Towards a Hybrid P300-Based BCI Using Simultaneous fNIR and EEG

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Abstract. Next generation brain computer interfaces (BCI) are expected to provide robust and continuous control mechanism. In this study, we assessed integration of optical brain imaging (fNIR: functional near infrared spectroscopy) to a P300-BCI for improving BCI usability by monitoring cognitive workload and performance. fNIR is a safe and wearable neuroimaging modality that tracks cortical hemodynamics in response to sensory, motor, or cognitive activation. Eight volunteers participated in the study where simultaneous EEG and 16 optode fNIR from anterior prefrontal cortex were recorded while participants engaged with the P300-BCI for spatial navigation. The results showed a significant response in fNIR signals during high, medium and low performance indicating a positive correlation between prefrontal oxygenation changes and BCI performance. This preliminary study provided evidence that the performance of P300-BCI can be monitored by fNIR which in turn can help improve the robustness of the BCI classification.

Keywords: BCI, P300, fNIR, Performance, Optical brain imaging, EEG.

1 Introduction

A brain-computer interface (BCI) decodes neurophysiological signals from the brain for direct controlling an external device without the brain's normal communication pathway of peripheral nerves and muscles. Electroencephalography (EEG) is by far the most studied technology for non-invasive BCI signal acquisition [1-3]. Apart from EEG, variant types of signal acquisition methods such as Magnetoencephalography (MEG) [4], functional near-infrared spectroscopy (fNIR) [5-9] and functional magnetic resonance imaging (fMRI) [10, 11] has been proposed to be applied in BCI. More recently, several studies showed that utilizing multimodal neuroimaging has the potential to enhance BCI performance [12-16]. These BCIs were generally referred to as hybrid BCIs in the literature.

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In this pilot study, our aim was to investigate combining fNIR and EEG for enhancing a P300 based BCI. P300 is an event-related potential usually elicited by the oddball paradigm. A typical P300-BCI show to the user sequences of stimulus and the user's task is to identify the infrequent occurrence of the target stimulus. Since early works of Farwell and Donchin in the 1980s [2], substantional progress has been made for enhancing the capability of the P300-BCI [See Mak and McFarland [17] for a detail review]. Despite the volume and depth of work conducted in this area, to our best knowledge, to date no study has been done to investigate the possible benefit of combining fNIR and EEG in a P300-BCI.

fNIR is an optical brain imaging technology for monitoring the changes in the concentration of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) in the cortex. Typically, neuronal activities in the active area of the cortex would eventually cause an overabundance of local blood oxygenation result from a mechanism known as neurovascular coupling [18]. Coyle et al in 2004 proposed using a single channel NIR for developing a mind-switch [5]. Sitaram et al [6] demonstrated multichannel optical BCI for hemodynamic pattern classification for motor imagery. Ayaz et al in 2007 proposed using fNIR cognitive tasks for on/off switch [7] while Fazli et al in 2012 showed that combining EEG and NIR can significantly improve motor imagery BCI [19]. The same group also showed that fNIR can serve as a predictor for the performance of EEG-based motor imagery BCI [20].

Recently, several studies investigated predicting the between-subject performance (or aptitude) of P300-BCI [21, 22] based on EEG predictors. In [21], the within-subject effects were also investigated but no significant predictors were found. Predicting the within-subject performance is of particular interest because it may provide information for generating more robust BCI classifiers. In [20], fNIR predicted motor imagery BCI performance was used for generating a meta-classifier which enhanced classification accuracy. In this study, we propose using a prefrontal cortex based fNIR for monitoring within-subject performance of a P300-BCI. It has been established in fMRI studies that the BOLD signal is associated with varies event-related tasks [23-25]. Previous work also suggested that the prefrontal cortex is associated with the level of alertness and attention [26-28] which can affect BCI performance. A fNIR study by our group showed that prefrontal activations were correlated with the performance of an n-back task [29]. The aforementioned evidence suggests a possible correlation between prefrontal activation and P300-BCI performance. For testing the hypothesis, prefrontal fNIR was recorded while subjects were using a spatial navigation P300-BCI that we proposed previously [30, 31]. Our preliminary results show that the subject-wise performance of P300-BCI may be monitored by prefrontal fNIR recording.

2 Materials and Methods

2.1 Participants

Eight right-handed healthy students from local universities participated in this study. The participants included 5 males, 3 females and ages between 22 to 26 years. All

participants did not have prior experience with BCI and gave written informed consent approved by the institutional review board of Drexel University for the experiment. The first three of the participants were excluded from the analysis due to technical issues such as missing synchronization markers or poor signal quality.

