Toward Multi-brain Communication: Collaborative Spelling with a P300 BCI

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Abstract. In a brain-computer interface (BCI), users perform specific mental tasks to convey messages or commands through direct measures of brain activity. Typically, users must perform each mental task for two or more seconds before their brain activity is distinct enough for accurate classification. In P300 BCIs, this usually entails silently counting specific flashes three or more times. Although numerous articles have explored the prospect of a P300 BCI that relies on only one flash, results consistently show that the resulting accuracy would be too low for effective communication. The goal of this article was to introduce a new way to reduce the time to identify a message or command. Instead of relying on brain activity from one subject, our system utilized brain activity from eight subjects performing a single trial. Hence, the system could rely on an average based on eight trials, which is more than sufficient for adequate classification, even though each subject contributed only one trial. Results confirmed that all eight subjects could not have attained effective control with a single trial, but could attain 100% accuracy when the other seven subjects' data were also used. This is the first time that people worked together to accomplish a goal with a BCI, and could encourage future research into collaborative brain-based communication and control.

Keywords: brain-computer interface (BCI), brain-machine interface (BMI), multi-brain computing, multi-brain gaming, EEG, ERP, P300, spelling.

1 Introduction

Brain-computer interfaces (BCIs) translate direct measures of brain activity to command and control signals. Typically users perform or repeat a task for one or more seconds to generate distinct patterns of brain activity which can then be utilized for output control. For example, in BCIs that rely on event-related desynchronization

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(ERD) and/or steady-state visual evoked potentials (SSVEP), users imagine specific movements or focus on the same visual target for two or more seconds [11], [14], [20]. In P300 BCIs, users have to follow a mental count strategy for the same flash three or more times [6], [8-9], [11], [19], [21].

The only reason subjects must spend some time to perform a task is to provide sufficient information for accurate classification. In principle, subjects do not need such long periods to generate mental activation patterns, such as developing motor imagery or detecting specific targets. In other words, BCIs could be substantially faster, if shorter periods of time could allow accurate classification.

Reducing the number of flashes, but still keeping accurate classification, has been a prevalent topic in the P300 BCI literature since the first P300 BCI [5]. P300 BCI articles often report the actual or estimated classification accuracy with only one or more trials, partly to foster consideration of single-trial BCIs [5], [11], [19]. To our knowledge there have never been any articles, or even conference posters or talks that demonstrated an effective noninvasive single-trial P300 BCI. The "variable averaging" approach, in which the BCI only presents new trials until a desired classification accuracy has been reached, indicated that multiple trials are necessary for accurate classification [2], [10], [11], [19]. Single trial P300 classification may be feasible with an invasive BCI [4], but invasive systems entail neurosurgery, which greatly limits possible user groups. Among noninvasive BCIs, only one article highlighted a P300 BCI based on single trials, claiming the fastest BCI in the literature [15]. However, this feat entailed accuracy below 50%, which could not allow effective communication, and thus cannot be regarded as a successful single-trial BCI [3], [18]. In summary, there have not been any papers that reported effective communication with a single trial noninvasive P300 BCI, despite extensive effort.

The primary goal of the present study was to introduce a new approach to a single-trial P300 BCI. Eight subjects tried to spell the same letters, and the corresponding eight single trials from all subjects were processed together to explore a possible cooperative BCI. We also compared the accuracy in a cooperative BCI to the estimated accuracy for each subject in a conventional "solo" mode.

2 Methods

2.1 Experimental Procedure

Eight subjects (1female, age: 28.75±4.9 years) participated in the study. All subjects were free of medication, had normal vision or vision corrected to normal, and no history of central nervous system abnormalities. All subjects provided informed consent before participating in the study. Subjects were prepared for recording with eight recording sites as shown in Figure 1. A reference electrode was placed over the right earlobe, and the ground electrode was placed over electrode position Fpz.

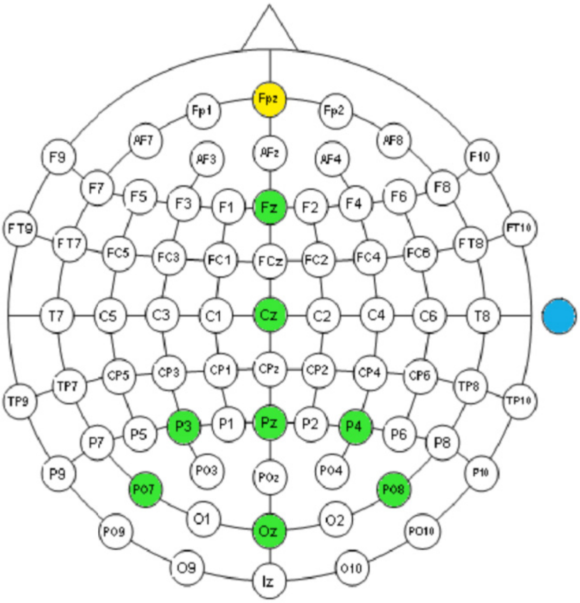

Fig. 1. Each subject used the same locations on the scalp for the recorded sites. Signal channels are highlighted in green (Fz, Cz, P3, Pz, P4, PO7, Oz and PO8), the GND channel is represented by the yellow highlighted Fpz and the REF position is shown in blue located on the right earlobe.

