A Hybrid EOG-P300 BCI with Dual Monitors

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***Abstract*—P300 brain computer interface (BCI) is one of the most widely studied BCI paradigm. It detects the specific wave form, produced in response to task-relevant stimuli. In visual stimulus based P300 BCI system, the subjects select the target item by gazing at it. With regarding that the accompanying eye movements to change a gazing object can evoke the electrooculography (EOG) responses, P300-based BCI and EOG-based gaze tracking system can be beneficially integrated to improve the performance. Based on this idea, we investigate novel hybrid EOG-P300 BCI system with dual monitors. From the ordinary P300 interface, we split the menu items into dual monitors. The system analyzes EOG signals to find which monitor was focused by the subjects, then in the monitor, the P300 system identifies the item focused by the subjects. With reducing the number of items in a screen, we can reduce by almost half the time required to select a single item. To evaluate our hybrid P300 system, we computed classification accuracy and practical bit rate (PBR), and the system was compared with the conventional P300 system. The hybrid system scored classification accuracy of 80% and 0.5556 PBR. When we compared the hybrid BCI with the ordinary P300 BCI, the classification accuracies of the systems were almost same that is p-value between two groups of accuracies was estimated to be 0.3217 by one tailed t-test. In PBR, the hybrid BCI showed 70% higher PBR than the conventional P300 BCI. These evaluation results proved possibility of the hybrid BCI for practical use with high speed and reliability.**

***Keywords*—brain computer interface (BCI); electroencephalogram (EEG); electrooculogram (EOG); hybrid BCI; P300**

I. Introduction

Brain computer interface (BCI) is technology that directly links brain to an external device by translating the observed subject's intention or mind into the control command of the device without depending on peripheral nerves and muscles. BCI is very important for patients, suffering from various neuromuscular degenerative disorder, because they have much limited communication channels.

Among various brain imaging techniques, electroencephalogram (EEG) is broadly used for BCI [1], because of its useful characteristics (non-invasive measurement, relatively low price and high temporal resolution). Synchronization and desynchronization evoked by motor imagery [2], steady-state visually evoked potentials [3] and P300 event-related potential [4] are well known brain responses and are widely used in BCI researches.

P300 potential is a positive peak that is generated by an auditory, visual or somatosensory stimulus. In ordinary P300 BCI systems, the system recognizes the item, which is concentrated by a subject, by detecting the P300 potential evoked by the stimulus of the item. In general visual P300 BCI, a series of menu items are shown on a screen and they are randomly intensified. If the subjects focus to one item, then P300 is generated only when that item is intensified [5], [6]. By detecting the occurrence of P300, the system can discriminate whether the subjects focus to the item, or which item is focused by the subjects.

In ordinary P300 systems, limitation of low information transfer rate (ITR) was remaining as a drawback [7]. One simple solution of the problem is to increase the number of selectable items, which are shown on the interface. However, if we increase the number of items on a screen, more stimuli are needed to cover the additional items, further the response time of the system is also increased. Various P300 BCI studies have tried to reduce the response time and increase ITR, simultaneously, by using new experimental paradigms, for instance, the standard row/column paradigm [5], checkerboard paradigm [8], and half checkerboard paradigm [9].

In this paper, we present a novel hybrid BCI for the drawback. In 2010, G. Pfurtscheller *et al.* suggested the concept of hybrid BCI that is to exploit advantages of different approaches by combining the different approaches in a system [10]. In our approach, electrooculogram (EOG) system and P300 BCI system were combined in a hybrid system. EOG is generally used for eye movement detection by recording standing corneal-retinal potential [11]. With this EOG system, ordinary P300 paradigm, which uses single monitor, can be extended to new hybrid P300 paradigm that uses dual monitors. In our hybrid system, which adopts the new paradigm, a monitor gazed by subject was detected by EOG, and an item focused by subject was identified by P300 potential. By using dual monitors, we separated the menu items, shown on a screen in ordinary P300 BCI, into two groups, and each group was displayed at each screen. In this manner, the hybrid P300 system showed items of the half number in each screen than conventional P300 system. With this reduced number of items on individual screen, our hybrid system decreased the number of stimulus to the half. By this manner, Hybrid EOG-P300 BCI reduced running time and increase ITR. To evaluate our hybrid system, it is compared with conventional P300 system in classification accuracy and practical bit rate (PBR) [7]. With the evaluation, our hybrid system gave us high confidence for practical use with high speed and reliability. In the last of this paper, we will lightly concern about further advantage

