Quantitative Evaluation of a Low-Cost Noninvasive Hybrid Interface Based on EEG and Eye Movement

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***Abstract*—This paper describes a low-cost noninvasive brain-computer interface (BCI) hybridized with eye tracking. It also discusses its feasibility through a Fitts' law-based quantitative evaluation method. Noninvasive BCI has recently received a lot of attention. To bring the BCI applications into real life, user-friendly and easily portable devices need to be provided. In this work, as an approach to realize a real-world BCI, electroencephalograph (EEG)-based BCI combined with eye tracking is investigated. The two interfaces can be complementary to attain improved performance. Especially to consider public availability, a low-cost interface device is intentionally used for test. A low-cost commercial EEG recording device is integrated with an inexpensive custom-built eye tracker. The developed hybrid interface is evaluated through target pointing and selection experiments. Eye movement is interpreted as cursor movement and noninvasive BCI selects a cursor point with two selection confirmation schemes. Using Fitts' law, the proposed interface scheme is compared with other interface schemes such as mouse, eye tracking with dwell time, and eye tracking with keyboard. In addition, the proposed hybrid BCI system is discussed with respect to a practical interface scheme. Although further advancement is required, the proposed hybrid BCI system has the potential to be practically useful in a natural and intuitive manner.**

***Index Terms*—Electroencephalograph (EEG)-based brain-computer interface (BCI), eye tracking, Fitts' law, noninvasive hybrid interface.**

I. Introduction

NONINVASIVE brain-computer interfaces (BCIs) have been of huge interest because of their potential [1], [2]. A noninvasive recording procedure is safer and its recording device is less expensive than for invasive procedures. Furthermore, it is relatively easy to apply and large human population tests are possible. Many interesting studies have examined the feasibility of noninvasive BCI for applications for either physically disabled or healthy people: reactive BCIs using P300 potential [3]–[5] or steady state visually evoked potential (SSVEP) [6]–[8], and active BCIs based on sensorimotor rhythm [9]–[14]. Although noninvasive BCI techniques have been significantly improved, their practical real-world usage has yet to be realized. This is because current noninvasive BCIs are still of limited frequency range and are usually restricted to binary commands. In addition, the information transfer rate is low for communication.

To extend its applicability, even with the limitations, attention has been paid to hybrid BCI [15]–[17]. The concept of hybrid BCI suggests using different brain signal protocols together or even combining nonbrain signals. In this way, more extended control capacity is realized. Among the various possible combinations of signals, integrating simple interfaces together, for which each requires relatively little training, can be thought to enhance the convenience with respect to practical interface, while increasing the number of commands. There are some implementations of hybrid BCIs which combine EEG-based protocol with other protocols: fusion of EEG and electromyographic (EMG) activities [18], fusion of joystick and BCI controls [19] and so on.

The development of eye tracking-based control interfaces has a long history and has made significant progress [20]. Eye movement input requires no intensive training and it operates impressively fast [21]. In addition, eye movement can naturally express the user's focus of attention. It also makes some tasks performable for the physically disabled as well as older people. Technical improvements have made it possible to obtain reasonable performance, even with low-cost eye-tracking systems [22], [23]. In addition, a low-cost binocular eye tracker was proposed for 3-D gaze estimation [24]. However, eye tracking is not yet popular for use in real-life HCI applications, because using one's hands to move a mouse is still much more convenient than that of using an eye to move a cursor. Intended or unintended inputs are hard to be distinguished so unintended input can cause unintended pointing or selection. A critical issue is that it is difficult to find a proper algorithm for the selection operation. Most eye-tracking solutions rely on the dwell time. A user's gaze has to remain fixed to a target for a certain period to confirm its selection. However, this raises the question of determining the optimal dwell time. Due to the complexity of various tasks, it is almost impossible to optimally fix the dwell time [25]. Furthermore, while in the case of binary decisions, an eye-based method would possibly be better, by proving that BCI and eye interfaces can coexist for simple binary transactions, future BCI protocols such as P300 or SSVEP could be used to allow more than two commands, which are much more difficult to do with eye movements alone.

The concept of the hybrid BCI and the potential of eye tracking motivate the creation of a hybrid BCI system which combines eye tracking with a simple protocol of noninvasive BCI. The hybridization of the two is expected to complement

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each other's deficiencies and to establish a better performing interface. Gaze estimation from eye tracking yields impressively higher information transfer rates than current BCIs and is adequate for performing search tasks. Meanwhile, an appropriate noninvasive BCI protocol can be responsible for the selection operation. A simple BCI protocol is expected to demand less training and to achieve faster selection operations than using dwell time with eye tracking. In addition, BCI-based selection is a more natural and intuitive scheme than dwell time-based selection.

In fact, Zander *et al.* argued that a multimodal interface combining eye gaze and a BCI can be a robust and intuitive device for touchless interaction [25]. However, their eye tracker and BCI device were too high-end and expensive to accommodate use by the general public. They did not take into account real-world applicability. In addition, their analysis focused solely on the accuracy of correct selections and task completion time.

Recently, inexpensive products to measure EEG signals noninvasively have been commercialized. They provide the potential to extend BCI to practical HCI applications. Commercialization is an important aspect of BCI technology [26]. In this respect, the currently available devices need to be tested. One direction of BCI among its research issues is to become a part of daily life as a convenient approach to interfacing with the environment [17], [26]. This work intentionally uses a user-friendly system to contribute in this aspect.