Figure 2 shows the eight subjects in this study. Subjects sat together in a room and were instructed to relax and remain as still as possible.

Fig. 2. The eight subjects were placed in front of a wall showing a projected screen

All subjects viewed the same display on a projector screen, which showed the intendiX (g.tec medical engineering GmbH, Austria) row/column (RC) spelling matrix shown in Figure 3. The matrix contained 36 characters (the 26 letters of the English alphabet, numbers from 0 to 9).

Fig. 3. The speller matrix consists of six rows and six columns leading to 36 characters in total

All eight subjects participated in a training run, followed by an online spelling run, at the same time as the other subjects. Subjects were asked to train the intendiX classifier by spelling the phrase “MERRYXMAS” in an offline mode without feedback to calibrate the system. After training, the intendiX system automatically determined weight vectors for each subject to maximize accuracy.

The subjects viewed the same display and instructions during the training and online spelling runs. At the beginning of each trial, the target letter was highlighted for four seconds, so the subjects could identify the target. Then system started flashing a randomly selected column or row for 100 ms, followed by a 60 ms break before a different row or column was highlighted. Each row and column was highlighted 15 times for each letter. Therefore, one run had 30 flashes for each target character, leading to 270 target trials in total.

2.2 Hardware and Software

Figure 1 shows the electrode configuration and the electrode locations used for the study. EEG recordings were based on the active EEG electrode system g.GAMMAsys equipped with Ag/AgCl g.LADYbird electrodes. The electrodes were fixed to an EEG electrode cap (g.GAMMAcap2) according to the extended international 10/20 electrode system.

EEG data were acquired using four daisy chained and synchronized g.USBamps (24 Bit bio-signal amplification unit, g.tec medical engineering GmbH, Austria) with a sampling frequency of 256 Hz. The EEG signals were then converted to double precision, band-pass filtered between 0.1 and 30 Hz, and then down-sampled to 64 Hz. Figure 4 presents a schematic overview of the system used in this study.

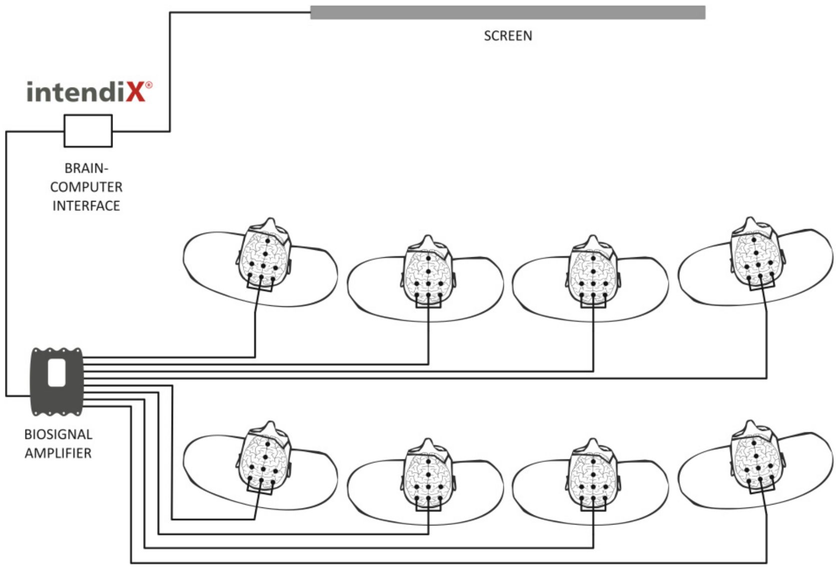

Fig. 4. Schematic overview of the system

3 Results

Figure 5 presents the event-related potentials (ERPs) elicited by target flashes during the online spelling run. Each row presents data from a different subject, and each column reflects a different electrode channel. Each cell reflects averaged data from 270 target flashes. The x-axis represents time in seconds (the vertical red line indicates the flash onset), and the y-axis presents the voltage in microvolts. For baseline correction a pre-trigger interval of 100 ms before flash onset for a baseline correction was used.

Each subject's ERP data were subsequently used to estimate the accuracy if that subject spelled without including other subjects' data. Figure 6 presents the combined accuracy for all subjects, as well as the accuracy for each individual subject. The best subject would have attained 100% accuracy with averages of two or more trials, whereas all subjects together achieve 100% even after one trial.

