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Performance Evaluation of a "Switch-To-Target" Based Asynchronous SSVEP BCI Paradigm*

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Abstract—**Because of the strong advantages such as anti-interference capability, less electrode montage, higher information transfer rate and no need of specific training for participants, steady-state visual evoked potentials (SSVEP) based brain-computer interface (BCI) has attracted more and more attentions. In order to achieve high accuracy and maintain considerable stability, this paper proposed an eye tracking technique based asynchronous SSVEP BCI method by directly localizing asynchronous eye-tracking-based switch to desired stimulation target to accelerate the BCI process. And real-time visual gaze feedback was also provided in necessity when participants could not focus their gaze to achieve satisfactory target identification results. By combining the heterogeneous signals of eye gaze position with a conventional asynchronous BCI paradigm, the proposed method reduced the trial duration while considerably high identification accuracy was maintained. Experiments were carried out on four participants with an average accuracy above 93% when the trial duration was 3s, while considerable performance can also be achieved when the trial length was shorten to 2s.**

I. Introduction

Brain-computer interface (BCI) is a type of human-computer interaction channel independent of human muscle and peripheral nerve pathways. It usually utilizes electroencephalograph (EEG) signals to control external devices [1] and has been widely used in neurological rehabilitation and robotic control fields [2][3]. Steady-state visual evoked potential (SSVEP) BCI is based on the steady-state brain responses elicited from periodic visual stimuli, where the responses are mainly located in occipital region in human visual cortex. Since the power of SSVEP responses mainly converges on stimulation frequency bins, SSVEP-based BCIs have many advantages like high information transfer rate, less electrodes montage, strong anti-interference capability, and no need of specific training for participants when compared to other EEG-based BCI paradigms [4]. Farmaki et al. [5] developed a SSVEP-based BCI along with a low-cost custom radio-controlled robot-car to test and assess the applicability of SSVEPs in real time navigation in realistic environments.

SSVEP-BCI technology can be divided into two implementation patterns, i.e., the synchronous mode and the asynchronous mode [6]. Compared to the synchronous BCI mode that the start/stop operation was operated by the operant system rather than the BCI users, the asynchronous BCI represents a more flexible communication method of freely giving commands to control external devices without restriction of predefined start/stop time [7]. In this study, in order to improve the accuracy of asynchronous BCI while to maintain a stable performance, an asynchronous SSVEP BCI system based on "Switch-To-Target" paradigm was designed. The "switch" function was used to manipulate the turn on/off of the following asynchronous BCI to make sure that the targets of the BCI system could not be falsely triggered.

There are many ways to implement a "switch" function in BCI applications. Middendorf et al. [8] and Birch et al. [9] respectively designed the brain switches with the homogeneous brain signals that the former utilized the SSVEP flicker and the latter extracted spontaneous motion imagery signals to construct the brain switches. Due to the homogeneous characteristic between the switch signals and the BCI signals that they all belong to EEG signals, these traditional brain switches may have false-trigger or low-accuracy problems. In this study, these problems were solved by combining the eye tracking technique into the eye-tracking-based switch. Due to the fact that eye tracking is a mature technique and has been applied successfully in several fields like robot controls [10], the proposed method has the advantages of reducing the false trigger caused by visual shift and also the reduction of the time break between the switch and the target selection, which could promote the implementation efficiency of BCI systems.

The successful SSVEP BCI applications have proved that the relevant frequency components of EEG signals could be extracted by Fourier transform, canonical correlation analysis

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(CCA) and other feature extraction algorithms. Former studies have shown that CCA is one of the most effective methods to realize feature extraction of EEG signals [11]. Tanaka et al. [12] compared and analyzed the BCI accuracy and information transfer rate among several algorithms, they proved that CCA with the linear discriminant analysis (LDA) classifier is the superior method to recognize the target frequency among different participants. In this study, we utilized the CCA based LDA algorithm for SSVEP feature extraction and classification, and the LDA training data came from our four participants.