This work aims to evaluate the promising hybrid interface scheme of eye movement and noninvasive BCI, particularly, with an inexpensively built and comfortable system. Instead of focusing on advancing the performance of this hybridization, this work attempts to evaluate its feasibility as a potential approach to real-world applications through quantitative performance comparison of the developed interface with other pointing interfaces. Fitts' law-based assessment has been a great theoretical tool for the innovation of interface designs and the Fitts' law has been widely adopted in 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 [27]. Therefore, it has been used to validate the effectiveness of computer pointing devices such as a mouse, joystick, touchpad and eye tracker as a standard tool (ISO9241-9) [27]. In most BCI studies, evaluation was conducted based on metrics such as accuracy and information transfer rate [3]–[14]. However, those may not be enough to express synthetic assessment, especially with respect to practical HCI. Previously, an investigation applied Fitts' law for BCI evaluation [28]. However, no attempt of quantitative evaluation of a hybrid BCI case has been reported. This work uses Fitts' law for overall assessment of the proposed hybrid BCI system.

II. Methods

A. Hybrid BCI System

This work uses a low-cost BCI and eye-tracking system: Emotiv Epoc EEG recording headset [29] and custom-built eye-tracking equipment. The EEG recording headset consists of 14 electrode channels plus CMS/DRL references around the sensorimotor cortex as shown in Fig. 1. The headset was designed as a personal interface system for HCI. It is relatively much cheaper than standard EEG recording systems. Its potential as a reliable recording system has been studied in some previous reports [3], [30], [31]. Fig. 1 also shows the eye-tracking system. The total cost to build it was less than \$40 USD. An eye tracker was built based on previous studies [22], [23]. It consists of two components, an infrared camera and light-emitting diodes (LEDs). Five LEDs are fixed around the lens of the infrared camera that is connected to a glasses frame at about 8 cm away from a left eye. When a subject wears the glasses frame, the camera is pointed toward the left eye to capture its image. LEDs illuminate the eye to enhance the contrast between the pupil and the iris. The eye-tracking system applies standard image processing methods for pupil detection based on the open source [32], [33].

The combination of the low-cost BCI and eye-tracking systems comprise the hybrid BCI system used for this study (see Fig. 1). Each system's modules for data acquisition and processing were developed separately, and synchronous operation of the two systems was implemented using the .NET framework. Performance measurement and calibration modules for each system were also implemented. However, due to the use of open source libraries, the effort required to implement our hybrid system was minimized, reducing the total cost of the system further. For use in this study, the eye-tracking system detects eye movements, which is interpreted to be a cursor pointing trajectory while the BCI system provides explicit commands for selection operation.

B. Data Acquisition

This pilot study originally involved ten healthy subjects without any prior experience with eye tracking and EEG-based BCI. They all gave written informed consent. The KAIST Institutional Review Board approved the proposed experimental protocol of this study. However, one of them failed to acclimate to both eye tracking and BCI protocols. Hence, the data from nine subjects (age 24.44 ± 3.02 (mean$\pm$SD) years) excluding the previously mentioned subject were used for evaluation. 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 BCI 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. The EEG recording headset is known to record data at sampling frequency of 128 Hz from a 14–channel layout (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).

C. Tasks

This work evaluates the proposed hybrid system through multidirectional pointing and selection task experiments. A subject wearing the hybrid interface looks at the 48-in display as shown in Fig. 2(a). At the beginning of each trial, a cursor is placed at the center of the screen and no target is visible. Among the 12 possible circular target placements in a circular arrangement, an arbitrary one appears in red. Then, a subject should move the cursor within the target circle as quick as possible.

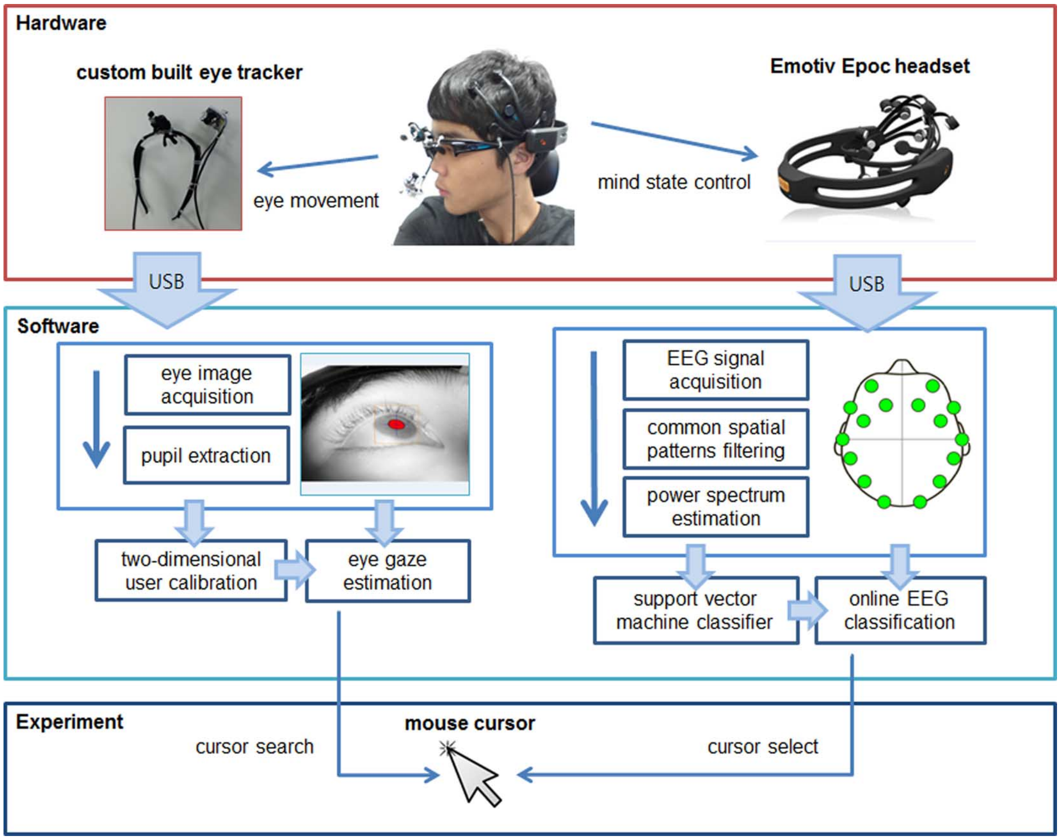

Fig. 1. Proposed noninvasive hybrid interface system.

