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Hybrid EEG and Eye Movement Interface to Multi-Directional Target Selection

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Abstract— **This work addresses the development of a low-cost hybrid interface with eye tracking and brain signals. Eye movement detection is used for search task and EEG-based brain computer interface (BCI) for selection task. Multi-directional target selection experiments with the hybrid interface device were conducted with five subjects to evaluate the proposed hybrid interface scheme. The task asked each user to move a cursor onto a circular target among twelve possible positions and select it. Using the Fitts' law, the interface performance was compared with the computer mouse. With two BCI selection confirmation schemes, the hybrid interface attained 2-2.7 bit/s overall. Based on the results, the potential of the proposed hybrid interface was discussed.**

I. Introduction

EEG-based BCIs have been of huge interest because of their potentials [1-2]. The sensors are noninvasive, therefore, users feel convenience relatively and the recording procedure is safer. Many interesting studies have demonstrated the feasibility of EEG-based BCI as applications to improve the quality of life of either physically disabled or healthy people. Although EEG-based BCI techniques have significantly been improved, its practical real-life usage is yet in reality. The techniques have limited bandwidth, and mostly require intensive training for the system to be tuned optimally for a specific user.

As an approach to overcome the limitations, hybrid BCI has been paid attention to [3-5]. The concept of hybrid BCI suggests to use different brain signal protocols together or to combine BCI with non-brain signal-based protocols. In the way, more extended control capacity is realized. Among various possible combinations of signals, integrating simple interfaces together, which asks little training, can be thought to enhance the adaptability of users with respect to practical purpose, while increasing the number of commands.

This work aims to evaluate the promising hybrid interface scheme of eye movement and EEG-based BCI, especially, with an inexpensively built comfortable system. Instead of focusing on advancing the performance of the hybridization, this work attempts to examine its feasibility as a potential approach to real-world applications through quantitative performance evaluation. The Fitts' law has been widely adopted in human computer interaction (HCI) as a description of a frequent elemental task such as pointing and target selection as well as a predictive model to estimate the response time [6]. In most cases of BCI studies, evaluation was conducted based on some quantities such as accuracy and information transfer rate [7-10]. However, those may not be enough to express synthetic assessment especially with respect to practical HCI. Previously, an investigation applied the Fitts' law for BCI evaluation [11]. However, no attempt of quantitative evaluation of a hybrid interface case has been reported. This work uses the Fitts' law for overall assessment of the proposed hybrid interface system.

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II. Hybrid Interface

A. System Overview

This work uses both low cost BCI and eye tracking systems: Emotiv Epoc EEG recording headset [12], and hand-made eye tracking equipment. The EEG recording headset consists of fourteen electrode channels plus CMS/DRL references around the sensorimotor cortex (see Fig. 1). The headset was designed as personal interface system for HCI. Its cost is very cheap ($299) relatively compared with standard EEG recording systems (at least $5000). Its potential as a reliable recording system has been studied in some previous investigations [10, 13].

Figure 1. Hybrid interface system.

Fig. 1 also shows the eye tracking system. The total cost to build it was less than $40. An eye tracker was built based on previous studies [14-15]. It consisted of two components: an infrared camera, and light-emitting diodes (LEDs). Five LEDs was fixed around the lens of the infrared camera that was connected to a glasses frame at about 8 cm away from a left eye. When a subject wore the glasses frame, the camera was toward human left eye to capture its image. LEDs illuminated an eye to enhance the contrast between the pupil and the iris. The eye tracking system applied standard image processing methods for pupil detection based on the open source [16].

The combination of the two low cost BCI and eye tracking systems comprised a hybrid BCI system used for this work. Each system modules for data acquisition and processing were developed separately, but integrated using the .NET framework to realize synchronous operation of the two systems. Performance measurement and calibration modules for each system were also programmed.

