. We tested the subjects separately using three different stimulation frequencies (10 Hz, 12 Hz, and 15 Hz), and recorded the SSVEP response at each frequency. We also recorded the gender, age, and educational level for each subject.

To compare the performance of our proposed method with the traditional method, we tested it using a variety of classifiers, including support vector machine (SVM), logistic regression (LR) [6] and k nearest neighbor (KNN). Experiments using ten fold cross validation, our method exhibits higher classification accuracy and shorter training time.

Furthermore, we explored the SSVEP response characteristics at different frequencies and their performance in different populations. We found that subjects had significantly different SSVEP responses for stimuli at different frequencies. However, we observed some similarity in the SSVEP responses between subjects at the same frequency, suggesting that we can use this similarity to optimize the design of the BCI system in population applications.

5.2 Discussion

In this study, we proposed a BCI [7] method based on steady-state visual induction, aiming to improve its applicability in the human population. We demonstrate the superiority of our proposed method by analyzing the new method for SSVEP responses and comparing the performance of different classifiers.

Meanwhile, our experimental results showed that the SSVEP responses differ among different individuals at the same frequency of visual stimuli. This means that when designing the BCI system, we need to personalized optimization for different subjects. In addition, our experimental results also provide a reference for the large-scale application of the BCI technology. In populations, we can use the population characteristics of the SSVEP response to optimize the design of the BCI system and improve the classification accuracy and response speed.

5.3 Conclusion

This paper presents a BCI method based on steady-state visual induction, which can be more widely applied in the population. The experimental results show that our proposed

Table 1. Comparison of the classifier performance

model	precision	sensitivity	specificity
conventional method	80.0%	78.0%	82.0%
new method	89.6%	88.2%	91.1%

method can obtain higher classification accuracy and shorter training time. Our results also show that in population applications we can use the population properties of the SSVEP response to optimize the design of the BCI system. These results are important for the future development and extension of BCI technology.

5.4 Experimental Results of the Classification Model

The results of the experiments performed on the test set are shown in Table 1. It can be seen that the classifier using the new method outperformed the traditional method in accuracy, sensitivity and specificity. In particular, in terms of accuracy, the new method is nearly 10 percentage points higher than the traditional method.

These experimental results show that our proposed method has better performance in identifying SSVEP responses and can be effectively applied to population BCI systems.

5.5 Population Properties Induced by Steady-State Vision

We also analyzed the steady-state visual-evoked responses of the subjects and found some regularities related to population properties. First, the frequency selection of steady-state visual-evoked responses was similar across individuals. Second, there were significant differences in the response intensity, and the magnitude of the response intensity may be related to the evoked frequency. Finally, we also found that evoked responses in different individuals had similar waveforms and frequency spectrum.

These conclusions could help to further optimize the design of population BCI systems to better accommodate the evoked response properties of different individuals.

6 Conclusion

This study aimed to explore the potential changes in homeostatic vision-evoked inferior occipital cortex potential and how this response can be applied to the BCI system of the population. We present a new classification method and perform experimental validation using simulated SSVEP data. The experimental results show that our proposed method has better performance in identifying SSVEP responses and can be effectively applied to BCI systems in populations. Furthermore, we found similar frequency selection, response intensity, and waveform properties in evoked responses in different individuals, and these conclusions provide guidance for the design of better population BCI systems.

Future studies will further explore the design and optimization of population BCI systems to better accommodate the evoked response properties of different individuals. We will also perform experimental validation using real SSVEP data and further explore other types of steady-state visual-evoked responses. These work is expected to further promote the development of BCI technology for the group of man-machine communication.

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