In this paper, we designed the asynchronous SSVEP-BCI system with a "Switch-To-Target" paradigm to reduce the false trigger rate and to make the system respond quickly. The eye-tracking-based switch was designed by using the gaze position information obtained by eye tracking technology, and acted as a real-time visual feedback channel in the running of asynchronous SSVEP BCI. And this paper adopted CCA based LDA algorithm for SSVEP feature extraction and classification. The purpose of this study is to make asynchronous SSVEP BCIs more accurate, stable and practical.

II. Methodology

A. System Layout

The asynchronous SSVEP-BCI system implemented in the "Switch-To-Target" paradigm included the asynchronous gaze position acquisition module and the asynchronous SSVEP BCI module. The gaze position acquisition module was designed as an eye-tracking-based switch and responsible for providing real-time visual feedback. The two modules ran on two MATLAB environments, respectively. The gaze position information collected by the eye tracker device was transmitted to the SSVEP BCI module via TCP/IP transmission protocol for real-time display. The SSVEP BCI module was designed to be operated in an asynchronous mode. In other words, EEG signals were real-time acquired and analyzed continuously in the BCI module.

As shown in Fig. 1, a red circle as the real-time gaze position was displayed on both the switch and BCI interfaces, where its position was determined by the average value of the horizontal and vertical positions of the left and right eye coordinates respectively. The red circle with a diameter of 10 pixels was used as real-time visual feedback to indicate the participant's gaze position on the computer screen. Top, left, right and bottom black circles with 50-pixel diameter were the asynchronous eye-tracking-based switches. When the participant's gaze position focused on any of the four switches, the focused switch would turn on and then the switch interface vanish, and the participant began to attend to the stimulation target placed in the BCI interface at the exact position of the previously vanished switch. After the completion of the asynchronous BCI task, the switch would automatically turn off and the switch interface would reappear again to replace the BCI interface, then participants could determine whether they want to begin the next trial or not.

The BCI interface was designed with four checkerboard targets corresponding to four different stimulus frequencies to induce SSVEP responses. For each target, a gray and white alternated checkerboard pattern was adopted with the most outer diameter of 100 pixels [13]. The checkerboard pattern moved in an oscillating contraction and expansion motion with its modulation phase gradually shifting between 0 and π