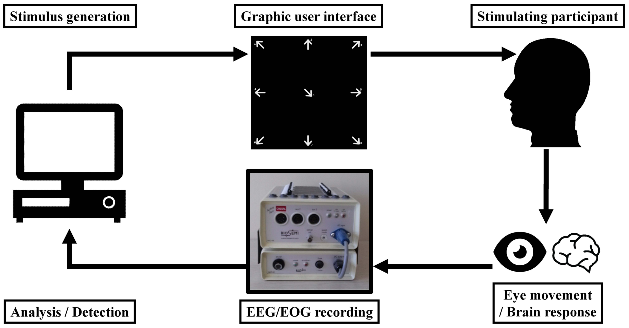

Fig. 1. Overview of the EEG-EOG hybrid BCI system

accompanied with the dual monitors in P300 paradigm that is the dual monitor system give us clues about the solution for the limited space problem, mentioned by E. W. Seller *et al.* [12].

II. Methods

A. Subjects and Environmental Condition

Single healthy male subject engaged in this experiment. Age of the subject was 30 years old. For the subject, it is very first time to use the interface, like naive subject. This is why, the subject was indicated experimental notifications about the interface and mind work. During experiment, the subject was asked to sit at comfortable chair and watch monitor with relax.

B. Experimental Devices and Data Recording

Brain signal recording was done by eight channel EEG system. The electrodes of the eight channel system were mounted around the vertex and primary visual cortex (Fz, Cz, Pz, Oz, P3, P4, O1 and O2) of the subject's scalp. The positions of the electrodes were determined to observe P300 potential, a brain response to visual stimulus. Positioning of the sensors was according to the international 10-20 system. Sampling frequency of EEG recording was 2048 Hz. Two channel EOG was adopted for recording corneal-retinal potential. Each electrode was placed lateral side of left and right eye, separately. These EEG and EOG recording electrodes were grounded with common mode sense (CMS) active electrode and driven right leg (DRL) electrode. CMS and DRL electrode were separately located around the pate following the guideline of the recording device. All of the recording electrodes was referenced by forehead (Nz).

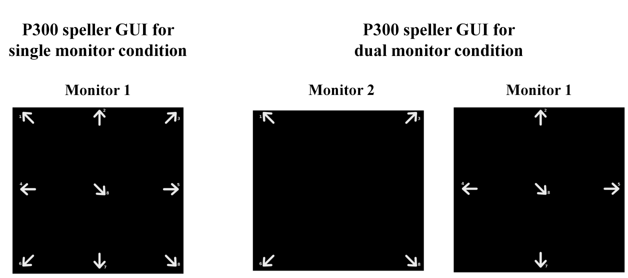

Fig. 2. Graphic user interfaces for conventional and hybrid P300 speller

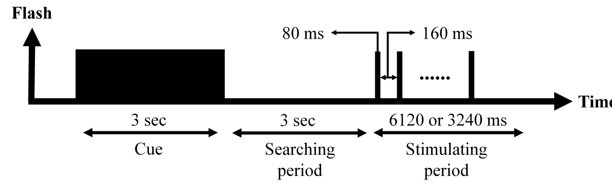

Fig. 3. Timing of sequence of stimulus

C. Experimental Design

Single monitor interface has eight direction icons at outer of 3×3 matrix. In dual monitor mode, the eight icons were separated into two groups. The right side monitor, which was the first monitor, involved up, down, left and right icons and the left side monitor, which was second monitor, had up-left, up-right, down-left and down-right icons. In both cases, the center of the first monitor was place for cue.