B. Data Acquisition

The data sets in this pilot study were recorded from ten healthy subjects (age 24.60 ± 3.38 (mean±SD) years) without any prior experience with eye tracking and EEG-based BCI. They all gave the written informed consent. The KAIST Institutional Review Board approved the proposed experimental protocol of this study. Each participant was seated comfortably in a chair facing the monitor screen, which was placed about 1 m in front of the subject on a table. Each subject wore the hybrid interface system. The head mounted eye tracker captured images of eye movement with a spatial resolution of 640×320 pixels at sampling rate of 60 Hz. Using the Emotiv Epoc headset, EEG data were recorded at sampling frequency of 128 Hz from fourteen channel layout (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 in international 10-20 standard locations). The recorded EEG data were band-pass filtered between 1 and 50 Hz.

C. Signal Processing and Decision Making

1) BCI

Before the experiment, each user was asked to go through a set of training sessions, which recorded the user's EEG signals in two different phases. These phases represented "neutral state" and "concentration state", and were presented 36 times, 6 seconds each with visual instructions. During the "concentration phase", the user was asked to gather his attention to a certain point on the screen, while he was asked to stay calm during the "neutral phase". Using the acquired data, the detection of the concentration state implemented the selection of a current cursor position. For the two class classification problem, which classifies to one of "neutral state" or "concentration state", a popular technique for feature extraction in EEG-based BCI, Common Spatial Patterns (CSP) algorithm [17], was used to find spatial filters which extract features for classification. Let X_1 and X_2 represent a set of signals during neutral state and concentration state respectively. Then, CSP found spatial filters w that extremized the following function.

$$J(w) = \frac{w^T X_1 {X_1}^T w}{w^T X_2 {X_2}^T w} = \frac{w^T {C_1}^T w}{w^T {C_2}^T w}$$

Each C_i indicates the spatial covariance matrix of an associated class assuming a zero mean for EEG signals. The zero mean assumption was met by preprocessing when EEG signals are band-pass filtered. Using the Lagrange multiplier method, the optimization problem was transformed to be a standard eigenvalue problem. The eigenvectors of ${C_2}^{-1}C_1$ which corresponded to its largest and lowest principal eigenvectors respectively are selected as the spatial filters for extremization. Then, the EEG signals from the whole channels were projected onto the filters. The power spectrum of projected signals was estimated using the Burg method based on an autoregressive (AR) model of order p (p=12 in this work). The power values between 7 and 13 Hz from each EEG signal were assigned to be extracted features. Then, an optimal classifier based on the features acquired from EEG signals was determined by Support Vector Machines (SVM) algorithm. The MATLAB SVM functions were used to implement the computation of the SVM-based classification.

In real-time, data points acquired from every 1 s time window with 125 ms increment were used to classify a selection state. To finalize selection robustly, two selection confirmation schemes were designed: the first scheme, short selection confirmation, required detection of two consecutive selection states to confirm final selection. The second scheme, long selection confirmation, enforced the final confirmation by requesting four consecutive selection states instead of two.

2) Eye tracking

Points in the contour between pupil and iris from each binarized image were extracted, and then, were fitted to an ellipse to estimate the center of the pupil. The RANSAC algorithm was applied to eliminate outliers among the extracted points. Using a second-order polynomial for each axis, horizontal and vertical, a gaze point was interpolated. The coefficients of the polynomials were calculated through the calibration procedure.

D. Experiment Design

This work evaluated the proposed hybrid interface through multidirectional cursor control tasks. Among twelve possible circular target placements in a circular arrangement, any one appeared on the 48 inch screen. There were two task modes: search and selection. At the beginning of each trial, a cursor was placed at the center of the circular arrangement and no circular target was visible. When a red circular target at an arbitrary location appeared, a subject had to move the cursor to the target circle as quick as possible. This is the search task mode. Then, each subject had to select the target. This is the selection task mode. A successful target selection was complete when any point in the target circle was selected within a limited time of 6 s since a trial begins. If selection was not rightly performed within the time limit, the trial was regarded to be failed. Each target appeared exactly one time in a random order during a sequence of twelve trials, therefore each subject tried all the twelve target selections one time per each. Three different (large, middle, small) sizes of circular targets, and two different (short, long) distances were assigned so that cases were differentiated to classify the task difficulty levels. Experiments were repeated at different task difficulty levels.