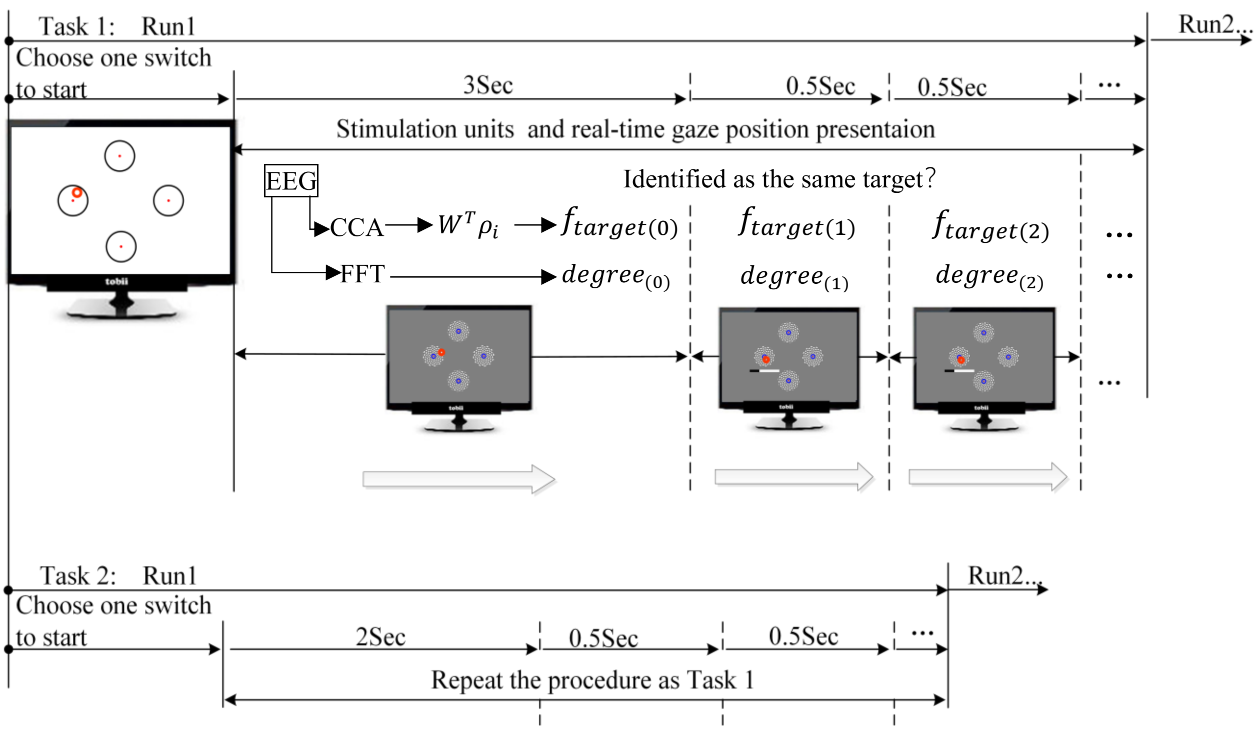

Figure 1. The experimental flow chart

in a sinusoidal way. The motion direction change rate, which refers to the motion-reversal frequency, was defined as the fundamental stimulation frequency in the present study.

B. Participants and EEG Recordings

Four graduate students (one female and three males) from Xi'an Jiaotong University (Shaanxi, China) participated in this study as the volunteer participants. They are all able-bodied and had normal or corrected-to-normal visions. And no history of psychological disorders and no sensory deficits were reported. All written consent of the review committee of Xi'an Jiaotong University was provided before the experiments.

As shown in Fig. 2, in accordance with the 10-20 International Electrode Placement System, six electrodes over PO3, POz, PO4, O1, Oz and O2 positions were used in this study to collect multi-channel EEG signals that reflects brain activities in the visual cortex area. In addition, the reference electrode was attached to one-side earlobe (i.e., A1 or A2 position), and the ground electrode was placed at the forehead area of FPz position [14]. EEG signals were acquired using the g.Nautilus (g.tec Medical Engineering GmbH, Austria) amplifier with a sampling rate of 500 Hz, a bandpass filter between 2 and 100 Hz and a 50-Hz notch filter.

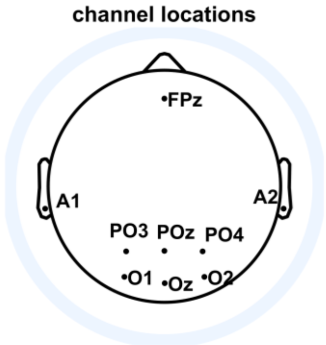

Figure 2. The channel location over the visual cortex area (Recording electrodes: PO3, POz, PO4, O1, Oz, O2; Reference electrode: one-side earlobe position, i.e., A1 or A2; Ground electrode: FPz).

C. Installation of Eye Tracking Device

The Tobii X2-30 compact eye tracker system with infrared video-oculography technique was used to monitor participants' eye movements and to record gaze coordinates with a sampling rate of 30 Hz. Participants were allowed to blink their eyes during the experiments, which would bring no interference to the eye-tracking procedure.

Figure 3. The placement of the eye tracker device

As showed in Fig. 3, the eye tracker was attached to the bottom center of the computer screen with 20°deviation from the vertical direction. The horizontal distance from the top edge of the eye tracker to the screen was 2.5 cm and the vertical distance was 1.5 cm. Calibration procedure was performed before gaze data acquisition and the standard Tobii calibration procedure with five fixed points was applied.