During three seconds, before onset of stimulus, one of the items was shown as task indicator on the center of the menu matrix, which was in the first monitor. Just after the cue, there was three seconds searching period. According to the cue, the subject was asked to find and watch the indicated icon in the menu items over the searching period. Then, the subject was request to count number when it flashed. The stimulus duration and the inter-stimulus-interval were 80 and 160 ms, respectively. The signals of each stimuli was collected with 600 ms time window from onset of the stimuli. A sequence of stimulus comprised 24 stimuli - each element was flashed definitely three rounds in a pseudo random order without continuous flashing. As a result, each sequence of stimulus was 6120 ms ($= (80{+}160){\times}23{+}600$) long with 24 ($= 8$ selectable items $\times$ 3 rounds) epochs. In this manner, single experiment was about 12.12 seconds long in single monitor experiment. In our hybrid BCI, two monitors were employed. With the dual monitors, the 3×3 menu matrix was separated into two different 2×2 menu matrices at each monitor. Thus, single sequence of stimulus was 3240 ms ($= (80 + 160) \times 11 + 600$) long. Timing of cue and searching period were set like single monitor case. Flash timing of two monitors was completely synchronized for P300 detection.

D. P300 Potential Detection

First step of P300 potential detection was frequency filtering. Bandpass frequency filter between 1 and 12 Hz was applied to the EEG signals. The filtered EEG signals were downsampled with 32 Hz and segmented with 600 ms length (0 to 600 ms after a stimuli), consecutively. Let us denote the signal matrix $\boldsymbol{X}^{EEG} \in \mathbb{R}^{8 \times T}$ for the segmented EEG signals corresponding to the single stimuli, where T is the temporal length of the segment. To obtain the feature, we concatenated $\boldsymbol{X}$ as

$$\boldsymbol{x}^{P300} = \left[\boldsymbol{X}_1^{EEG}, \cdots, \boldsymbol{X}_8^{EEG} \right], \tag{1}$$

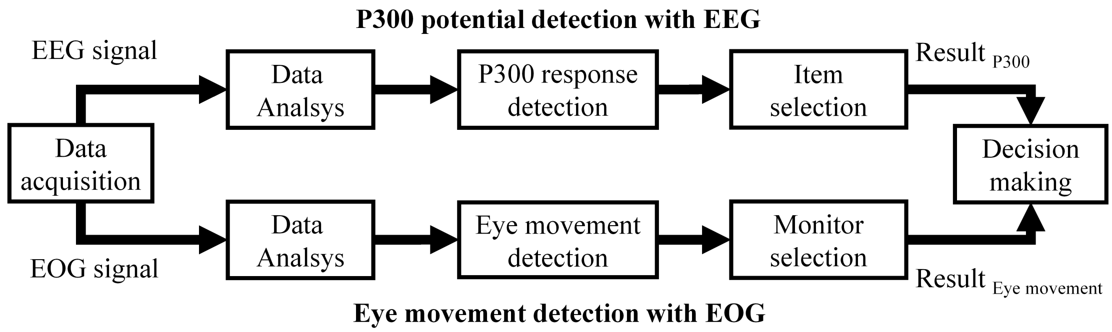

Fig. 4. In this hybrid system, EEG and EOG systems were separately analyzed. P300, which was detected from EEG signals, was used to find focused item and eye movement, which was found with EOG signals, was exploited to identify aimed monitor.

TABLE I
CLASSIFICATION ACCURACY OF CONVENTIONAL P300

Subject	P300 detection		
	Session 1	Session 2	Session 3
Subject 1	70%	90%	90%
Overall	83.33%		

TABLE II
PRACTICAL BIT RATE

Subject	Experimental Condition	
	Conventional P300	Hybrid P300
Subject 1	0.3268	0.5556

where $\boldsymbol{X}_c^{EEG}$ is the c-th row vector of $\boldsymbol{X}^{EEG}$ for channel c. We can specify $\boldsymbol{x}^{P300}$ into $\boldsymbol{x}_{j,k}^{P300}$, when the stimuli corresponding to $\boldsymbol{x}^{P300}$ is flashed for j-th item in k-th round. To average the signals over all rounds, we calculated

$$\boldsymbol{f}_j^{P300} = \left(\boldsymbol{x}_{j,1}^{P300} + \boldsymbol{x}_{j,2}^{P300} + \boldsymbol{x}_{j,3}^{P300}\right)/3. \tag{2}$$

If the subject focused to the J-th item, we collected $\boldsymbol{f}_{j=J}^{P300}$ as the positive set including P300, while collected $\boldsymbol{f}_{j\neq J}^{P300}$ as the negative set not including P300. In the training procedure, we train the linear support vector machine (SVM) classifier [13]. In the testing procedure, we detect the item, focused by the subject, with classification result, which showed the highest probability to belong to the positive set.