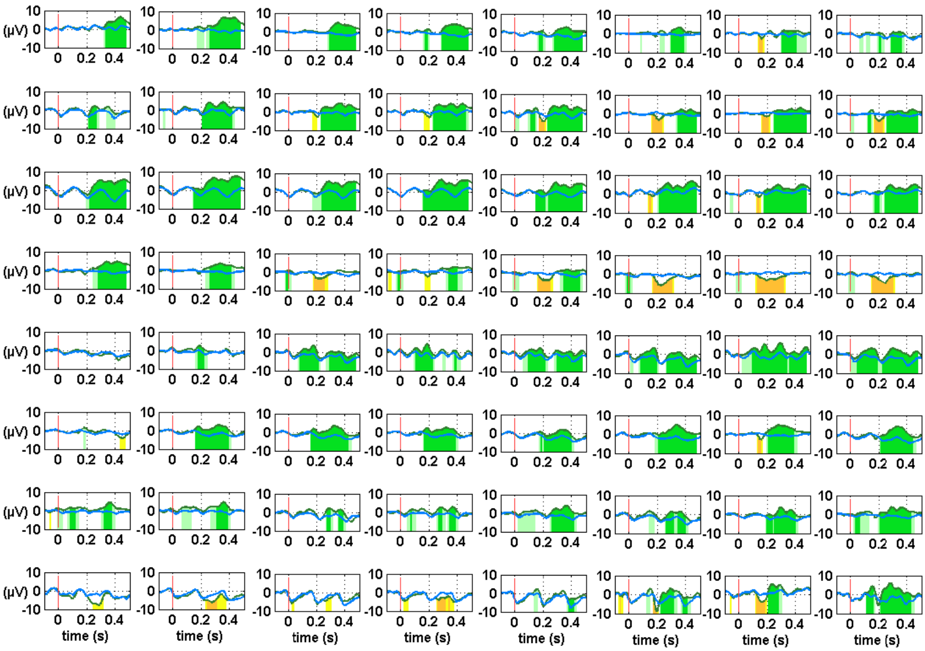

Fig. 5. The boxes contain averaged target trials (green line) and non-target trials (blue line) for each subject and channel. The red line indicates the flash onset. Each row contains all eight channels from an individual subject. The green/yellow areas highlight significant positive/negative differences of a target trial compared to a non-target trial.

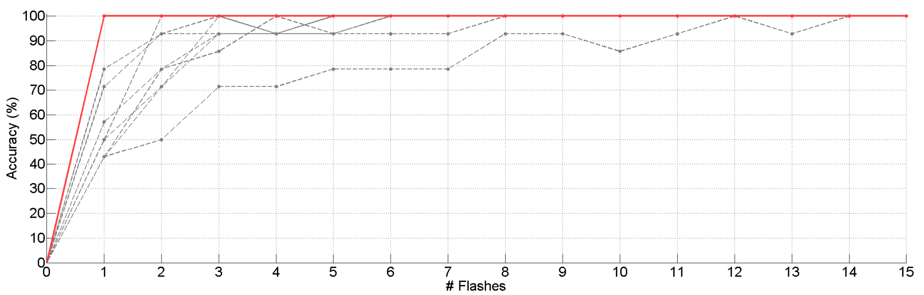

Fig. 6. The accuracy for each individual subject is presented by grey dotted lines. The solid red line shows the overall accuracy with combined data from eight subjects.

4 Discussion

The results confirmed that an individual subject using a BCI could accomplish a goal more quickly than otherwise possible by incorporating data from different subjects performing the same task. None of the subjects could spell effectively with a conventional single-trial BCI. However, using data from the other seven subjects could increase accuracy to 100%.

To our knowledge, this is the first time that people worked together to accomplish the same goal with a BCI. It is not the first time that a BCI was designed to consider activity from more than one user. For example, some groups have demonstrated BCIs or related systems for competitive games that involve pong, bluffing, or competitive relaxation. These systems are specifically designed to use brain activity from two users. More generally, several groups have described BCIs or related systems that allow individuals to control games, which could be used to play with or against other people using a BCI or another interface [13], [16-17].

Whether this article constitutes the first effective single-trial BCI is a matter of semantics. From each user's perspective, only one trial was needed. Overall, eight trials were needed, and thus a practical noninvasive P300 BCI based on only one trial from one user has yet to be demonstrated. Such a BCI may be feasible in the near future due to innovative new paradigms that can enhance the P300 complex and might lead to more accurate classification with less data [1], [7], [11-12], [19].

The main significance of this work is as a milestone in BCI research, rather than an immediately applicable technology. There are few practical situations in which eight people would work together to spell the same word with a BCI instead of other means of communication. However, the work in this paper, or other cooperative BCI efforts, could be appeal to users for fun or novelty. Also, now that multi-brain computing has been validated, further efforts could explore other tasks in which people could work together through BCIs or related technologies.

The multi-brain computing approach could also be adapted for voting or other potentially competitive situations, in which users each express a message or command that may differ from other users' messages or commands. For example, in the popular online game Star Wars: The Old Republic, users sometimes vote on key decisions during quests. Users might vote via BCIs, and a decision would be based on the largest number of votes (perhaps weighted by the strength of the voters' EEG).

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