2.2 Experiment Setup

The experimental setup was based on a spatial navigation P300-BCI we proposed in [31]. Subjects sat conformably inside a faraday cage. There were two monitors: one was the stimulus presentation monitor placed approximately 30 inches in front of subject on a desk for displaying the P300 BCI matrix; the other was the environment monitor placed on the left hand side of the stimulus presentation monitor for displaying the 3D virtual maze using MazeSuite software [32, 33] (Drexel University). EEG was recorded using Neuroscan Nuamp amplifier and 32 channel EEG cap at 250Hz sampling rate from 9 locations according to 10-20 international system: FCz, Cz, CP3, CPz, CP4, P3, Pz, P4, and Oz. The BCI2000 platform [34] was used for stimuli display and EEG data recording. For online and offline signal processing, MATLAB was used. Prefrontal cortex hemodynamic response was recorded using a16-channel continuous wave fNIR system developed at Drexel University [35] and manufactured by fNIR Device LLC. The sampling rate for fNIR was 2Hz. The COBI Studio Software [32] (Drexel University), which was installed on another desktop, was used for fNIR data recording. Triggers were sent from BCI2000 P3Speller application module to COBI Studio using a serial port periodically for synchronizing the two data streams for offline analysis. Fig.1 shows an overview of the experimental setup.

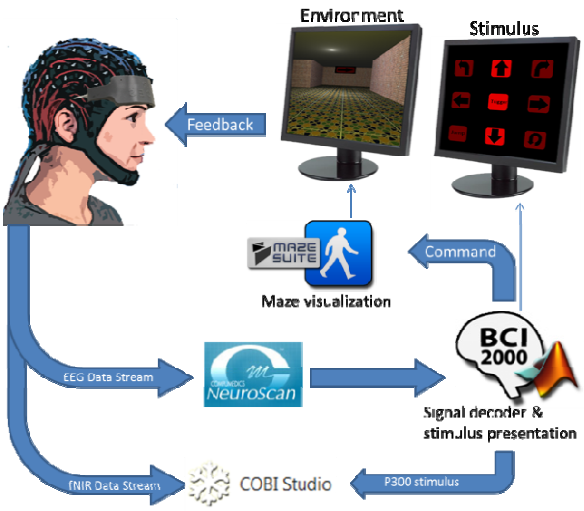

Fig. 1. Experiment setup overview

2.3 Protocol

The visual presentation of P300-BCI included a 3 by 3 matrix of spatial navigation icons (turn left, move forward, turn right, strafe left, trigger, strafe right, jump, move backward and look around, see Fig. 2 Left). During stimulus presentation, row and columns of the matrix were intensified in pseudo random order. The stimulus duration was 80ms and the inter-stimulus interval (ISI) was 160ms. A *sequence* of stimulus included six stimuli – each row and column was intensified exactly once. A *run* included ten sequences at the end of which a command would be outputted from the BCI to the maze.

The experiment included two parts: Part 1 and Part 2. Part 1 was for collecting EEG data in order to calibrate the P300-BCI. It included 24 runs. Before the start of a run, visual instruction was given to the subjects indicating which icon they should attempt to choose by counting the number of times it flashed. For each run, after the end of stimulus presentation, a keyboard with 10 buttons was shown for the subjects to manually record the icon they attempted to choose through activation of the BCI(see Fig. 2 right).

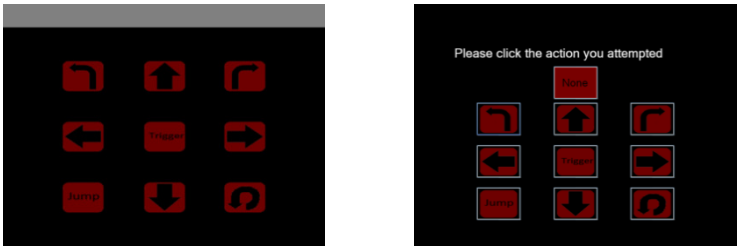

Fig. 2. Left: The 3×3 P300 BCI matrix used in this study. Right: Keyboard shown to the subject.

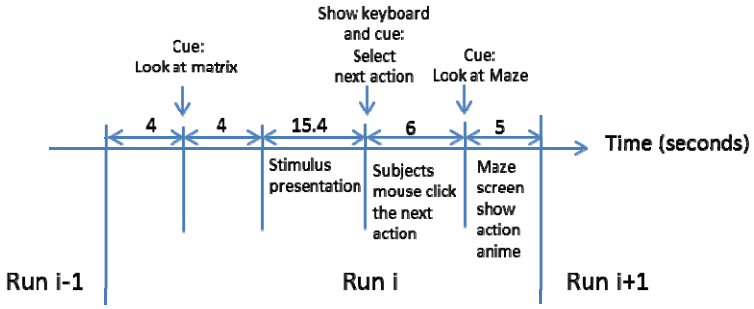

Fig. 3. Time line for a run

Part 2 was for the subjects to navigate freely in 3D virtual mazes using the BCI. Each subject navigated a small mirror maze eight times with possibly different starting points. Fig. 3 shows the timeline of a run in Part 2. The subjects started by looking at the maze screen to decide their next action. A cue 'Look at matrix' would then show on the maze screen asked the subjects to turn their attention to the stimulus

