Wearable Hybrid Brain-Computer Interface for Daily Life Application

Yongwon Kim and Sungho Jo
Dept. of Computer Science
KAIST
Daejeon, Republic of Korea
{sabipeople, shjo}@kaist.ac.kr

***Abstract*—We present the development of a wearable hybrid interface based on noninvasive brain signal detection and eye-gaze tracking, and its evaluation through scenarios based on real-world application. Our system combines a low-cost Electroencephalogram (EEG) headset with a custom-built eye-gaze tracker to determine the human's intent and track eye movements. The proposed interface allows users to pinpoint an electronic item of interest by gazing at it and turn on the object by concentrating. We show how our system can be applied as a tool in real-world environments. Seven healthy subjects volunteered to examine the performance of our interface. Fitts' law was applied for the evaluation and throughput (*TP*) which was an ISO standard for evaluation of pointing devices was derived. The experimental results demonstrate the potential of the proposed interface to fit into daily life.**

Keywords— Brain-computer interface, Electroencephalogram, Eye-gaze tracking, Hybrid interface, Wearable interface, Fitts' law.

I. INTRODUCTION

Now more than ever, people interact with diverse objects in their daily life and many approaches have been proposed to support the interaction between man and machine. Among many approaches, brain-computer interfaces (BCIs) have acquired huge interest due to their potential uses. However, the uses of BCIs mainly stay in laboratory environments. A strategy of improving its practical applicability is to combine the BCIs with other components such as eye-gaze tracking (EGT). Such a strategy is called hybrid BCI system. We propose a hybrid interface where users` mental states and eye movements directly have effects on the operation of electric devices. Specifically, we present a prototype wearable hybrid BCI that is low-cost and noninvasive to turn on electric devices in three-dimensional (3D) daily life environments.

Among diverse BCIs, electroencephalogram (EEG)-based BCIs have advantages in cost and safety [1]. In addition, EEG recording sensors have advanced in accuracy to meet the demands to control objects, and recent studies verified this [2, 3]. These studies tried to control only pre-selected object in 3D space with multi-states classification [2] or in two-dimensional (2D) computer screen [3]. These studies forced the user to be in front of computer screen without any movements. However, multi-class BCI requires intensive training and it is not easy for human to maintain multi-states mental concentration constantly. Furthermore, it is necessary that giving an ability to choose/pinpoint an object of interest to interact with in 3D space and allowing the users to make movements. In this context, two-class BCI could be favorable because of its relative simplicity, but has disadvantage in pinpointing an object in 3D space. To make up for the week point, hybridization with EGT could be a reasonable solution.

Line of sight of a user can be interpreted as an interest. EGT records eye movements and estimates user`s gazing spot, thus let a system know where or what the user is looking at even in 3D space. Both EEG-based BCI and EGT are intuitive and natural way of expressing human`s interest and intention, and allow the user to move his hands freely. These properties give the proposed wearable interface the potential usability in daily life application; specifically remotely turn on electric devices.

Our goal is to develop a low-cost and easy-to-use wearable hybrid interface which allows the users to remotely turn on objects with their mental states and eye movements, and doesn`t force the users to be in front of the computer screen without any movements.

The rest of this paper presents the design decision, experiment and result, and discussion and conclusion.

II. METHODS

A. Wearable hybrid interface system

Fig.1 (a) shows the overview of our wearable hybrid interface system. The interface consists of a low-cost commercial EEG acquisition headset (Emotive Epoch) and a custom-built eye-gaze tracker. The headset is much cheaper than the state-of-art EEG acquisition systems. It consists of 14 electrode channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) plus CMS/DRL references. It also has gyro sensor. The acquired EEG signals and gyro data are wirelessly transmitted to a PC. Its potential as a reliable recording system has been studied in previous study [4].