E. Eye Movement Detection

EOG signals recorded over searching period, were exploited for eye movement detection. EOG data vector $\boldsymbol{X}^{EOG}$ was obtained by low pass frequency filtering at 0.2 Hz and downsampling at 32 Hz. The $\boldsymbol{X}^{EOG}$ was in $\mathbb{R}^{2\times T}$. EOG signals, which are recorded during eye movement, shows different patterns by direction of eye movement. For example, if the subject moves his eyes from left to right, the EOG signal from the lateral side of left eye goes to negative, and the EOG signal from the lateral side of right eye goes to positive, vice versa. To use this property as a feature, we estimated difference between two channels of $\boldsymbol{X}^{EOG}$ by following manner,

$$\boldsymbol{x}^{EYE} = \boldsymbol{X}_1^{EOG} - \boldsymbol{X}_2^{EOG}, \tag{3}$$

where, $\boldsymbol{X}_c^{EOG}$ represent signal of channel c in the c-th row vector of $\boldsymbol{X}^{EOG}$. When the searching period was before j-th sequence of stimulus, $\boldsymbol{x}^{EYE}$ can be specified into $\boldsymbol{x}_j^{EYE}$. The maximum value of 1st order derivative of the $\boldsymbol{x}_j^{EYE}$ was calculated as shown below,

$$f_j^{EYE} = \max\Big(\frac{d}{dT}\boldsymbol{x}_j^{EYE}\Big). \tag{4}$$

Positive set was collected when the target item was in 2nd monitor and negative set was collected in another case. During training procedure, linear SVM classifier was trained. In test experiment, concentrated monitor was decided by classification result of the linear SVM classifier.

F. Combination for Hybrid BCI

In dual monitor condition, individual P300 response is related to two other items in two different monitors, and eye movement contains information about the monitor concentrated by the subject. By this manner, the hybrid BCI firstly removed six unexpected items by P300 potential detection method. Then, one of two remaining items was selected by result of eye movement detection.

III. EXPERIMENTS

To test our hybrid BCI, training and test experiment were executed. Training experiment was for collecting EEG and EOG data in order to calibrate linear SVM classifiers. The experiment was constructed with 10 sequences of stimulus. The calibrated classifier was used to discriminate data, recorded over the test experiment. Three test sessions comprised test experiment. Each test session contained 10 sequences of stimulus.

Training and test experiment were same at single and dual monitor condition. Conventional P300 BCI resulted in 83.33% averaged accuracy with 11.5 standard deviation (SD) and hybrid BCI showed averaged accuracy of 80.00% with zero SD. p-value was estimated to be 0.3217 by one tailed t-test

TABLE III
CLASSIFICATION ACCURACY OF HYBRID P300

Subject	P300 detection			Eye movement detection			Combination		
	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3
Subject 1	80%	80%	80%	100%	100%	100%	80%	80%	80%
Overall	80%								

between two groups of accuracies, obtained with hybrid and conventional P300 BCI. Both of single and dual case, one of eight menus was selected in a sequence of stimulus. Raw bit rate (RBR) of conventional and the hybrid P300 BCI were roughly calculated to be 0.492 (= 3 bits per 6120 ms) and 0.9259 (= 3 bits per 3240 ms), respectively. With these RBRs, PBRs were obtained as,

$$P^{BR} \quad = \quad R^{BR} \times (1 - 2 \times Err), \tag{5}$$

where, P^{BR}, R^{BR} and Err mean PBR, RBR and error rate of the system, separately. Then PBR of single monitor mode was 0.3268 and dual monitor mode was 0.5556.

