A Collaborative Brain-Computer Interface for Accelerating Human Decision Making

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Abstract. Recently, collective intelligence has been introduced to brain-computer interface (BCI) research, leading to the emergence of collaborative BCI. This study presents an online collaborative BCI for improving individuals' decision making in a visual Go/NoGo task. Six groups of six people participated in the experiment comprising both offline and online sessions. The offline results suggested that the collaborative BCI has the potential to improve individuals' decisions in various decision-making situations. The online tests showed that using Electroencephalogram (EEG) within the first 360 ms after the stimulus onset, which was 50 ms earlier than the mean behavioral response time (RT) (409±85 ms), the collaborative BCI reached a mean classification accuracy of 78.0±2.6% across all groups. It was 12.9% higher than the average individual accuracy (65.1±8.1%, $p<10^{-4}$). This study suggested that a collaborative BCI could accelerate human decision making with reliable prediction accuracy in real time.

Keywords: brain-computer interface (BCI), group decision making, Electroencephalogram (EEG), collaborative BCI.

1 Introduction

In human-performance studies, a team of individuals usually outperforms individuals especially when performance requires diverse skills, judgments, and experiences under time constraints [1]. Two heads are better than one, known as collective intelligence, the mechanism and neural basis of which has recently attracted growing attention of researchers in psychology and neuroscience [2, 3].

Recently, the collective intelligence has been introduced to the brain-computer interface (BCI) research field. For Instance, the concept of collaborative BCI has been proposed in [4] and [5]. Through offline demonstrations of collaborative BCIs, these studies suggest that a collaborative BCI, which integrated neural information from multiple individuals, can outperform a single-brain BCI. More recently, we implemented the first online collaborative BCI in a visual target detection task [6].

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The huge potential of using a collaborative BCI to improve human performance has attracted many researchers and engineers' interests. For instance, Riccardo et al. [7] reported the application of a BCI system in a simulated spacecraft control task and the potential benefits of its extension to a collaborative multi-user BCI system. Riccardo et al. [8] subsequently explored the advantages of using an off-line collaborative BCI in a simple visual matching and a decision-making task. The g.tec company also demonstrated a collaborative P300 speller [9]. These studies suggested that combining brain activity of multiple users preforming the same task might improve the overall BCI performance, compared to individual BCIs, and lead to extended applications of BCIs.

Here, this study presents the design and implementation of a truly online collaborative BCI for improving individuals' decision-making performance in a visual Go/NoGo task. To the best of our knowledge, this is the first demonstration of a single-trial EEG-based group decision making using an online collaborative BCI. To further explore the advantages of using the collective BCI system, this study also evaluates its performance under the tasks with different difficulty levels with an offline analysis.

2 Material and Methods

2.1 Subjects

Thirty-six (aged 19 to 28 years, mean age 23, 8 females) healthy university students from Tsinghua University participated in this study. They were divided into six groups (six participants in each group).

2.2 Experimental Setup and Paradigm

As illustrated in Fig. 1, the collaborative BCI system comprises six 16-channel EEG amplifiers synchronized by trigger signals from a server computer, which was also used for stimulus presentation and data analysis. A Media-Key multimedia teaching

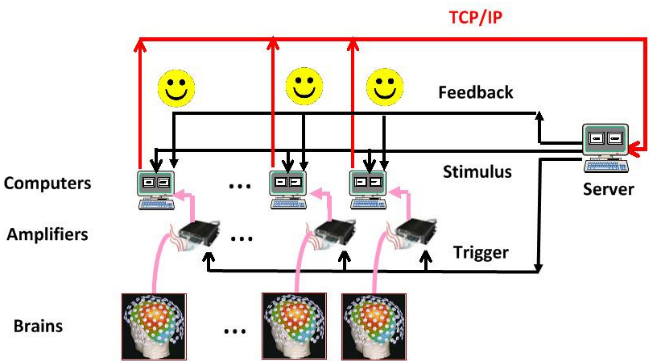

Fig. 1. Experimental setup of the collaborative BCI system

system delivered the stimulus to six LCD monitors (one in front of each subject) simultaneously. EEG data from each subject were sent to a computer via TCP/IP for real-time analysis.