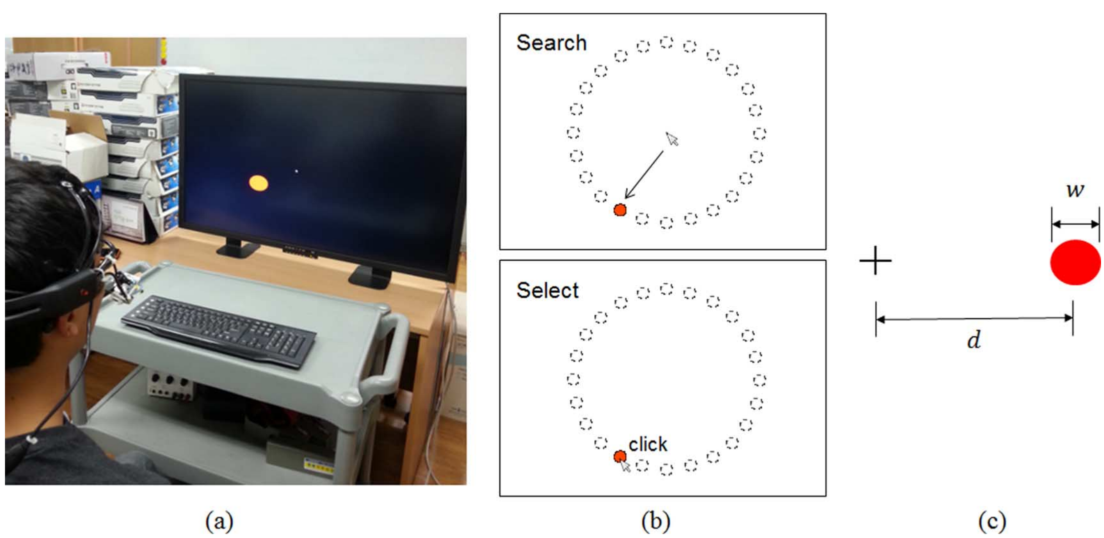

Fig. 2. (a) Interface system with a subject during a task. (b) Pointing and selecting task procedure (dotted target circles are invisible). (c) Task parameters: distance to a target and its size.

This is the pointing task mode [see Fig. 2(b)]. Then, each subject should select the target. This is the selecting task mode [see Fig. 2(b)]. A successful target selection is complete when any point in the target circle is selected within a limited time of 6 s since a trial begins. When a selection is successfully finished, the circular target disappears immediately. If selection is not performed within the time limit, the trial is considered a failure. In Fig. 2(c), w and d indicate the diameter of a circular target and the distance from the center of the circular arrangement to the center of the target, respectively. Three different sizes (large, middle, small) of circular targets, and two different distances (short, long) are assigned so that the six tasks are differentiated: $w = 120, 80, 40$ pixels (7.8, 5.2, 2.6 cm), and $d = 320, 480$ pixels (20.8, 31.2 cm).

The targets are selected in a random order during a sequence of 12 trials, therefore each subject tries all 12 target selections one time per trial. This work pays attention to overall performance rather than specific individual performances to evaluate the interface protocols. Thus, 108 trials per each scenario are acquired.

For the purposes of evaluation, four interface protocols are compared:

1) Mouse: point and select with mouse;
2) Eye Manual: point with eye tracker and select with keyboard;
3) Eye Dwell: point with eye tracker and select with eye tracker using dwell time;
4) hBCI (Short, Long): point with eye tracker and select with noninvasive BCI.

(1) Conventional interface, (2) eye tracking with manual input, (3) eye tracking only, and (4) hybrid BCI are selected for comparison. The proposed hybrid BCI system is used in case (4). In the hybrid case, two BCI selection confirmation schemes (hBCI Short, hBCI Long) are applied as explained in Section II-D.

D. Signal Processing

1) BCI: The BCI protocol is used to select a point within a circular target. Subjects are asked to concentrate on the target point. The BCI-based selection is designed to be a binary classification problem. The two mental states indicate selecting state (through concentration) and pointing state during eye tracking, respectively. When a focus on concentration is detected, the system interprets a subject's intent to select the target point. To discriminate the two classes, a popular technique for feature extraction in EEG-based BCI, the Common Spatial Patterns (CSP) algorithm [34], is used to find spatial filters which extract features for classification. Let $e_{1,n}$ and $e_{2,n}$ denote a set of EEG signals representing concentrated state and neutral state, respectively, from the nth trial. Suppose that, to obtain data for each state, EEG signals are recorded from L channels and the number of samples is M. Then, each $e_{i,n}$ is transformed to a feature vector, $x_{i,n}$

$$e_{i,n} \in R^{L\times M} \mapsto x_{i,n} \in R^d, \quad i = 1, 2.$$

CSP finds spatial filters s that extremize the following function:

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

where $X_i \in R^{d\times N}$, $i = 1, 2$, is a set of feature vectors as a matrix and N denotes the number of trials.