IV. CONCLUSIONS

Simple and novel EEG-EOG hybrid BCI was presented and evaluated in this paper. This hybrid P300 system displayed clear benefits by using dual monitor condition. The hybrid system showed 3.33% lower classification accuracy than the ordinary system, however p-value did not show significant difference between two groups of accuracies. In PBR, the hybrid system improved PBR at 70% than ordinary P300 speller. With these results, we thoguht that the hybrid EOG-P300 BCI system showed us the possibility for the practical use of the interface.

Furthermore, there were reports that checked the menu size dependent performance change with ordinary P300 BCI system [14], [12]. According to the E. W. Seller's report, to select correct size of menu matrix and items is important issue to the performance of P300 BCI. It is difficult problem to select correct size, because it is tradeoff situation between the size and the number of items. When we tested dual monitors in our hybrid system, we noticed that the system is available to increase the feasible space of the menu matrix and items as well as its performance. With this clue about the solution of the drawback, we thought that the hybrid system is useful when we want to use more menu items on P300 BCI without performance drop. In further study, we will compare the hybrid system and ordinary system in the maximum number of capable items, and check how the additional space, accompanied with the dual monitors, is useful in general P300 BCI.

One of the remaining limitations on this approach is that we just used the original P300 speller paradigm in the hybrid system. There are various preliminary approaches that studied useful speller paradigms for P300 BCI. For the next step, we will try to adopt various advanced P300 speller paradigms, and compare them to achieve better P300 BCI. Moreover, we will find the criteria of P300 speller paradigm for the hybrid system. We believe our challenging investigation will be beneficial for expediting development of P300 BCI approaches.

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REFERENCES

[1] P. L. Nunez, *Electric fields of the brain: the neurophysics of EEG*. Oxford University Press, 2006.

[2] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proceedings of of the IEEE*, vol. 89, no. 7, pp. 1123–1134, 2001.

[3] R. Ortner, B. Z. Allison, G. Korisek, H. Gaggl, and G. Pfurtscheller, "An SSVEP BCI to control a hand orthosis for persons with tetraplegia," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 19, no. 1, pp. 1–5, 2011.

[4] E. Donchin and D. Smith, "The contingent negative variation and the late positive wave of the average evoked potential," *Electroencephalography and clinical Neurophysiology*, vol. 29, no. 2, pp. 201–203, 1970.

[5] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988.

[6] M. Kaper, P. Meinicke, U. Grossekathoefer, T. Lingner, and H. Ritter, "BCI competition 2003-data set IIb: Support vector machines for the P300 speller paradigm," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 6, pp. 1073–1076, 2004.

[7] J. Jin, B. Z. Allison, T. Kaufmann, A. Kübler, Y. Zhang, X. Wang, and A. Cichocki, "The changing face of P300 BCIs: a comparison of stimulus changes in a P300 BCI involving faces, emotion, and movement," *PloS one*, vol. 7, no. 11, p. e49688, 2012.

[8] G. Townsend, B. LaPallo, C. Boulay, D. Krusienski, G. Frye, C. Hauser, N. Schwartz, T. Vaughan, J. Wolpaw, and E. Sellers, "A novel p300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns," *Clinical Neurophysiology*, vol. 121, no. 7, pp. 1109–1120, 2010.

[9] C.-C. Postelnicu and D. Talaba, "P300-based brain-neuronal computer interaction for spelling applications," 2011.

[10] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Mueller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Frontiers in neuroscience*, vol. 4, 2010.

[11] R. Barea, L. Boquete, M. Mazo, and E. López, "System for assisted mobility using eye movements based on electrooculography," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 10, no. 4, pp. 209–218, 2002.

[12] E. W. Sellers, D. J. Krusienski, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "A P300 event-related potential brain–computer interface (BCI): the effects of matrix size and inter stimulus interval on performance," *Biological psychology*, vol. 73, no. 3, pp. 242–252, 2006.

[13] C. C. Chang and C. J. Lin, "LIBSVM: A library for support vector machines," 2001. [Online]. Available: http://www.csie.ntu.edu.tw/ cjlin/libsvm

[14] B. Z. Allison and J. A. Pineda, "ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 11, no. 2, pp. 110–113, 2003.