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Study on an Online Collaborative BCI to Accelerate Response to Visual Targets

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***Abstract*— Using brain-computer interfaces (BCIs) to improve human performance has become a state-of-the-art research topic. The concept of collaborative BCIs, which aimed to use multi-brain computing to enhance human performance, was proposed recently. To further study the feasibility of collaborative BCIs, here we propose to develop an online collaborative BCI to accelerate human response to visual target stimuli by detecting multi-subjects' visual evoked potentials (VEPs). A spatial filtering algorithm which maximized the signal-to-noise ratio was used to extract VEP components from multichannel EEG. A two-layer support vector machine was subsequently used for target detection. Results of an offline analysis indicated that the system could achieve high accuracies (above 90%) at the stage before the behavioral response time (RT) (332±98ms). In online experiments with three groups of participants (each with three subjects), the system achieved significantly enhanced accuracies (79%, 82%, and 95% for three groups, respectively) at 120 ms after the target onset, which on average was 11% higher than the average individual accuracy, and 6% higher than the best individual accuracy.**

I. Introduction

Brain-computer interfaces (BCIs) are direct communication channels between the human brain and the external devices [1]. It has long been proposed that BCI can be used not only to help patients with motor disabilities to improve their quality of life, but also to assist normal people to enhance human performance [2-10]. One of the most challenging problems towards practical BCIs for healthy people is the low signal-to-noise ratio (SNR) of EEG signals measured in real-world environments. To overcome this bottleneck, Wang et al. [11] proposed a collaborative BCI paradigm to accelerate human motor response, which used multi-brain information to enhance the SNR of EEG signals. The framework of a collaborative BCI proposed in that study sets a solid foundation for augmenting human performance using BCIs [11].

Although the concept of a collaborative BCI has been established in [11], the feasibility and practicality of a collaborative BCI have not been fully tested. In addition, it is of interest to explore new BCI paradigms for improving human performance.

This study demonstrates an online collaborative BCI for detecting visual targets by measuring the visual evoked potentials (VEPs) from the visual cortex. An offline experiment first proved the superiority of the VEP detection from multiple brains to accelerate human motor responses. An online experiment further tested the feasibility and practicality of the proposed online collaborative BCI system.

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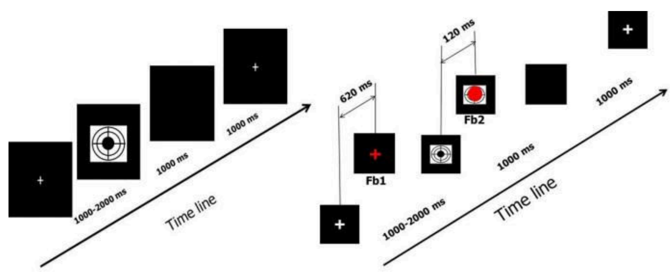
II. Materials and Methods

A. Subjects

This study consisted of three different experiments: behavior experiments, offline BCI experiments, and online BCI experiments. Three groups of people (each with three subjects) with normal or corrected-to-normal vision aged 24 to 27 years (mean age, 25) participated in the behavior and offline BCI experiments. Another three groups of people (each with three subjects) aged 20 to 30 years (mean age, 26) attended the online BCI experiments. Subjects were paid 50 RMB/hour and signed a consent form before participating in the study.

B. Experimental Paradigm

The behavior experiment aimed to measure subjects' motor response time (RT). The aim of the offline BCI experiment was to verify the feasibility of the system and determine the parameters optimized for the online application. The online experiment tested the practicality of the system through evaluating the online performance. Fig. 1 shows a timeline of a single trial in the behavior and offline experiments (Fig. 1(a)), and the online experiment (Fig. 1(b)).



(a) (b)

Fig. 1. Time sequences of cue and feedback presentation in a trial in (a) the behavior and offline experiments, and (b) the online experiment. Fb1 and Fb2 denote the first and second feedbacks in an online trial respectively.

In the behavior and offline experiments, a fixation cross was presented in the center of the screen for a random duration from 1 to 2 seconds, followed by a visual target presented to the subjects for one second. There was a one-second rest period before the next trial started. Note that, in the behavior experiment, subjects were instructed to press a key as quickly as possible when they saw the target, whereas in the offline and online experiments, subjects were only required to gaze at the stimulus and no motor responses were required.