Each $C_i \in R^{d\times d}$ indicates the spatial covariance matrix of an associated class assuming a zero mean for EEG signals. The zero mean assumption is met by preprocessing when the EEG signals are band-pass filtered (1–50 Hz). Using the Lagrange multiplier method, the optimization problem is transformed to be a standard eigenvalue problem. The eigenvectors of ${C_2}^{-1}C_1$, which corresponds to its largest and lowest principal eigenvectors, respectively, are selected as the spatial filters for extremization. EEG signals from all of the channels are projected onto the filters. The power spectrum of projected signals is estimated using the Burg method based on an autoregressive (AR) model. The model order of the autoregressive model is fixed as 16 based on the result of a previous study [35]. The power values between 11 and 19 Hz are assigned to be extracted features. The frequency band is selected based on the observation of preliminary tests from subjects. Then, an optimal classifier based on the features acquired from EEG signals is determined by the Support Vector Machines (SVM) algorithm. SVM was selected because it is known to have good generalization properties and insensitivity to overtraining [36]. The properties would be effective for the use of the low cost BCI system. The linear kernel SVM was implemented.

For robust confirmation of selection, the following procedure is implemented. In real-time, data points in a 1 s time window with 125 ms increment are used to classify a selection state. Two BCI confirmation schemes are tested. With a short selection confirmation scheme, selection is confirmed if two sequential selection states are classified the same (hBCI Short). Hence, a short selection confirmation takes 250 ms, theoretically, if the selection succeeds at once. Whereas, a long selection confirmation scheme requires four sequential selection state detections by classification to be identical (hBCI Long). Thus, a long selection confirmation takes 500 ms theoretically.

2) Eye Tracking: Points forming the contour in between the pupil and iris from each binarized image are extracted. The points are then fitted to an ellipse to estimate the center of the pupil. The RANSAC algorithm is applied to eliminate outliers among the extracted points. Using a second-order polynomial for the horizontal and vertical axes, a gaze point is interpolated. The coefficients of the polynomials are calculated through the calibration procedure. In the case of using eye tracking alone for the control interface, the dwell time was used to determine the target selection. The selection is confirmed if a gaze point stays within a small circle for a certain time period, which is the dwell time. It is extremely difficult for the human gaze to stay perfectly still for any amount of time. Thus, a small circle is assigned and a gaze point is considered static as long as the point stays within the circle for the specified dwell time. As soon as an experiment begins, an initial gaze point becomes a possible selection position. If the gaze stays within a small circle whose center is the initial point for the dwell time, the selection would be confirmed at the initial point. However, if a subject moves his or her eye toward a target circle, the gaze point will leave the small circle too quickly before the dwell time expires. At this point the gaze point just outside of the small circle becomes the possible selection spot, and a small circle around the new position is considered in the same manner as before. This procedure is repeated until a selection point is confirmed by the dwell time. In this work, the dwell time is set to be 1 s empirically after repeated trials with different dwell time values. The size of the small circle to indicate a static gaze position is fixed to be 40 pixels (2.6 cm) in diameter. The size was selected through a simple experiment. Subjects were asked to focus a point with no eye movement for a while. Then, the diameter of a minimal circle to include actual gaze trajectory was extracted.

E. Training

Each subject was allowed to become acclimated to both the eye tracking and BCI systems for a certain amount of time because the subjects had no prior experience. The amount of time spent acclimating to the eye tracker varied from about 10 minutes to 1 hour depending on the subject. Subjects become familiar with the BCI module relatively quickly, within 20 to 30 minutes. Whether subjects were ready for the experiments was determined by checking the accuracies of using the modules with simple calibration protocols.

To ascertain the accuracy of the eye-tracking module, the calibration routine of the eye-tracking module requested each subject to point at a series of nine point marks displayed on the computer monitor 1 m away from the subject's eyes.

To obtain a specific classification of the BCI module per subject, the following procedure was used. Each subject looked at a target circle when it appeared at a random position on the computer screen. The subject was asked to concentrate on it when colored red and remain in the neutral state (without concentrating) when colored yellow. At six target locations, scenarios of concentration and nonconcentration were repeated six times, respectively. Hence, in total, 36 trial training data were collected per subject where a trial includes one concentrated and one nonconcentrated states. The most appropriate SVM classifier was then set per subject using the data.

F. Performance Evaluation

To evaluate the interface systems, this work uses the Fitts' index of difficulty (ID) which describes the relative difficulty of a particular movement used in a task, based on two factors [27]. In the general Fitts' law, movement time is set to a function of ID. In this work, the designed task consists of point movement and point selecting tasks. Hence, the complete task time is the sum of the target pointing and selection task times. Previous studies reported the point movement task's performance relies on two factors [21], [28]: the distance (d) from a starting point to a target point, and the diameter (w) of the circular target. Furthermore, this work presumed that the target selecting task performance is affected at least by the target size w, based on a previous report [37].

For this work, the following Fitts' law formulation is used:

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

where CT indicates a total time taken to complete a target pointing and selection task.

In addition, the information transfer rate (ITR) (bits/s) is calculated by taking the reciprocal of the slope b in the linear regression equation

$$\mathrm{ITR} = \frac{1}{\mathrm{b}}.$$

Using Fitts' law, it can be shown how quickly tasks at different difficult levels can be performed and how much information an operating interface can transfer. Comparison of the results across subjects and interfaces is used for evaluation. The task difficulty increases as w decreases or d increases.

TABLE I
ACCURACY OF EACH OF EYE TRACKING AND BCI SYSTEM

Subjects	Eye calibration error (cm)	Angular eye calibration error (degree)	BCI classification accuracy (%)
S1	0.63	0.35	100
S2	0.58	0.32	100
S3	0.47	0.26	83.33
S4	0.47	0.26	100
S5	0.58	0.32	83.33
S6	0.31	0.18	100
S7	0.63	0.35	100
S8	0.68	0.37	83.33
S9	0.47	0.26	100
Average	0.54± 0.11	0.30± 0.06	94.44± 7.86

This work used Fitts' law to evaluate performances with different interfaces and repeated measures analysis of variance (RMANOVA) which provides a statistical interpretation for comparison as well.