D. Target Recognition with CCA and LDA

As shown in Fig. 1, this study used a target recognition method that was based on CCA and LDA.

1) CCA. CCA was used to detect the target frequency based on the canonical correlation values. Here two groups of signals are computed in CCA. One group is EEG signals *X* recorded from *C* different channels (*C* equals 6 for this study) within the time window of *S* sampling points. The other group is the pure sine and cosine reference signals with frequencies corresponding to the visual stimulation frequencies used to induce the EEG responses. The pre-constructed reference signals Y_I is formed by a series of sine and cosine waves at the stimulation frequency $f_i(i=1,\cdots,k)$ as

$$Y_I=\begin{pmatrix}\cos(2\pi\cdot f_i\cdot t)\\ \cos(2\pi\cdot f_i\cdot t)\\ \vdots\\ \cos(2\pi\cdot Hf_i\cdot t)\\ \cos(2\pi\cdot Hf_i\cdot t)\end{pmatrix}, t=\frac{1}{F_S},\cdots,\frac{S}{F_S} \tag{1}$$

Where *Fs* is the sampling rate; *H* is the number of harmonics and was defined as 1 and 0.5 corresponding to the fundamental and subharmonic frequency components; *S* is the number of sampling points.

Considering multidimensional variables *X*, Y_I and their linear combinations:

$$\begin{aligned} x &= X^T W_x \\ y_i &= Y_i^T W_{yi}, \end{aligned} \tag{2}$$

CCA seeks two weight vectors W_x and W_{yi} to maximize the linear correlation between *x* and y_i, through solving the following optimization problem:

$$\rho(\mathrm{x},y_i)=E(x^Ty_i)\Big/\sqrt{E(x^Tx)E(y_i^Ty_i)}$$

$$=\frac{E(W_x^TXY_i^TW_{yi})}{\sqrt{E(W_x^TXX^TW_{yi})E(W_x^TY_iY_i^TW_{yi})}} \tag{3}$$

2) CCA based LDA classification. For each frequency

$f_i(i = 1, \cdots, k)$, the correlation coefficient ρ_i is obtained through CCA, which forms an k-dimensional vector defined as:

$$\rho_i = [\rho_1, \rho_2, \ldots, \rho_k]^T \tag{4}$$

According to [15], the criterion is considered as:

$$J_{(W)} = \frac{W^T S_B W}{W^T S_W W} \tag{5}$$

Where $W \epsilon R^{K \times L}$ and $L < K$. The generalization of the within-class covariance matrix to the case of K classes is S_B, and the between-class covariance is S_W:

$$S_B = \frac{1}{K} \sum_{i=1}^{K} (m_i - m)(m_i - m)^T \tag{6}$$

$$S_W = \sum_{i=1}^{K} \sum_{\rho \epsilon \rho_i} (\rho - m_i)(\rho - m_i)^T \tag{7}$$

Where m is the sample mean.

According to [15], The eigenvectors W was displayed by the matrix $S_W^{-1} S_B$ corresponding to the largest of the eigenvalues. To obtain W for each participant, we used the dataset labeled frequency f_i.

To classify the input vector, the Euclidean distance between the input and the vector was determined by $W^T \rho$. And, generally speaking, the better the raw data signals, the better the separability of the classification results. The target was detected by:

$$f_{target(j)} = \arg\min \sqrt{(W^T \rho - m_i)^T (W^T \rho - m_i)} \tag{8}$$

Where $j = 0,1,2 \ldots$.

E. Experimental Procedure

After participants passed the eye tracking calibration, they entered the "Switch-To-Target" based asynchronous SSVEP BCI experiment. First, they entered the asynchronous switch interface. After the switch was turned on, the participant entered the asynchronous SSVEP BCI interface. They were asked to look at one of the checkerboard targets corresponding to the previously vanished switch until the result of the target recognition came out. Through the real-time visual feedback by the eye tracker, the participants voluntarily chose the start time of the task.