Visual feedbacks were added in the online experiment. As shown in Fig. 1(b), the first feedback was given at 620ms after the onset of the fixation cross, while the second feedback was given at 120ms after the onset of the target. The type of the feedback was determined by the collaborative BCI via classifying the EEG data during two different stages (Non-target: 500ms to 620ms after the onset of the fixation cross; Target: 0ms to 120ms after the onset of the target). When the system decided that the EEG segment was in the "Target" stage, the current cue would change (i.e. the color of the cross changed to red, or the color of the dot in the center of the target image changed to red), otherwise, the image would remain the same.

The behavior experiment included 120 trials for each subject. The offline and online BCI experiments consisted of two blocks with 120 trials each.

C. Data Recording

Subjects' motor response time to the target was recorded in the behavior experiment via a program developed using Psychtoolbox [12].

In both offline and online BCI experiments, for each group, multichannel EEG signals were recorded from three subjects at the same time. A customized 16-channel EEG amplifier was used for each subject's EEG recording. Nine channels (P3, Pz, P4, PO3, POz, PO4, O1, Oz, and O2) of the standard international 10-20 system were used to record VEP signals. The Cz channel was used as the reference. The sampling rate was 1000 Hz.

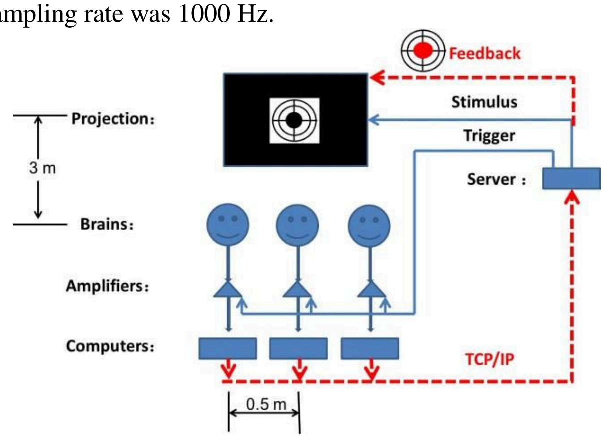


Fig. 2. Experimental setup of the offline and online experiments.

Fig. 2 illustrates the setup of the offline and online experiments. The collaborative BCI system comprised three EEG amplifiers synchronized by trigger signals from a server computer which was also used for stimulus presentation and data analysis. The stimulus was delivered to subjects using a projector with a 60 Hz refresh rate. The distance between subjects and the stimulus (the projector screen) was 3 m, and the distance between subjects was 0.5 m. The target size was 0.5×0.5 m^2. As shown in Fig. 2, the red dashed lines showed that, in the online experiment, real-time EEG data from each subject were sent from a data-recording computer to the server via TCP/IP for providing visual feedback based on real-time EEG classification.

D. Data Analysis

1) Behavior data

This study calculated the mean, standard deviation and distribution of the motor response time recorded in the behavior experiment.

2) EEG data

For each subject, single-trial EEG epochs with a length of 1.5 s were extracted from 500 ms prior to the target stimulus onset. Signals were resampled at 200 Hz, and digitally filtered at 1-30 Hz with a zero-phase filter. All the epochs were baseline corrected with respect to the mean over the 500 ms period preceding the target onset. To detect the visual target using a classification paradigm, this study defined two conditions within one epoch. Fig. 3 shows an example of the Target and Non-target conditions in an epoch. Two data segments with a length of L ms, starting from the beginning of the epoch and the target onset, were selected for representing the two conditions respectively.

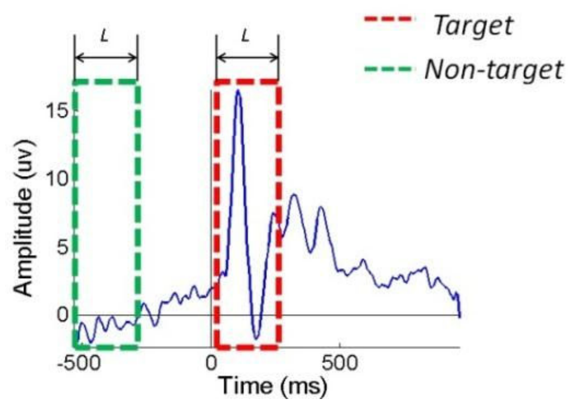


Fig. 3. An example of ERP signals corresponding to the Target and Non-target conditions in one epoch. L denotes the length of the time window used for extracting data.