G. User Study

A simple survey about the proposed hybrid interface was requested to be completed by participating subjects after the experiment. They answered four questions by comparing their performance with that of using a mouse.

Q1 : Score your ability to move a cursor by eye tracking between 0 (much different) and 10 (exactly the same).

Q2 : Score your ability to select a target through BCI between 0 (much different) and 10 (exactly the same).

Q3 : Score how convenient the hybrid interface is between 0 (much different) and 10 (exactly the same).

Q4 : Score your satisfaction level during task performance between 0 (much different) and 10 (exactly the same).

III. RESULTS

A. System Accuracy

Before conducting experiments, the eye tracking and BCI systems were evaluated to estimate their accuracy with the determined settings. Table I summarizes the evaluation results. Over all of the subjects, an averaged error of 0.54±0.11 cm was attained at eye-tracking calibration. This error is translated into the angular error of 0.30±0.06 degrees. The estimated error is on par with commercially available eye-tracking systems. For instance, the angular accuracy of the EyeLink II ($25,000 USD), a binocular eye tracker, was reported to be <0.5 degrees [24]. A custom-built eye tracker reported in [22] achieved accuracies of 0.6–1.71 cm positioned about 60 cm away. Based on the evaluation, it was judged that the subjects could use the eye-tracking system properly.

The accuracy of the BCI classification is also shown in Table I. To compute the accuracy, 12 target locations were randomly shown with either red or yellow color on the screen.

TABLE II
SUCCESS RATES OF FIVE INTERFACES AVERAGED ACROSS SUBJECTS (%)

ID (bits) (d,w)(cm)	Mouse	Eye Manual	Eye Dwell	hBCI Short	hBCI Long
2.4 (20.8,7.8)	100± 0.00	90.74± 6.14	86.11± 13.61	97.22± 3.93	97.22± 3.93
3.0 (20.8,5.2)	100± 0.00	89.82± 8.59	87.04± 6.93	87.96± 13.67	89.82± 12.90
3.6 (31.2,5.2)	99.07± 2.62	82.41± 13.86	86.11± 13.61	86.11± 22.57	76.85± 25.09
4.0 (20.8,2.6)	99.07± 2.62	69.45± 21.52	85.19± 15.60	80.56± 22.57	75.93± 21.32
4.6 (31.2,2.6)	100± 0.00	72.78± 17.73	76.82± 17.47	81.48± 18.33	74.03± 25.06

TABLE III
TASK COMPLETION TIMES OF FIVE INTERFACES AVERAGED ACROSS SUBJECTS (S)

ID (bits) (d,w)(cm)	Mouse	Eye Manual	Eye Dwell	hBCI Short	hBCI Long
2.4 (20.8,7.8)	1.11± 0.21	1.82± 0.37	2.79± 0.36	1.78± 0.89	2.01± 0.83
3.0 (20.8,5.2)	1.31± 0.35	2.49± 0.31	2.96± 0.24	2.00± 0.98	2.06± 0.42
3.6 (31.2,5.2)	1.30± 0.24	2.60± 0.50	3.10± 0.38	2.23± 0.76	2.32± 0.60
4.0 (20.8,2.6)	1.39± 0.37	2.56± 0.58	3.12± 0.39	2.39± 0.80	2.63± 0.66
4.6 (31.2,2.6)	1.42± 0.23	2.80± 0.68	3.44± 0.30	2.91± 0.94	2.92± 0.54

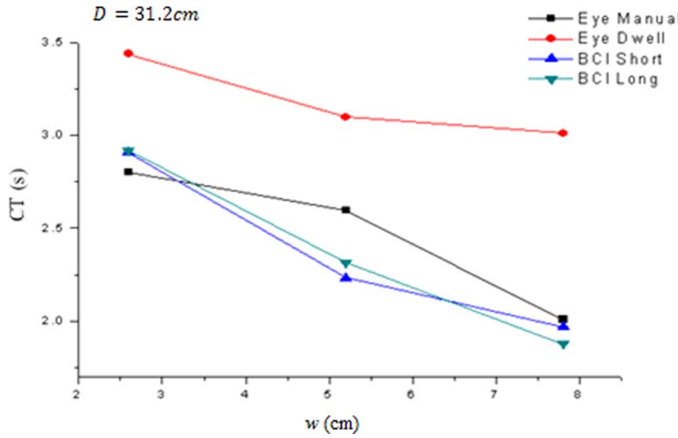

Fig. 3. Task completion times over the target sizes with four interfaces that use eye tracking for pointing at a fixed distance ($d = 31.2$ cm).

Subjects were instructed to imagine pushing a corresponding target and stay neutral when its color was red and yellow, respectively. As a result, the classification accuracy was above 94% on average. Six subjects achieved 100% accuracy and three subjects misclassified two times among 12 cases. Based on the subjects' performances with both systems, it was assumed that subjects were sufficiently proficient using the interfaces. Then, task experiments were conducted.

B. Success Rates and Task Completion Times

Overall success rates and completion times of the tasks are indicated in Tables II and III, respectively. The task implementation mentioned in Section II-B by the four different interface protocols are compared. The task difficulty (ID) ranged from 2.4 to 4.6 (bits). The success rate was computed by counting the total successful tasks out of 108 trials, 12 directional tasks across subjects. CT indicates how fast a task was completed.

At the most difficult level of 4.6 (bits), the proposed hybrid interface with long and short confirmations resulted in 74.03% and 81.48% on average, respectively. In the case of CT, the interface reported 2.92 and 2.91 s.

At the easiest task level of 2.4 (bits), the proposed hybrid interface achieved a success rate of about 97% with both confirmation schemes and took 1.78 and 2.01 s with short and long confirmations.