Our aim was to minimize the time of EEG data collection while maintaining the classification accuracy. So in this study, the displaying time of the checkerboard stimulus unit was not fixed, and the completion of each trial was determined by the fact that whether the system could accurately detect the target or not. As shown in Fig. 1, there were two tasks in total. The lengths of the original window of the two tasks were different, which were 3s for Task 1 and 2s for Task 2, respectively. And as shown in Fig. 4, EEG signals were segmented by using the time sliding window. The time window length was adopted as the length of the original window according to the two tasks, where the sliding window length of Task 1 was 3s while 2s for Task 2. After that, the length of the sliding window did not change, and the sliding interval was 0.5s. When the identification results of two adjacent sliding windows were the same, i.e., $f_{target(j)} = f_{target(j+1)}$, then the recognition in that trial was completed.

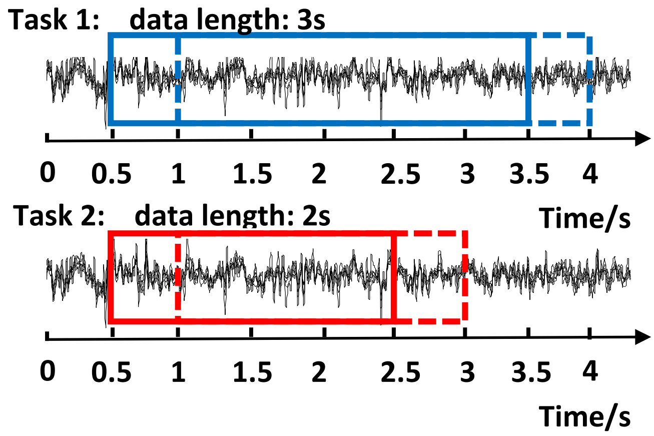

Figure 4. EEG data segmented by using the time sliding window

In this study, each task contained 40 runs and each 10 runs for each stimulus frequency. The stimulus frequencies were set as 8.57 Hz, 10 Hz, 12 Hz, and 15 Hz, respectively. The elongated indicator below the checkerboard unit indicated the spectral degree of SSVEP signals, and the degree was calculated as:

$$degree_{(n)} = \frac{Amp(f_z) + Amp(f_z/2)}{\sum_{i=1}^{4} (Amp(f_{zi}) + Amp(f_{zi}/2))} \times 100 \tag{9}$$

Where *degree* indicates the spectral degree of SSVEP signals, f_z is the target stimulation frequency, $Amp(f_z)$ is the amplitude spectrum at frequency f_z, and i is the number of the stimulus unit. Here $n = 0,1,2 \ldots$.

III. Results

There were 320-run (2 tasks × 4 participants × 4 frequencies × 10 runs) EEG datasets collected from different participants. By removing the transient visual evoked potentials that existed during the initial phase of the SSVEP signals collected during each trial, the first 0.5-s EEG data of each trial was removed from the analysis. CCA based LDA classification was implemented on the preprocessed EEG signals, which integrated six-channel data to determine the target stimulation frequency and calculated the identification accuracy. Fourier transform was carried out on the average value of EEG data collected from Oz channel with the most prominent signal quality to calculate the value of *degree*.

Table I summarizes the average accuracy and *degree* values of four stimulus frequencies among four different participants in two tasks, as well as the average time required for each participant to accurately identify the target. According to the above experimental procedure, as the time window slides, if the target identified in two adjacent time windows is the same one, i.e., $f_{target(j)} = f_{target(j+1)}$, then the trial is finished. According to the statistics in Table I, the average time required to accurately identify the target indicates that, the correct target can be roughly judged in the second identification.