After data preprocessing, A fast spatial filtering algorithm (the signal-to-noise ratio maximizer (SIM)), which maximize the ERP power while being maximally orthogonal to spontaneous activities [13], was used to extract each subject's VEP components through spatial filtering multichannel EEG. The first three VEP components were selected as features for classification. Fig. 4 illustrates the diagram of feature extraction and classification in the collaborative BCI system. A two-layer support vector machine (SVM) classification was subsequently applied for target detection. The first layer was used for individual classification. For each subject, the output was the probability that the EEG segment was considered to be in a target condition. The second-layer classifier was used for collaborative classification with the feature vector constituted by the outputs of the first-layer classifiers.

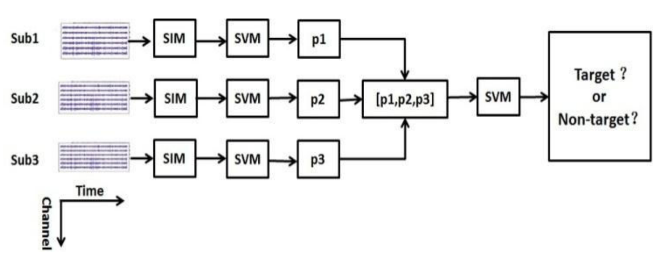


Fig. 4. Diagram of feature extraction and classification in the collaborative BCI system.

The linear kernel SVM was used and 5-fold cross validation was done in the training set to search for the optimal parameters of the SVM classifiers. Towards realistic implementation of the system, in both offline and online experiments, the first block (with 120 trials) was used as the training set and the second block was used as the test set. Compared with the commonly used cross-validation method in offline analysis, we think that this approach is more suitable for estimating the system performance in the online situation. The offline study evaluated the individual and collaborative accuracies of single-trial classification (Target vs. Non-target) with different time window lengths (L ranged from 80 ms to 140 ms with an interval of 10 ms, and from 140 ms to 200 ms with an interval of 20 ms). In the online experiment, the length of the epoch was set to 120 ms for real-time processing.

III. RESULTS

A. Behavior Results

Fig. 5 shows the distribution of the motor response time. The mean of RT was 332±98 ms, and in most of the trials, RT was not earlier than 200 ms.

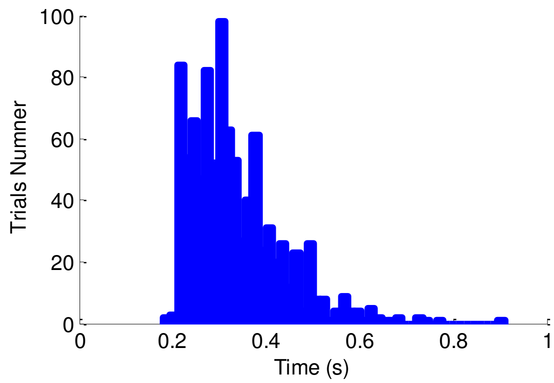


Fig. 5. Distribution of response time.

B. Offline Analysis

1) VEP

Fig. 6 shows time courses of the grand averaged VEPs. As shown in Fig. 6 (b), the VEP at channel Oz consists of three major components (P1, N2, and P3). The P1 and N2 components played important roles in classification since the time window length (L) evaluated in offline analysis ranged from 80 ms to 200 ms.

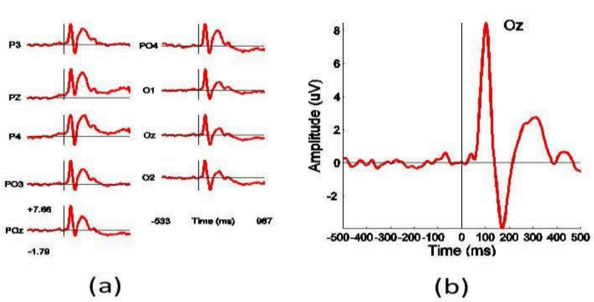


Fig. 6. (a) Time courses of grand averaged VEPs for all channels. (b) Grand averaged VEP at channel Oz.

2) Classification accuracy

Fig. 7 shows the individual and collaborative accuracies of single-trial classification. For all time window lengths, the collaborative system achieved significantly enhanced performance than the individual classification. For example, at 120 ms after the target onset, which is about 200 ms earlier than the motor response time (330 ms), the collaborative BCI achieved classification accuracy higher than 90%.