As shown in Fig.1 (b), the custom-built eye-gaze tracker combining with EEG headset consists of reflexive acrylic panel,

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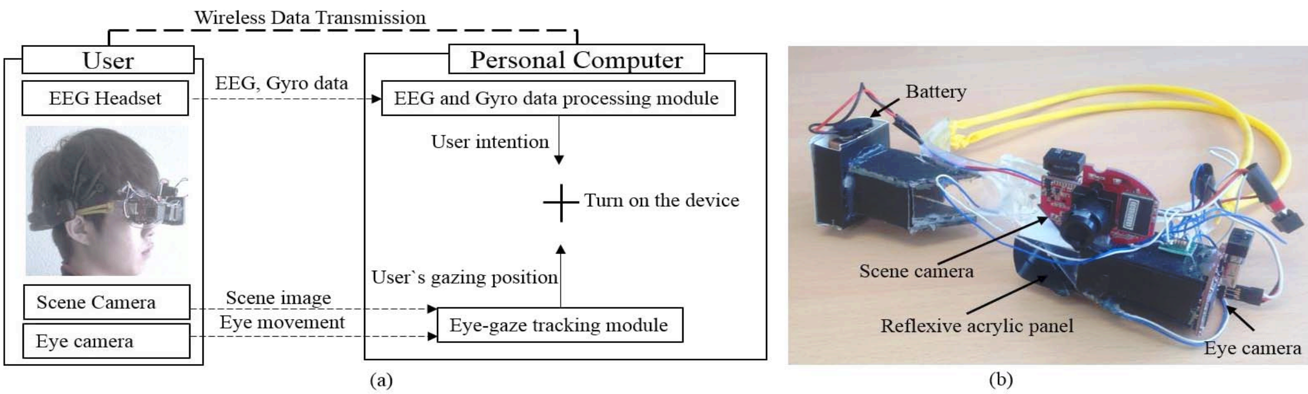

Fig. 1 (a) The overview of our proposed wearable interface system. (b) A custom-built eye-gaze tracker.

scene camera, eye camera, and four infrared (IR) light-emitting diodes (LEDs). We attach eye camera inside the glass frame to capture eye images through a reflexive acrylic panel coated to split visible light. The IR band-pass filter is installed inside the eye camera. Four IR LEDs are located around the reflexive panel toward the eye to enhance the contrast between the pupil and the iris. The scene camera is installed outside the frame, and captures user`s forward-facing scene. Both eye and forward-facing scene images are wirelessly transmitted to a PC. The total cost of building the eye-gaze tracker was less than $300USD.

The EEG headset and eye-gaze tracker were integrated into a low-cost wearable hybrid interface, which is hands-free and wirelessly works. The wireless design potentially allows a user to move freely within the range of wireless communication.

B. *Algorithms*

Gyro data are used to determine user`s state. The variance of gyro data from a motional state are much larger than the data from a motionless state. Using this property, we define a threshold to turn off EEG processing module as a user was in a motional state. This approach prevents the EEG signals from false classification while the user makes movements.

EEG signals are processed to discriminate the intentional concentration from non-concentration. The EEG signals are filtered from 8 to 30Hz. To solve the two-class classification, we apply the Common Spatial Patterns (CSP) algorithm to find spatial filters to extract classification features [5]. CSP finds the spatial filter w that extremizes the following function.

$$J(s) = \frac{w^T X_1 X_1^T w}{w^T X_2 X_2^T w} = \frac{w^T C_1^T w}{w^T C_2^T w} \tag{1}$$

where X_1 and X_2 denote a set of EEG signals representing the concentration and the non-concentration state, respectively. C_1 and C_2 indicate the spatial covariance matrices of non-concentration and concentration classes assuming a zero mean for EEG signals. The zero mean assumption is met by preprocessing. Using the Lagrange multiplier method, the optimization problem is transformed to be a standard eigenvalue problem. Then, we make the first two largest and last two smallest principal eigenvectors of $C_2^{-1} C_1$ form the spatial filters. With the spatial filters, features $f_p, p = 1, 2, 3, 4$ are taken to be