The subjects were seated comfortably in armchairs at a distance of 80 cm from the monitor. During the experiment, a series of images including face images (Go tasks) and car images (NoGo tasks) were presented to the subjects. The subjects were instructed to press a button as quickly as possible when they recognized a face image, otherwise withhold the response. Once the button was pressed, an electrical event signal would be sent to the trigger channel of the amplifier and would be recorded in the software running on the computer. Sixteen-channel EEG data were collected by a standard EEG system. Electroldes were placed according to a standard international 10-20 montage at Fz, F3, F4, Cz, C3, C4, Pz, T5, T6, Oz, Fpz, F7, F8, P3, P4, POz, with a left-mastoid reference. The sampling rate was 1000 Hz.

The experiment comprised an offline training stage and an online test stage. The offline sessions were used to collect pilot data to train the classifiers, while the online sessions were used to evaluate the performance of the proposed collaborative BCI system. In the offline sessions, different difficulty levels were implemented to evaluate the performance of the collaborative BCI in decision-making under different situations. The difficulty level of the task was controlled by varying the phase coherence of the Go and NoGo images (45%, 35%, and 30%, difficulty level from low to high). The images of six conditions were equally and randomly distributed during the experiment. In the online experiments, for simplicity, only the images with the phase coherence value of 45% were used.

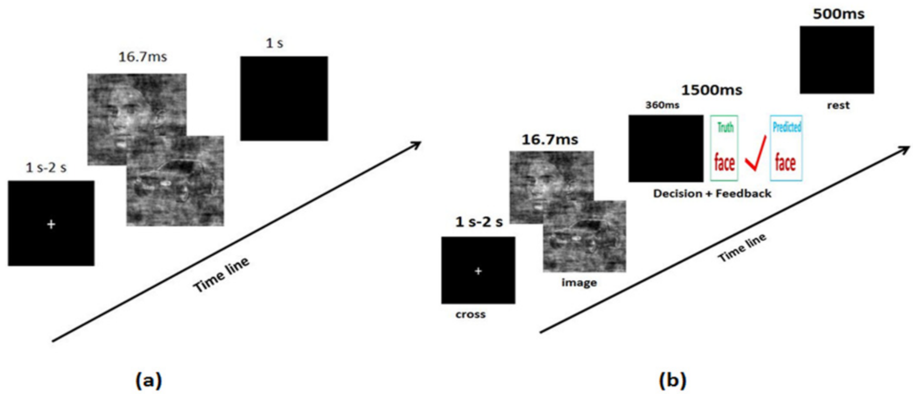

Fig. 2. Experiment diagram of (a) offline experiment and (b) online experiment

As illustrated in Fig. 2 (a), in the offline experiments, at the beginning of each trial, a fixation cross was presented at the center of the screen for a random duration from 1 to 2 seconds, followed by an image (about 16.5×16.5 cm) presented for 16.7 milliseconds (the period of one rendered frame). Following the image presentation, there was a one-second period for the subjects to make decisions and motor responses before the next trial started. Fig. 2 (b) illustrated the diagram of the online experiments. Compared to the offline experiments, the multi-channel (Fz, F3, F4, Cz, C3, C4, Pz, T5, T6) EEG data within the first 360 ms following stimulus presentation were used to predict the upcoming decision. After classification, visual feedbacks (presented and predicted image types) were presented on the screens. This decision and feedback stage lasted 1500 ms followed by a rest period of 500 ms.

The training stage consisted of five blocks of 120 trials each, resulting in a total of 600 trials. Of them, 200 trials at the phase coherence value of 45 were used to train the classifiers. The trained classifiers were applied to the online testing session consisting of a block of 120 trials (60 images of cars and 60 images of faces).

2.3 Data Analysis

Behavior Data

In order to evaluate the general behavior performance of the subjects, this study calculated the averaged motor response time and accuracies across all the subjects during the tasks with different difficulty levels.