E. Performance Evaluation

Fitts' index of difficulty (ID) describes the relative difficulty of a particular movement used in a task, and is based on the distance (d) from a starting point to a target point, and the width (w) of the target [6]. In the general Fitts' law, movement time (MT) is set to a function of ID. In our experiment tasks, not only pointing a target point but also selecting the point should be accomplished. Therefore, we define task completion time (T), which indicates the total time taken during tracking and selecting. The index of performance (IP) (bits/s) is calculated by taking the reciprocal of the slope b in the linear regression equation.

$$\mathrm{ID} = log_2 \frac{2d}{w}$$

$$\mathrm{T} = \mathrm{a} + \mathrm{b(ID)} = \mathrm{a} + \mathrm{b}\, log_2 \frac{2d}{w}$$

In this study, experiment parameters were set to $w = 120$, 80, 40 pixels (7.8, 5.2, 2.6 cm) and $d = 320$, 480 pixels (20.8, 31.2 cm) respectively. The combination of the parameters resulted in five different difficulty levels totally.

Using the Fitts' law, it can be shown how quickly tasks at different difficult levels can be performed and how much information the interface can transfer.

III. EXPERIMENT

Five subjects conducted the multi-directional search and select tasks using the proposed hybrid interface with two different selection confirmation schemes mentioned in section II.*D.1)*. The performances were compared with them using a commercial computer mouse. With the short selection confirmation scheme, the success rate of the task performance averaged across subjects was 96.67(±4.08) % and 78.33(±22.11) % at the lowest and highest ID levels respectively. With the long selection confirmation scheme, it was 96.67(±4.08) % and 73.33(±25.50) % at the lowest and highest ID levels respectively. In this experiment, the highest ID was 4.6 (bit). It indicates quite a difficult task generally.

TABLE I. INDEX OF PERFORMANCE ON CURSOR CONTROL USING THE DEVELOPED INTERFACE AND THE MOUSE WITH FIVE SUBJECTS

subjects		S1	S2	S3	S4	S5	Overall
Hybrid Short	IP (bit/s)	1.28	1.32	5.00	1.35	3.03	2.70
	R^2	0.71	0.87	0.58	0.93	0.54	0.58
Hybrid Long	IP (bit/s)	2.22	6.67	7.14	1.16	2.00	2.00
	R^2	0.35	0.16	0.18	0.88	0.75	0.81
Mouse	IP (bit/s)	3.13	9.09	20.00	5.88	33.33	11.11
	R^2	0.42	0.92	0.42	0.79	0.22	0.97

(Hybrid Short: hybrid interface with short selection confirmation, Hybrid Long: hybrid interface with long selection confirmation, R^2: correlation coefficient)

Table 1 summarizes the experimental result. The overall IP of the proposed hybrid interface was 2.7 bit/s and 2 bits with short and long selection confirmation schemes respectively, whereas the overall IP of the mouse was 11.11 bit/s. The short selection confirmation case obtained a bit higher IP in average than the long selection confirmation case. However, some subjects achieved higher IP with the long selection confirmation scheme. A specific subject S3 performed the tasks with the proposed interfaces at IP of 5 – 7.14 bit/s. Every subject achieved IPs above 1 bit/s. The Fitts' law relationship is illustrated in Fig. 2 with averaged estimation across subjects. The results of two selected subjects, best and worst performers, using the proposed hybrid interfaces are shown in Figs. 3 and 4 respectively. With both short and long selection confirmations, the subject S3 performed relatively evenly over the different difficulty levels. He completed tasks within 1.5 s and 2 s with short and long selection confirmations respectively. Meanwhile, the subjects S1 and S4 achieved lowest IP values with short and long selection confirmations respectively. Their performances depended on the difficulty levels.