From these results, the average success rates of interfaces other than the mouse tended to decrease as the task difficulty increased. However, as the difficulty level increased, in most cases the standard deviation tended to increase except in the case of the mouse. As shown in Table III, CT tended to generally increase as the difficulty level increased. The proposed hybrid interfaces were faster than eye-tracking interfaces over all difficulty levels except ID $= 4.6$ (bits). In this case they were slower than using the mouse. At the easier difficulty levels, the differences of CT between the proposed hybrid interfaces and mouse were less than 1 s. As the difficulty level increased, the difference tended to get larger. MTs of hBCI Short and hBCI Long were less than two times of MT of the mouse at ID $= 2.4$ (bits), but about two times of the mouse at ID $= 4.6$ (bits).

C. Fitts' Law Evaluation

The Fitts' law in our study considers the target size and distance. It is intuitive that they affect pointing performance, and previous studies verified it [21], [28]. Furthermore, it is presumed that the target size affects selecting performance based on a previous study [36]. To prove this assumption, the relationship between task completion time and the target size is investigated. In reality, it is difficult to identify pointing and selecting times separately because subjects do not always perform a selection after pointing. In some cases, selecting the right point failed and the subject tried again. Because four interface systems use the same eye tracking for target pointing, pointing performances are not significantly different over the four interface systems when conditioned on the same distance. Therefore, the examination of task completion times over different target sizes can indirectly point out whether selecting time relies on the target size. Fig. 3 shows that task completion times taken across different target sizes at the same distance ($d = 31.2$ cm) to see if performance using each interface system is different depending on the target sizes. It is observed that task completion time decreases as the target size increases. Statistical analysis verifies that task completion time relies significantly on the target sizes [eye tracking with keyboard ($F(2, 16) = 8.80$, $p < 0.01$), eye tracking with dwell time ($F(2, 16) = 5.24$, $p = 0.017$), hBCI Short ($F(2, 16) = 23.47$, $p < 0.01$, and hBCI Long ($F(2, 16) = 27.85$, $p < 0.01$)].

Based on this result, the Fitts' law relationship between ID and CT during pointing and selecting tasks is evaluated. Fig. 4 shows the Fitts' law relationships averaged across the subjects. Their estimated linear regressions are also included. The CTs of hBCI Short and hBCI Long showed no pairwise

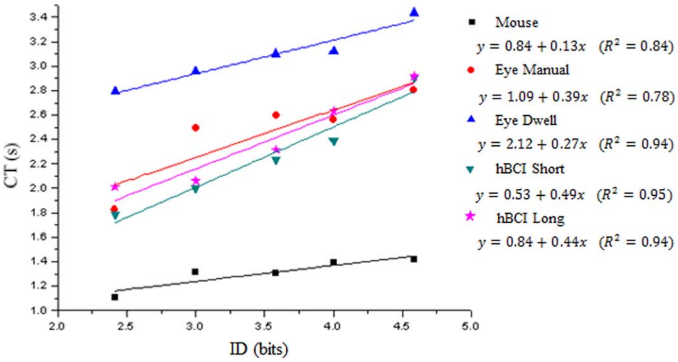

Fig. 4. Relationships between ID and MT averaged across subjects using the four interfaces (R^2 = correlation coefficient).

significant difference ($F(1,4) = 6.96$, $p = 0.058$) although the averaged CTs of hBCI Short were a bit lower than those of hBCI Long. The different interpretation between statistical analysis and comparison of the average values of hBCI Long may be due to the standard deviation difference as shown in Table III. Relatively high standard deviation in hBCI Short may imply that subjects' performances were less consistent over IDs. Using hBCI Short tended to complete a task quicker than hBCI Long as expected, but was less robust. Therefore, there is no significant difference within a statistical view.

Their ranges of CT were comparable to that of eye tracking with keyboard and quite less than that of eye tracking with dwell time. While CTs of the proposed hybrid interfaces were significantly different than those of a mouse ($F(2,8) = 50.88$, $p < 0.01$) and eye tracking with dwell time ($F(2,8) = 72.44$, $p < 0.01$), they were not significantly different than that of eye tracking with a keyboard ($F(2,8) = 1.96$, $p = 0.203$). This may imply that BCI selection mode is comparable to the keyboard clicking in terms of task time. Averaged CTs of the proposed hybrid interfaces apparently tended to increase a bit more than those of the other interfaces as ID increases (slopes $= 0.49, 0.44$). With the mouse, ID did not significantly affect CT ($F(4,32) = 1.41$, $p = 0.058$). Meanwhile, CT tended to rely on ID when using eye tracking with a keyboard ($F(4,32) = 5.80$, $p = 0.013$), eye tracking with dwell time ($F(4,32) = 5.87$, $p = 0.012$), hBCI Short ($F(4,32) = 8.91$, $p = 0.016$), and hBCI Long ($F(4,32) = 4.73$, $p < 0.01$).

The overall performance was well fitted with linear regressions as shown in correlation coefficient values. The Fitts' law linear regression resulted in ITR $= 2.02$ (bits/s) with $R^2 = 0.95$ for hBCI Short, and ITR $= 2.27$ (bits/s) with $R^2 = 0.94$ for hBCI Long.

D. BCI Classification Analysis

To perform the selecting task, subjects were asked to mentally concentrate when the hBCI interface was used. This section attempts to analyze whether the BCI protocol was reasonably implemented. Fig. 5 illustrates typical brain activity difference between the selecting and pointing states with respect to power spectrum density (PSD) per subject in the frequency band, between 11 and 19 Hz, in which feature vectors were assigned. Each plot was obtained by averaging the brain activity of each state. Each density difference at a particular electrode spot is visualized. The selected frequency band overlaps both the alpha wave (8–13 Hz) and beta wave (13–30 Hz) bands, more specifically low-to-mid beta wave band [38], [39].