EEG Data

In the offline analysis, EEG data were first downsampled to 200 Hz and then band-pass (1-40 Hz) filtered using the eegfilt function in EEGLAB [10]. To validate the collected EEG data, the data were first re-referenced to the common average reference (CAR), time-locked to stimulus onsets and averaged across trials and subjects to obtain grand averaged event-related potentials (ERPs). This study then used a machine-learning classifier to predict the Go/NoGo decision based on single-trial ERPs following stimulus presentation. To estimate the performance of the system, 5-fold cross validations were used to evaluate the prediction accuracies during the task with phase coherence value of 45%. Specifically, this study calculated the accuracies of the individual and collaborative single-trial EEG classification (Go vs. NoGo) of the six groups of people with different time window lengths (from 150 ms to 250 ms with an interval of 20 ms, and from 250 ms to 400 ms with an interval of 50 ms). As illustrated in Fig. 3, after band-pass filtering, the signal-to-noise ratio maximizer (SIM) algorithm [11] was used to extract each subject's ERP components from multi-channel EEGs through spatial filtering. The first three ERP components of each condition were selected as features for classification. A two-layer support vector machine (SVM) classifier was then applied to predict the Go/NoGo decision. The feature vector constituted by the outputs (the probability of the trial to be a Go task) of the first-layer classifiers for all subjects was forwarded into the second-layer classifier to make the group decision. The program was implemented using the LIBSVM toolbox [12].

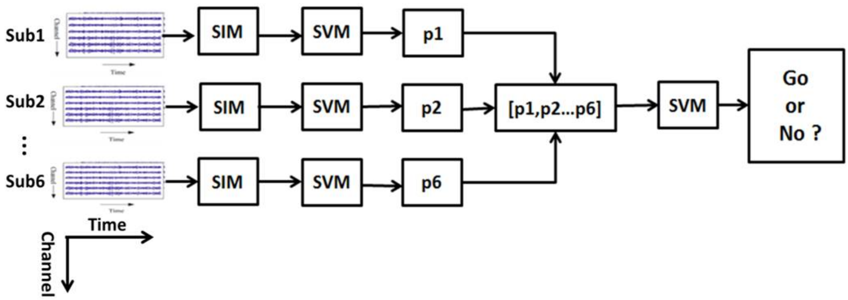

Fig. 3. Diagram of feature extraction and classification in the collaborative BCI system

It is also of great interest to see the potential of the collaborative BCI for making a group decision under the situations with high difficulties. To this end, in the offline analysis, 5-fold cross validations were used to estimate the accuracies under the tasks with phase coherence value of 35% and 30%. However, as the available samples of Go and NoGo conditions for each subject were limited and unbalanced according to behavioral performance (cf. Fig. 4(b)), we found that the individuals' single-trial EEG classification accuracy was close to the chance level in these situations. To improve the SNR of single-trial ERPs, we alternatively first averaged the signals across all the subjects participated in the experiment (hence, the group size was 36). The resultant cross-subject averaged ERPs were forwarded to the SIM algorithm to derive spatial filters and then classified by the SVM.

In the online experiments, the signals of each trial were resampled at 200 Hz, and digitally filtered at 1-30 Hz with a twentieth-order causal filter. The feature extraction and classification methods illustrated in Fig. 3 were subsequently applied for prediction. The length of time window used for real-time data analysis was set to 360 ms.

3 Results

3.1 Behavior Results

Fig. 4 (a) shows that subjects' response time increased as the task difficulty level increased. The response times were 409±85 ms, 461±113 ms, and 470±113 ms at the phase coherence of 45%, 35%, and 30%, respectively.

Fig. 4 (b) shows that subjects' detection accuracies decreased when the phase coherence value decreased (92±1.5%, 74±3.8%, 64±3.5% corresponding to phase coherence values of 45%, 35%, and 30%). This phenomenon was more pronounced in the Go trials (decreasing from 96±2.0% to 63±6.7%, and 41±6.0%). It may suggest that the subjects tend to response very cautiously during the experiments, preferring holding the button rather than making a response.

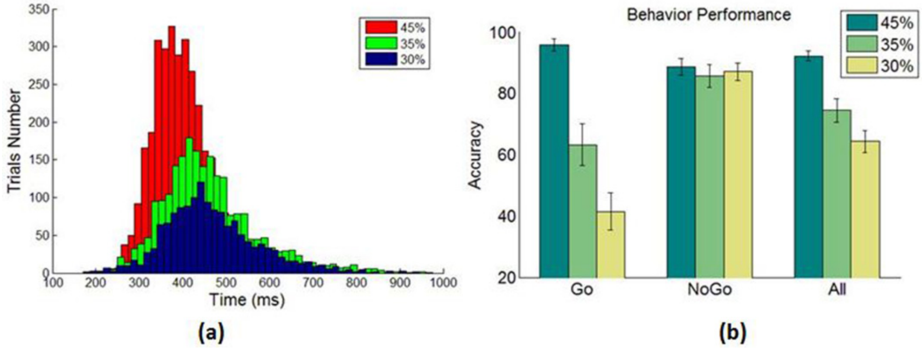

Fig. 4. (a) The distributions of response time of correctly responded Go trials with different difficulty levels. (b) Behavior accuracies of different tasks. Go, NoGo and All denote the Go (face) trials, NoGo (car) trials and overall (Go and NoGo) trials respectively.