presentation screen. After that, the 10 sequences of stimulus for generating P300 response would be shown at the end of which a keyboard (see Fig. 2. right) was displayed on the same screen for the subjects to record their intended actions in this run. Finally, a cue would show to let the subjects turn their attention back to the maze screen in order to see the maze action animation such as moving forward corresponding to the command output by the BCI.

2.4 Data Processing and Analysis

P300 BCI Classification. Raw EEGs were band pass filtered from 0.5 to 12 Hz and downsampled to 36 Hz. A stepwise linear discriminant analysis (SWLDA) was applied to distinguish target from non-target stimulus based on the EEG amplitudes from 0 to 800ms after the onset of a stimuli. The data collected in Part 1 was used to determine the weights for the classifiers which were then applied to predict the data collected in Part 2.

Performance Criterion for P300 BCI. The performance criterion adopted was the single sequence prediction accuracy (*SeqAcc*) for each run. Target icons were first predicted using the EEG data of each single sequence (note that for a single sequence, each row and column intensified only once). The prediction accuracies for each run were then calculated. Since each run included 10 sequences, this is an ordinal variable with 11 levels of measurement (i.e. from 0 to 1 with 0.1 increments). This criterion gives a finer resolution of the performance and reduced the ceiling effect compared to a simple dichotomous variable indicating whether or not the target of the run has been correctly predicted. Table 1 shows the average and standard deviation of *SeqAcc* for each subject. It can be seen that for subject 4 and 7, their target icon prediction accuracy was the same 100% but *SeqAcc* revealed that the signal quality for subject 7 (*SeqAcc*=0.88±0.12) was much better then subject 4 (*SeqAcc*=0.48±0.19).

fNIR Processing. fNIR signals were first low-pass filtered at 0.1Hz. An automatic artifact detection algorithm, sliding window motion artifact rejection (smar) was employed for eliminating saturation and motion artifact containing segments [35, 36]. Oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) changes were calculated for each P300-BCI run from 0-15s using a local rest period as baseline. To further reduce noise, spatial averaging was performed for both left and right hemisphere separately by averaging the channels located at the left and right hemisphere respectively.

3 Results

P300-BCI Classification. Table 1 listed the sample sizes, target icon prediction accuracy and *SeqAcc* in Part 2 for each subject. Raw sample sizes are different for each subject due to possibly different paths taken during maze navigation, the additional number of runs required for correcting the BCI mistakes and the ratio of rejected run.

Table 1. Sample sizes, target icon prediction accuracy and the Avg. and Std. of *SeqAcc* for each participant

Subject	4	5	6	7	8
Run #	34	81	49	16	58
Accuracy	1.00	0.89	0.78	1.00	0.86
SeqAcc Mean±SD%	0.48±0.19	0.44±0.18	0.38±0.16	0.88±0.12	0.42±0.20

fNIR Results. Fig. 4 shows the grand average fNIR responses for low performance runs and high performance runs during P300 matrix stimulus presentation periods. Each P300 BCI run was categorized into either the low performance group or high performance group subject-wise according to the following criterion:

$$G_{ij} = \begin{cases} High, & if\ S_{ij} > \tilde{S}_i \\ Low, & if\ S_{ij} \le \tilde{S}_i \end{cases} \quad \begin{matrix} i = 4,5,6,7,8 \\ j = 1,2,\dots,n_j \end{matrix}$$

Where S_{ij} is the *SeqAcc* for run j of subject i. $\tilde{S}_i$ is the median *SeqAcc* for subject i. n_j is the number of run for subject i.

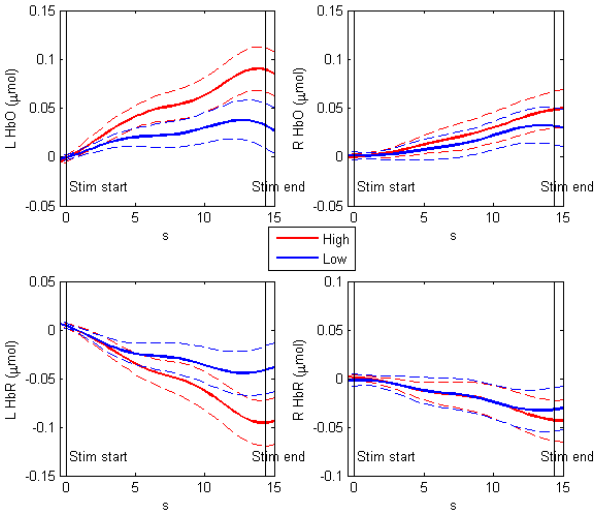

Fig. 4. Grand average fNIR for high performance and low performance runs. The left and right figures show HbO and HbR for left and right hemisphere, respectively. Dash lines stand for standard error of the mean (SEM).