TABLE I. STATISTICAL SUMMARY OF THE AVERAGE ACCURACY, THE AVERAGE TIME REQUIRED TO ACCURATELY IDENTIFY THE TARGET, AND THE *DEGREE* VALUES

Participants	Accuracy		Time		Indicator bar	
	Task 1	Task 2	Task1	Task2	Task 1	Task 2
	Mean/%		Mean (Std)/s		Mean (Std)/%	
P1	80	85	3.6 (0.2)	2.5 (0.1)	24.1 (1.6)	26.0 (1.6)
P2	97.5	75	3.6 (0.1)	2.6 (0.2)	29.6 (6.9)	28.5 (3.6)
P3	92.5	85	3.5 (0.1)	2.6 (0.2)	29.2 (1.1)	27.0 (2.5)
P4	95	70	3.6 (0.2)	2.6 (0.2)	30.3 (1.1)	23.7 (1.1)
Avg	93.5	78.8	3.6 (0.1)	2.6 (0.2)	28.3 (2.7)	26.3 (2.2)

Fig. 5 shows the average accuracy of four participants in two tasks at different frequencies. In task 1 and task 2, participants could achieve high recognition accuracy and the system performance maintained stability. The comparison results showed that the accuracies of Task 1 were higher than that of Task 2 for the four participants involved in the experiments, i.e., the accuracies of the data length of 3s were higher than that of 2s. However, even the time window for collecting EEG data was set as 2s, the grand averaged accuracy across participants could also reach above 78%. What's more, the *degree* value showed in Table I can be generally higher than 25%.

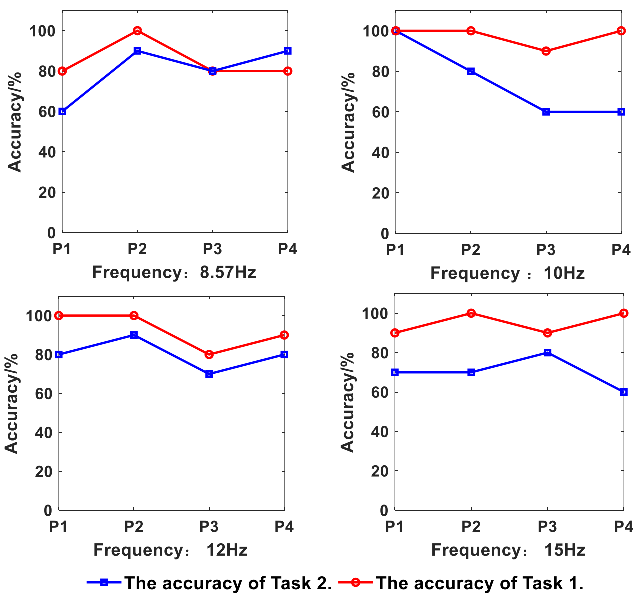

Figure 5. The average accuracy of four participants in two tasks at different frequencies

IV. CONCLUSION

In this study, asynchronous eye-tracking-based switch and real-time visual feedback were added to the asynchronous SSVEP BCI system, and CCA based LDA classification was used for target recognition. Our aim is to minimize the time it takes for the presentation of visual stimulations, such as the checkerboard motion stimulation in this paper, while ensuring high recognition accuracy. In this study, real-time visual feedback could provide participants with clear visual indication and positive guidance. Otherwise, the "Switch-To-Target" interval was also diminished due to our proposed design. The experimental results showed that when the EEG data were collected in 3-s length, the accuracy rate can reach 93%. The "Switch" function enabled the participants to obtain more rest time. In this study, the state of the same participant could be maintained persistently and the differences in between participants were not significant. Asynchronous SSVEP BCI systems are more practical than synchronous systems, providing participants with more choices and a better experience. In future studies, we can design more stimulation units to implement complex control commands, so that people with neuromuscular disorders or people in need of rehabilitation can better control intelligent systems. And more complex supervised machine learning methods can also be adopted to improve the performance of our proposed design.

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