$$f_p = \log\left(\frac{var(z_p)}{\sum_{j=1}^{4} var(z_j)}\right) \tag{2}$$

where $Z_j = (FX_i)_j$ for the concentration or non-concentration state. Then, Support Vector Machines (SVM) algorithm with linear kernel are used to generate an optimal classifier to discriminate the EEG signal into two classes. SVM is selected on account of its good generalization properties which were effective for the low cost BCI system [6]. For the real-time classification during experiments, a sliding window of 2 s with 0.25 s increments is applied to the acquired data set and four sequential sliding window are needed to be classified as a concentration state to turn on an object.

The EGT algorithm is implemented based on previous study [7]. First, it extracts pupil edge points as feature using a threshold. Second, the Random Sample Consensus(RANSAC) is used to fit an ellipse with the extracted points. Then, the algorithm returns the estimated pupil center coordinates. These points are converted to gaze coordinates through a calibration process. Through the calibration process, the system calculates the coefficients to map the pupil coordinates into gaze coordinates.

III. EXPERIMETNS

Seven healthy male volunteers (age27.7±2.93(mean±SD)) participated in our experiments. All of the subjects were informed about the purpose and entire protocol of the experiments. Each subject wore the hybrid interface during the experiments. The EGT system captured eye-images and forward-facing scene with a spatial resolution of 320×240 and 640×480 pixels, respectively. Both images were captured at sampling rate 21 Hz. The EEG headset recorded EEG signals at sampling rate of 128 Hz from a 14-channel layout. It also gathered Gyro data too.

A. *EEG training and EGT calibration*

For the EEG training, subjects wearing our interface sat comfortably in a chair placed in front of the computer screen. Two commands, “Concentration” and “Rest”, appeared on the screen for 5 s in a random sequence and 2 s preparation time were given after each command was shown. The participants

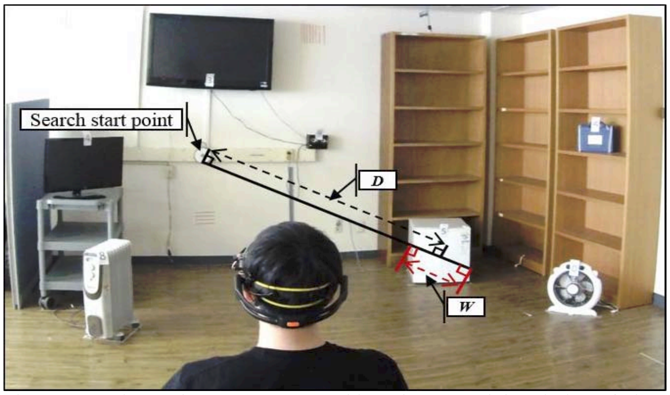

Fig. 2. Experimental setup (not every object shown) and description of Fitts' law parameter W and D.

tried to focus their attention when "Concentration" was shown and relaxed when "Rest" was shown on the screen. Each command appeared five times in a session. The session was repeated three times to collect the training data set with corresponding labels. Simultaneously, gyro data were also collected to define a threshold to determine the stationary state to turn on the EEG classifier during the experiments.

For the EGT calibration, we used a standard nine points calibration procedure. The subjects were asked to stand 2m away from the wall and saw the designated marker one at a time. On the wall, there existed nine makers we installed. While the participants saw the marker, the relative pupil positions were measured for 2 s. Once the subjects looked at all the nine markers, the calibration was complete.

B. *Fitt`s Law*

Fitts' law was first proposed in 1954 as a model that explained psychomotor behavior [8]. Because of its property to describe the relationship between target size, distance, and movement time, it has been widely used to predict movement time based on observed movement time and derive the dependent measurement of *TP* in human-computer interaction (HCI) area.