3.2 Offline Results

Grand Averaged ERP

Fig. 5 (b) shows the robust ERP components evoked by Go (face N170 at T6) and NoGo (larger N2 and P3 at Fz) trials. The difference waves were very pronounced at several scalp channels (see Fig. 5 (a)). Thus, it could be inferred that the components contributing most to the classification were the face-specific N170 component in the Go condition, and the larger N2 and P3 components in the NoGo condition.

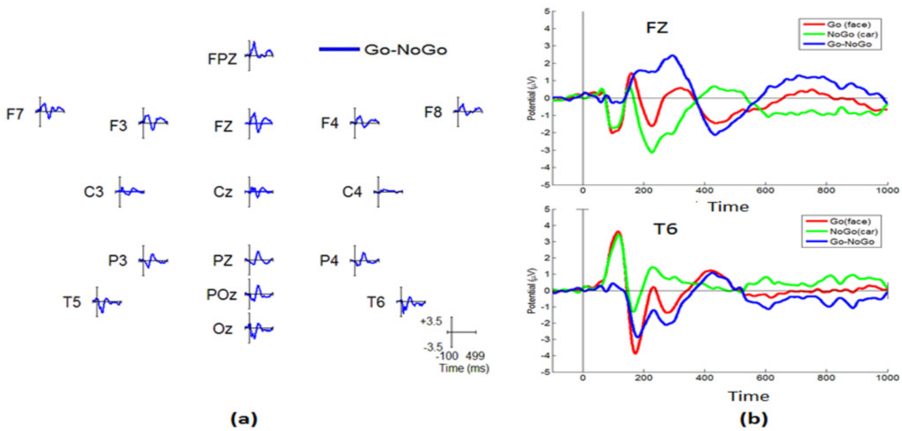

Fig. 5. Grand averaged ERPs for the task with the phase coherence value of 45%. (a) multi-channel difference waves (Go - NoGo). (b) ERP and the difference wave in Go and NoGo trials at channel Fz (top) and T6 (bottom).

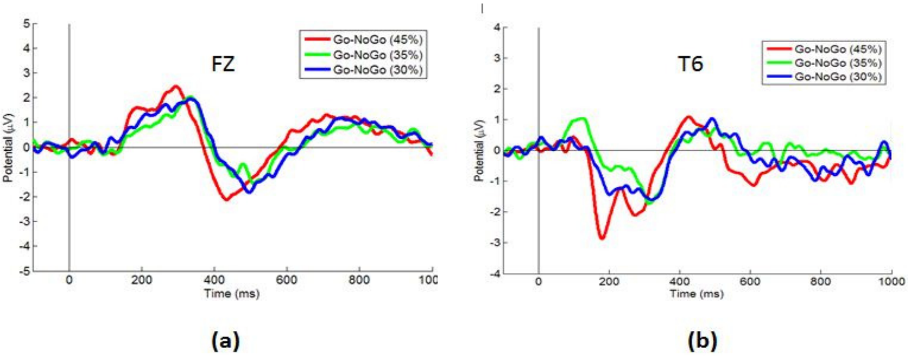

Fig. 6. Difference waves (Go- NoGo) under different difficulty levels at (a) Fz and (b) T6. The red, green and blue colors represent coherence values of 45%, 35% and 30% respectively.

Fig. 6 shows the difference waves between Go and NoGo conditions under different difficulty levels at channels Fz and T6. Intuitively, it seemed that as task difficulty increased, the amplitude of the difference wave decreased, while the latency of the difference wave increased. These response variabilities would make the EEG-based classification more difficult.

Single-Trial EEG Classification

Fig. 7 shows that the system's classification accuracy increased monotonously with the length of time window. It is also evident that the collaborative paradigm outperformed the mean of the individuals and the best individual in the group. The classification accuracy of the system could reach about 80% with a time window length of ~350 ms.