It can be seen that for both left and right hemispheres, HbO was increasing and HbR was decreasing relative to the baseline, consistent with higher activation for prefrontal cortex during the BCI task period. However, for high performance runs, HbO increased (and HbR decreased) at a greater rate compared to low performance runs. Additionally, this phenomenon was more significant for left hemisphere.

Next, the effect of P300-BCI performance on the left hemisphere fNIR response was analyzed. The performances of each BCI run were first categorized into high, medium and low subject-wise according to following criteria:

$$G_{ij} = \begin{cases} High, & if\ S_{ij} > \tilde{S}_i + 0.1 \\ Medium, & otherwise \\ Low, & if\ S_{ij} < \tilde{S}_i - 0.1 \end{cases} \qquad \begin{matrix} j = 1,2,\dots,n_j \\ i = 4,5,6,7,8 \end{matrix}$$

Where $S_{ij}$is the *SeqAcc* for run j of subject i. n_j is the number of run for subject i. $\tilde{S}_i$ is the median *SeqAcc* for subject i.

The fNIR responses were normalized subject-wise before analysis. To reduce sample size, fNIR responses for every three seconds from 0 to 15s were averaged which gives an ordinal time variable with 5 levels. Linear mixed models revealed significant fixed effects of performance ($F_{(2,665.2)}$=7.856, p<0.001; $F_{(2,809.4)}$=10.484, p<0.001) and time ($F_{(4,737.0)}$=10.55, p<0.001; $F_{(4,736.0)}$=11.621, p<0.001) for left hemisphere HbO and HbR, respectively. Bonferroni *post hoc* pairwise comparisons revealed a significantly higher left HbR for low performance runs compared to medium and high performance runs. Conversely, low performance runs have lower left hemisphere HbO levels relative to the medium and high performance runs. Fig. 5 shows the grand average left hemisphere HbO and HbR for the three performance groups.

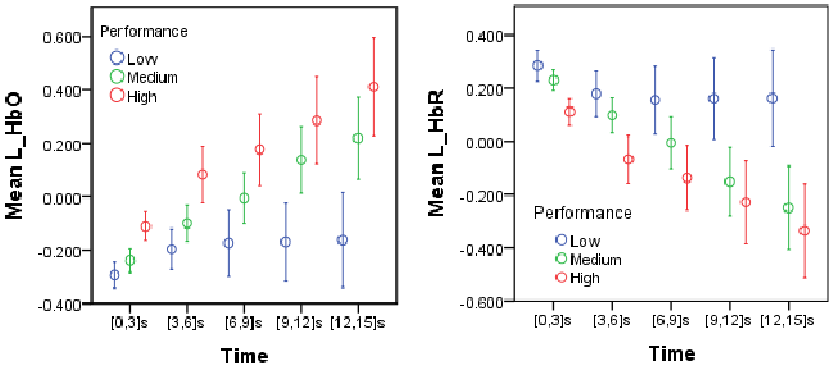

Fig. 5. Grand average left hemisphere HbO (left) and HbR (right) for low, medium and high performance P300-BCI runs. Error bar: standard error (SE).

4 Discussion

In this preliminary study, significant differences in prefrontal activations were found across three levels of within-subject P300-BCI performance. We showed that lower P300-BCI performance was associated with lower level of prefrontal activations, indicating a possible positive correlation between prefrontal activation and BCI performance. Interestingly, Halder et al. in 2011 [37] showed that the performance of a sensorimotor-rhythm BCI is positively correlated with the prefrontal activation. Generally, operating a BCI requires subjects to concentrate on the mental task. Prefrontal

areas, specifically the dorsolateral prefrontal cortex, are associated with attention [38, 39]. Hence, the differences in prefrontal activation across performance levels may be partly due to the different concentration levels during the task periods consistent with our previous results [35, 40].

Despite the encouraging results, more subjects and larger sample sizes are needed for validation. In addition, future studies would benefit from identification of low performance P300-BCI runs to inform a classifier which can help improve the robustness and usability of the BCI. An interesting question is whether some key P300-BCI features such as the amplitude and latency of the P3 and N2 components are correlated with the prefrontal activations. Being able to partially observe the change of these components across time may help adapting the covariate shift due to factors such as alertness and fatigue.

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