Although this work does not attempt any detailed neurophysiological analysis, a potential interpretation on this observation is possible. According to literature [38], [39], active concentration or alertness results in an increase of activity in the beta wave band and a reduction of activity in the alpha wave band. The beta activity is distributed symmetrically and observed over various areas, but prominently in frontal areas. The alpha wave occurs over the entire lobe, but strongly at the occipital lobe with eyes closed. Although the electrode channels of the current headset do not cover the entire scalp, they seem to detect the alpha wave attenuation on the parietal or occipital area and the beta wave amplification as shown in Fig. 5. In cases of subjects S1, S2, S5, and S8, brain activities over the occipital area attenuate during the selecting state at relatively low frequencies (11 to 13 Hz) while brain activity increases over the frontal area especially at relatively high frequencies (16 to 19 Hz). The rest of the subjects show stronger activities over the electrodes during selecting rather than when pointing, which may indicate the beta wave amplification.

E. Eye Movement Analysis

The proposed hybrid interfaces incorporated two modules, eye tracking and BCI-based selection. To evaluate each module's performance during these tasks, Fig. 6 illustrates the cursor trajectories recorded during the experiments. Black and red dots represent trajectory components from eye tracking and BCI selection modes, respectively. Most subjects realized almost straight cursor trajectories while eye tracking to all the 12 directions. In some cases, overshot trajectory patterns appeared right before selection. They are probably due to the speed of the eye being too fast. Some wobbles were sometimes observed in trajectories. Instant information loss by eye blinking or the device failing to detect a gaze caused this unsteadiness. However, all directional performances through the proposed interface were visually uniform overall. The directional indifference is statistically verified ($F(3,24) = 1.81$, $p = 0.17$).

F. User Study

Table IV shows the survey result. Based on statistical analysis using the Student's t-test under 95% confidence interval, subjects expressed a bit higher confidence in cursor movement control than selection operation. As for the BCI selection mode, some capability differences between subjects were expressed. The hybrid interface was convenient overall in their opinions and subjects felt about 73% satisfied.

IV. Discussion and Conclusion

In this study, nine subjects successfully performed the tasks with proposed interfaces in at least 11 trials among 12 trials at lowest difficulty level and in at least seven trials at the highest difficulty level. Maintaining a cursor within a circular target while selecting it seemed to be the most difficult part of the experiment based on the inspection of the cursor trajectories. This difficulty is based on the ability of the human eye to point

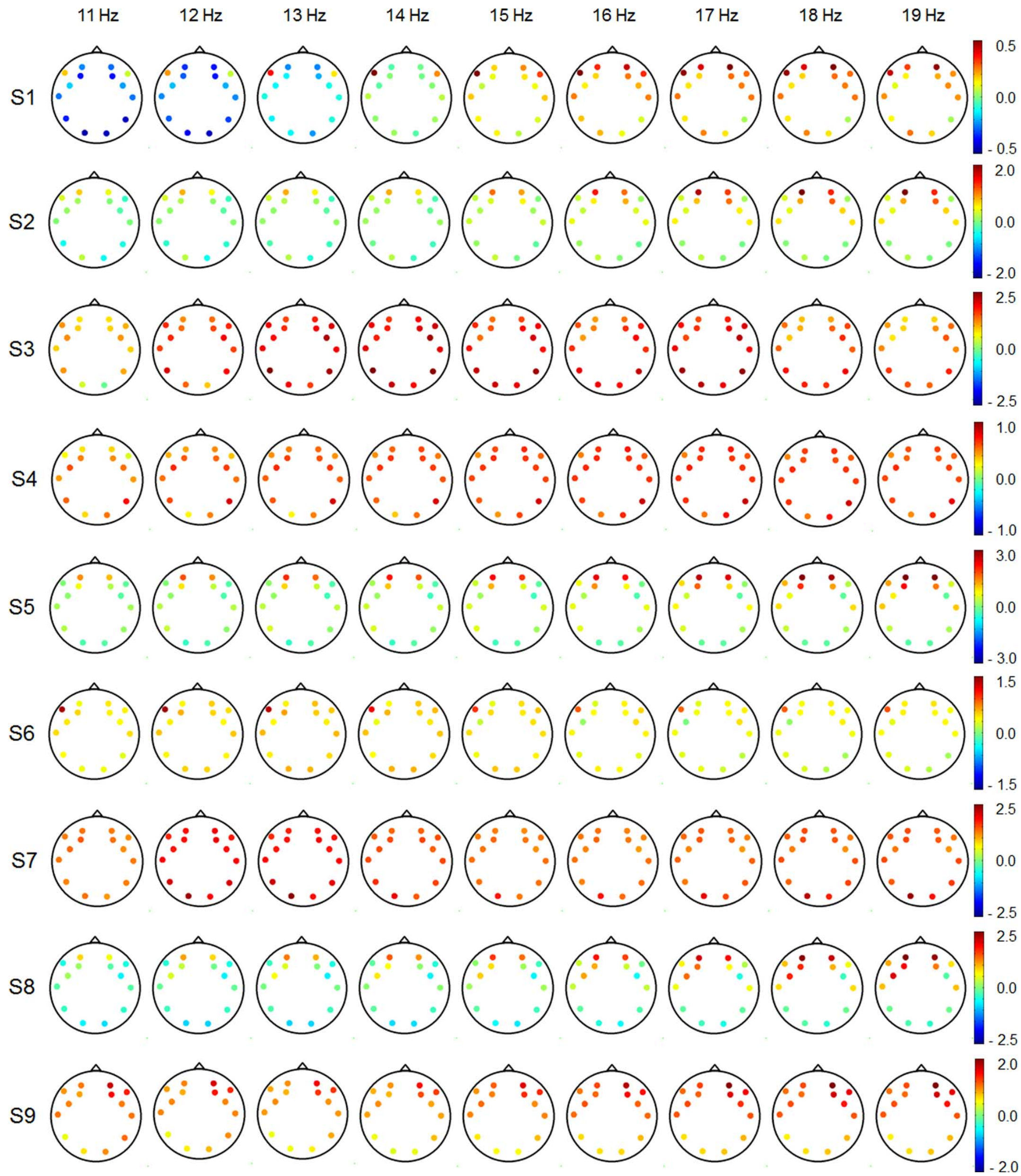

Fig. 5. Visualization of brain activities (selecting state– pointing state) per electrode over frequencies.