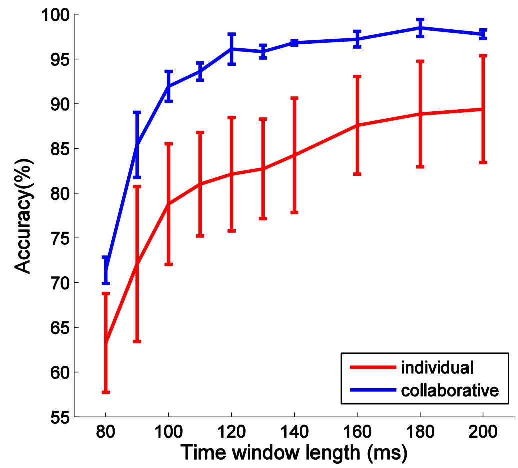


Fig. 7. Single-trial classification performance for the individual and collaborative classifications with different time window lengths.

C. Online Performance

Table I lists the classification results in the online experiment. True positive (TP) and true negative (TN) indicate the accuracy for the Target and Non-target detections respectively. At 120 ms after the target onset, the collaborative classification of the three groups achieved classification accuracy of 79%, 82%, and 95% respectively. As shown in Fig. 8, the collaborative system achieved significantly enhanced accuracy than the average individual and the best individual, which in average, was 11% higher than the average individual accuracy, and 6% higher than the best individual accuracy.

TABLE I. ONLINE PERFORMANCE

Group	Subjects ID	TP (%)	TN (%)	ACC (%)
Group 1	1	67.50	75.00	71.25
Group 1	2	59.17	66.67	62.92
Group 1	3	75.83	77.50	76.67
Group 1	collaborative	**76.67**	**87.50**	**82.08**
Group 2	1	59.17	68.33	63.75
Group 2	2	68.33	70.00	69.17
Group 2	3	65.00	79.17	72.08
Group 2	collaborative	**75.00**	**83.33**	**79.17**
Group 3	1	89.17	89.17	89.17
Group 3	2	88.33	86.67	87.50
Group 3	3	78.33	76..67	77.50
Group 3	collaborative	**94.17**	**95.83**	**95.00**

TP, TN and ACC denote true positive, true negative and total accuracy respectively.

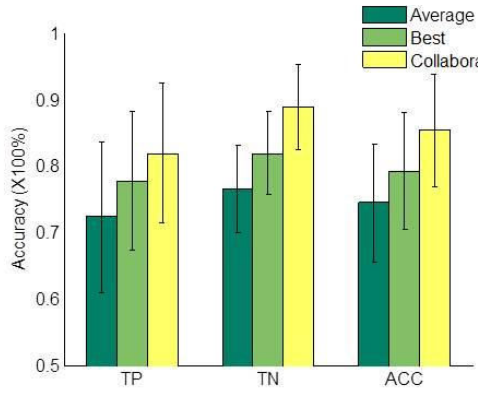


Fig. 8. Online performance of the collaborative BCI. The three legends indicate the average individual, the best individual and the collaborative performance. TP, TN and ACC denote true positive, true negative and total accuracy respectively.

IV. Discussion and Conclusion

This study presents a demonstration of an online collaborative BCI. The system used a collaborative classification approach to detect visual target by identifying the VEP signals from the visual cortex of multiple subjects. The advantage of using VEPs from multiple brains to accelerate human motor response was verified via both offline and online experiments. The classification results showed that even at a very early stage (e.g., 120 ms after target onset), the collaborative BCI achieved high accuracies (above 90%), which were significantly higher than the average individual performance.

Although the collaborative BCI achieved good performance (with the highest accuracy of 95%) in the online experiments, the average performance across all groups was poorer than that in the offline experiments. In online experiments, it should be noted that, to satisfy the requirement of real-time data processing and feedback presentation, the length of the epoch data was much shorter than that in offline analysis. This may affect the quality of filtering and lead to lower classification accuracies. Another possibility is that the visual feedback may affect the subjects' mental states, which could lead to additional artifacts in the EEG signal and thus the poorer performance. As the data samples in current experiments were very limited, optimization of the online system still needs further investigation.

This study shows a demonstration of using the VEP signal, which is the neural activity at a very early sensory stage and encodes little information about human cognition, to improve human motor performance. It will also be very interesting to exploit neural activities related to human cognition (e.g. the P3 signal) to develop an online cognitive collaborative BCI. Some recent studies have shown promising results in this direction [14-15].

In summary, this study proposes a framework of an online collaborative BCI. To the best of our knowledge, this is the first demonstration of an online collaborative BCI. This work may help to lay a solid foundation for augmenting human performance using the collaborative BCI technology.

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