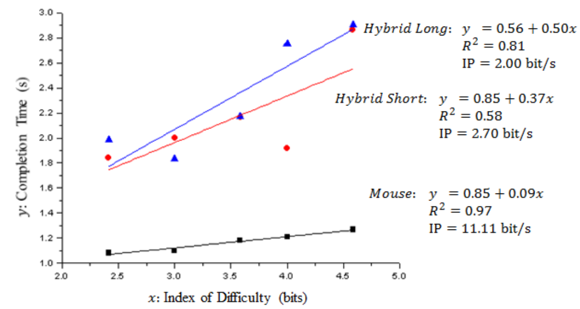

Figure 2. Relationship between T and ID with the developed interface and the mouse averaged across subjects

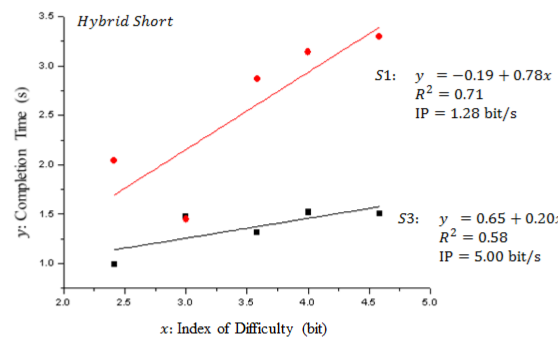

Figure 3. Relationship between T and ID with the developed interface for two selected subjects using the hybrid interface with short selection confirmation.

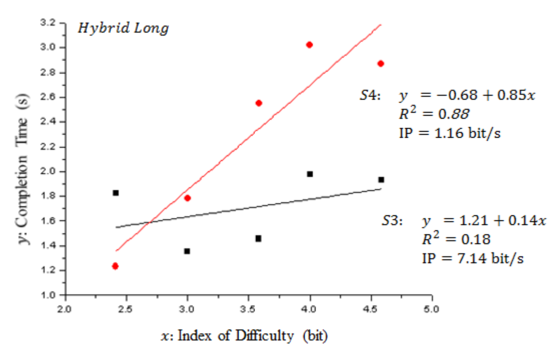

Figure 4. Relationship between T and ID with the developed interface for two selected subjects using the hybrid interface with long selection confirmation.

IV. Discussion and Conclusion

During the task implementation using the proposed hybrid interface, some subjects tended to feel difficult to maintain the point still in a target circle while the BCI protocol operated selection. However, although there is a clear difference over the adeptness in the system usage, subjects could complete tasks successfully most times within the time limit.

The overall IPs of the proposed hybrid interfaces were lower than that of the mouse interface (11.11 bit/s). However, they were higher than that (0.541 bit/s) of the BCI only interface reported in [11]. An interesting comparison is with the EMG interface. According to a previous report [18], the overall IP of the EMG interface was 1.299 bit/s, which is lower than them of the proposed hybrid interfaces. Therefore, the performance of the proposed hybrid interface was approximately twice better than that of the EMG interface, and five times better than that of the BCI only interface. Although the proposed hybrid interface could not perform as well as a mouse, the current results show that the proposed hybrid interface may be an appropriate choice for physically disabled people.

Cursor movement is controlled by eye tracking. Therefore, any directional cursor movement in the two dimensional plan is possible, and cursor speed can be controlled as a user wishes. The point selection or click is decided by a simple BCI protocol. It is much more intuitive and natural than the eye dwell time clicking interface mainly used in typical eye tracking methods, because the selection is triggered by an intuitive imagination such as that of attention focusing. The BCI protocol, which the developed interface relies on, requires no serious training session. Therefore, a user can easily be accustomed to the proposed interface device. As a user gets more familiar with the device, the performance would be dramatically more improved than the current results in this study.

This study presents important implications for future work on developing hybrid interface devices especially at low cost. The hybrid eye tracking and BCI interface system will be effective to any people as long as they have no degradation on the ocular-motor system and motor planning and decision making brain areas. In addition, its operation scheme is natural and intuitive. The proposed interface system should be tested with people with motor disabilities in the future to further confirm its feasibility.

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