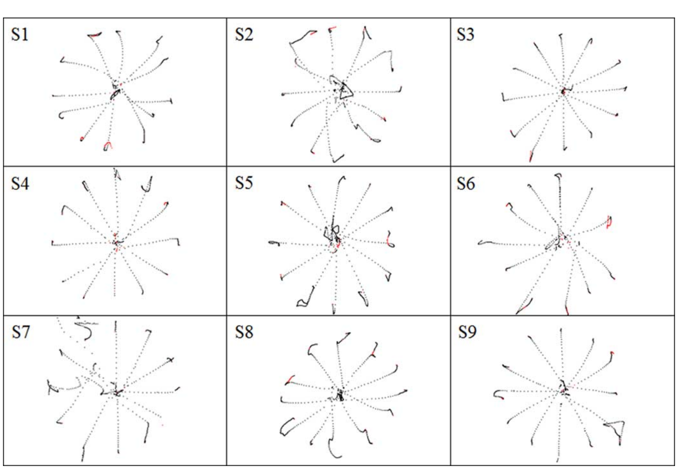

Fig. 6. Examples of cursor trajectories collected from subjects during tasks.

TABLE IV
SURVEY RESULT

Questions	Scores (in average)
Q1	8.00±0.82
Q2	6.56 ± 1.95
Q3	7.44 ± 0.68
Q4	7.33 ± 1.05

and the eye tracker's precision of detection. Blinking of the eyes also affected the cursor trajectory. Even while such limitations exist, eye tracking still possesses good advantages such as quickness and omnidirectional controllability. Although there was a clear difference in the adeptness of using the system, the subjects could, most of the time, complete tasks successfully within the time limit. Subjects tended to select their targets at the very center of targets rather than as soon as getting inside the targets. This tendency can be explained because the subjects should keep their eye inside the targets during necessary dwell time for successful selection. In other words, the subjects can reach their targets faster and reduce the completion time when they would make the selection at the edge of their targets. However, in this case, they usually failed the selection task because their eye positioning was out of the targets and did not satisfy the dwell time.

The performances of pointing and selection tasks were statistically comparable with that of the eye tracking with a keyboard. The proposed hybrid interface system achieved an overall ITR of 2.02–2.27 bit/s. It was lower than that of the mouse interface (7.61 bits/s) and a bit less than that of eye-tracking interfaces (2.58–3.64 bits/s). However, it was higher than that (0.541 bits/s) of the BCI-only interface reported in [28]. Furthermore, in terms of task speed, CTs of using the proposed hybrid interfaces were still faster than that of using eye tracking with dwell time and comparable with that of using eye tracking with a keyboard. CT of eye tracking with dwell time might be lowered further by reducing the dwell time interval, but its robustness would then suffer. The results indicate that BCI-based selection is competitive with keyboard clicking and eye dwell time when it is concurrently used with eye tracking.

An interesting comparison is with the EMG interface. Although EMG-based methods achieve a higher accuracy rate than EEG-based BCIs, the EMG-based methods still require muscle activation and translating the detection of this activation into certain kinds of interface commands. This intentional activation still presents an artificial, indirect mapping between intent and commands. It is the purpose of EEG-based BCI to eradicate this mapping in future computer interface systems. EEG-based BCIs enable the perception of subjects' intent directly from their brain and reflect the intent in controlling and communicating with machines. According to a report in [40], the overall ITR of the EMG interface was 1.299 bits/s, which is lower than those of the proposed hybrid interfaces. In addition, the range of ID in this work was from 2.4 to 4.6 (bits). It is similar to that of EMG interface in [40], but much greater than that of the BCI only interface in [28]. The report [28] mentioned that subjects missed the 3.7 bit ID commonly with a pure BCI interface scheme. Therefore, it had a limitation on performing high ID tasks. In the case of the EMG interface [40], the cursor movement was restricted to only horizontal and vertical directions. Multidirectional cursor movement is not yet reasonably achievable by either EMG or EEG only interfaces. Currently these interfaces are limited not by the physiological or psychophysical component, but rather a pragmatic one. In practice, some pragmatic limitations such as transition time between brain activities and EEG/EMG signals cannot be avoided perfectly. In order to overcome the current limitations, the proposed hybrid interface is derived with some techniques such as a sliding windows method. Developing these techniques increases the likelihood that brain signals-based discrimination method will be faster than a simple manual response in future. It is a valid remark that the proposed hybrid interface took advantage of eye tracking for moving cursors in terms of both movement speed and accuracy, and BCI-based selection was comparable to keyboard clicking. BCI-based selection may be natural and intuitive for disabled people or even for healthy people while their hands are busy.

In comparison with the mouse, the performances of all of the other interfaces tended to be less consistent over subjects (lower correlation coefficients). However, the developed interface relies on a simple BCI protocol, which a user can easily adapt to without a serious training session. Individual adaptation will be improved by gaining further experience to attain more robust and consistent performances.

This study presented important implications for future work on developing hybrid interface devices, especially using low cost equipment. Evaluation of the low cost hybrid interface is necessary for future work on developing real-world BCI interfaces. The hybrid eye tracking and BCI interface system will be effective to any one with no degradation in the ocular-motor system and motor planning and decision making areas of the brain. In addition, its operation 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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