TP combines both speed and accuracy by compressing several time measurements of movement into itself. It has contributed to compare and evaluate pointing devices as an ISO standard. *TP* has been selected for an ISO standard describing the evaluation of pointing devices. It uses *bits per second (bits/s)* as a unit [9]. *TP* is given by:

$$TP = \frac{1}{y}\sum_{i=1}^{y}\left(\frac{1}{x}\sum_{j=1}^{x}\frac{ID_{ij}}{MT_{ij}}\right) \quad (3)$$

where y and x are the number of subjects and movement conditions, respectively. *MT* indicates total time taken to complete an entire task. *ID* is the index of difficulty defined by [9]:

$$ID = log_2(^{D}/_{W} + 1) \quad (4)$$

where D is the distance from the starting point to the target center and W is the target width. See Fig. 2 for additional explanation about D and W. As it is represented, the parameter W means the target width as it appears from the angle of approach.

For Fitts' law regression line, we used the formula given by:

$$MT = a + b \times ID \quad (5)$$

TABLE I
EYE CALIBRATION ERROR, BCI CLASSIFICATION ACCURACY, SUCCESS RATE, AND THROUGHPUT OF EACH SUBJECT

Subjects	Eye calibration error(SD) (cm)	BCI classification Accuracy(SD) (%)	*TP* (bits/s)	Success rate (%)
Subject00	0.69(0.44)	89.15(0.44)	0.2736	94.0
Subject01	0.75(0.34)	92.17(3.09)	0.4126	97.0
Subject02	0.54(0.29)	87.65(2.29)	0.3738	92.0
Subject03	0.65(0.28)	95.11(5.65)	0.2705	98.0
Subject04	0.55(0.30)	86.45(3.65)	0.3225	96.0
Subject05	0.45(0.30)	89.47(4.66)	0.3140	93.0
Subject06	0.63(0.36)	89.21(0.51)	0.3481	99.0
Mean	0.61	89.89	0.3308	95.6
SD	0.10	2.90	0.0518	2.6

where a and b are parameters to fit the model derived from observed *MT* and *ID*. The *ID* of each object is controlled to apply Fitts' law.

C. *Experimental Set up and Task*

Our experimental task simulates a person`s daily life; he/she sits on a sofa, and finds an electronic device (search phase) and turns it on (execution phase). Fig. 2 shows part of the experimental environment. Ten different objects were labelled by different numbers from zero to nine and deployed. During search phase, our interface allows the users to turn their head and body to find an object. The subjects are only needed to be in stationary as they are in execution phase. The execution phase is divided into two steps; pointing and concentrating.

The subject who wore the hybrid interface sat comfortably in a chair which was placed at a distance of 4.15 m from the search start point and looked at the start point. Once the experiment began, a randomly selected label number was announced, then the subjects started to search for the matched number. If he found the matched number, search phase was done. Then, he looked at the center of the object through the eye-gaze tracker. For the last step, he was required to be in stationary and focus his attention to turn on the object. This completed one trial and each trial had a 30 s limitation. Ten trials composed a session. At the end of each trial, a sound played to notify the participant. A 5 s preparation time was given to the participants to look at the start point before the next trial began.

During experiments each subject performed ten sessions. A trial was success if the gaze coordinate was located within the object contour as the concentration state was detected in four sequential windows.

D. *Experimental Results*

Table 1 shows calibration error, BCI classification accuracy, *TP*, and the success rate of each participant. For the BCI classification accuracy, 10-fold cross-validation were performed on EEG data which had been acquired during training. Table 2 shows the parameters of each object such as *ID* and *MT*. The *MT* of each object was averaged across subjects. Success rate for the objects is also shown in Table 2. The success rate was calculated by the number of successful tasks divided by the number of total trials. Repeated measured