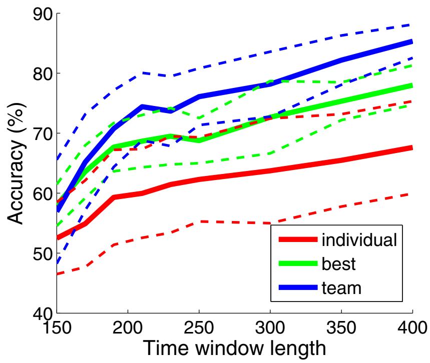

Fig. 7. Single-trial EEG classification accuracies as a function of time window length at the phase coherence value of 45% across all the six groups

Fig. 8 shows the single-trial EEG classification accuracies as a function of the length of time window at the phase coherence value of 35% and 30%, when all the 36 subjects were included in a group for calculation. Using the EEG from first 350 ms, the accuracy was 71.0% and 65.5% at the phase coherence values of 35% and 30%, respectively. These results were comparable to the individuals' behavioral results (74.0±3.8% and 64.0±3.5% at the phase coherence values of 35% and 30%, cf. Fig. 4(b)). To be noticed, in the Go condition, the average response time was 461 ms and 470 ms when the phase coherence values were 35% and 30%, respectively.

These results suggested that even under very difficult decision-making situations, when the subjects failed to make an accurate and quick decision, the collaborative BCI have the potential to improve individuals' decision speed with comparable accuracy.

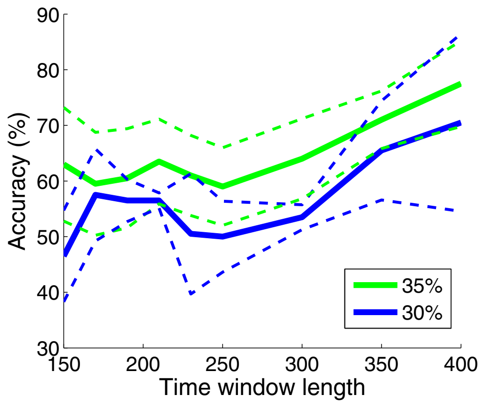

Fig. 8. Single-trial EEG classification accuracies as the function of time window length at the phase coherence value of 35% and 30% respectively

3.3 Online BCI Performance

Table 1 lists the performance of the online collaborative BCI. Consistent with the offline analysis, the online test showed that the prediction accuracy of the collaborative classification was significantly enhanced over that of the individual classification. Using EEG within the first 360 ms after the stimulus onset, which was 50 ms earlier than the mean behavioral response time (409±85 ms), the collaborative BCI reached a mean classification accuracy of 78.0±2.6% (range: 75%-82%) across all groups. It was 12.9% higher than the average individual accuracy (65.0±8.1%, $p<10^{-4}$), and 3.3% higher than the best individual accuracy (74.7±4.2%, p<0.1). These results suggest that a collaborative BCI could accelerate human decision making with reliable prediction accuracy in real time.

Table 1. Accuracy of the online collaborative BCI (%)

Group#	Sub #1	Sub #2	Sub #3	Sub #4	Sub #5	Sub #6	Team
1	63	68	51	61	63	58	76
2	62	73	68	66	52	68	82
3	79	73	74	65	72	65	80
4	79	77	56	53	64	59	75
5	73	58	58	73	58	63	77
6	63	48	68	73	76	65	78

4 Conclusion and Discussions

This study presented the design and implementation of an online collaborative BCI for improving individuals' decision making in a visual Go/NoGo task. The performances of the collaborative BCI during the tasks with different difficulty levels were also evaluated. The offline results suggested that even in the difficult decision-making situations, where the subjects were difficult to make quick and accurate decisions, the collaborative BCI can still have the potential to improve individuals' decision speed with comparable accuracy. In summary, the collaborative BCI technology provides an efficient way for achieving collective intelligence from brain activities of multiple subjects.

The proposed BCI system does have some limitations. First, the data transmission and analysis of the system was implemented in a centralized fashion. Too much data transmission and computation would affect the speed and performance of the system. In the online experiments, we found that the data transfer speed varied across trials, bringing some delays in the feedback presentation. To alleviate this problem, a distributed framework, which involves less data transmission and performs data computation in a distributed fashion, may be a good choice. Furthermore, more efficient multi-brain computing methods are also of great importance to improve the system performance. The collaborative filtering and transfer learning may be promising along this direction [13].

The proposed paradigm may also have potential in reducing errors in impulsive decision making of a group within chaotic and data-poor environments. In addition to BCI applications, the proposed framework might have potential for EEG-based group brain imaging of social processes and behavior.

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