TABLE II

FITTS' LAW PARAMETERS, AVERAGED MT AND SUCCESS RATE OF EACH OBJECT

Objects	*D* (cm)	*W* (cm)	*ID* (bits)	*MT*(SD) (s)	Success rate (%)
Object00	94.0	65.5	1.28	6.66(2.03)	100.0
Object01	130.0	59.5	1.67	6.68(2.08)	100.0
Object02	200.0	62.0	2.08	7.76(2.05)	98.6
Object03	180.0	39.0	2.49	7.00(1.62)	100.0
Object04	100.0	16.5	2.82	9.99(3.72)	81.4
Object05	304.0	36.5	3.22	9.14(3.03)	95.7
Object06	310.0	27.5	3.62	10.14(3.41)	97.1
Object07	500.0	34.0	3.97	11.46(4.11)	95.7
Object08	600.0	30.0	4.39	11.24(3.61)	95.7
Object09	600.0	16.0	5.27	12.42(4.72)	91.4
			Mean	9.25	95.6
			SD	2.13	5.7

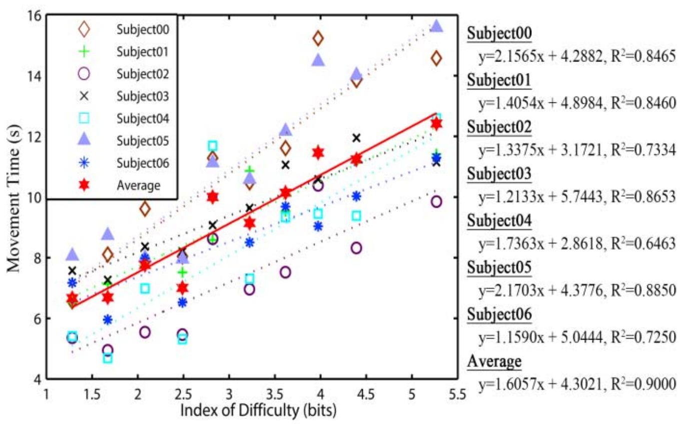

Fig. 3. Relationship between *ID* and *MT*.

analysis of variance (RMANOVA) was used to analyze sessions and Fitts' law regression line.

To see whether the repeated sessions improved *MT*, RMANOVA was performed. Analysis was performed on the predicted means of each subject which was averaged across *ID* from the least-squares regression of each session. There was no significant difference between trials [$F(9,54)=1.560$, $p=0.15$]. Because the repeated sessions did not significantly affect to the *MT* of each participant, averaged *MT* across sessions was used to apply Fitts' law.

Fig. 3 describes the Fitts' law regression lines and formulas of all subjects. The *X* and *Y* axis represent *ID* and its corresponding *MT* respectively. Statistically, *MT* was influenced by *ID* [$F(9,54)=31.416$, $p<0.01$].

IV. DISCUSSIONS AND CONCLUSION

This paper proposed a wearable hybrid interface which combined an EEG-based BCI and EGT. The combination of relatively simple two-class BCI protocol and EGT makes it easy for the users to learn and use our device. In addition, the approach our interface uses to read user`s intention is intuitive and natural.

The experiments aimed to examine the potential performance of the suggested interface in the real-world. For this reason, the most of the objects were intentionally located outside of subjects' view comparable to reality. To prevent the subjects from memorizing the location of the objects, the label numbers were shuffled before each session started. Therefore, whenever a new session started, the subjects should search for the designated object. In other words, our observed *MT* included searching, pointing, and concentrating time. Generally, the searching time occupied about 50% of *MT*.

It is maybe possible to perform the same task by using EGT alone, but EGT has a disadvantage to trigger execution command. Most of EGT systems rely on the dwell time. However, because the complexity of the task are various in real-world, it is almost impossible to determine an optimal fixed dwell time. Furthermore, distinguishing intended and unintended gaze fixation is hard so unintended gaze fixation could result in turning on a device unintentionally, and this could be dangerous in real-world. For this reason, the hybridization with EEG-based BCI is reasonable .

Our experimental results give meaningful information that suggest the possibility of improving the proposed device as a new contactless electronic equipment control interface. The hardware design can be extensively modified to further make use of other BCI protocols such as P300 [10] and steady state visually evoked potential (SSVEP) [11].

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