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Wearable Wireless Interface Based on Brain Activity and Eye Movement

Yongwon Kim[1] and Sungho Jo[1*]

1 Department of Computer Science, KAIST,
Daejeon, Republic of Korea, 305-701, (e-mail: shjo@kaist.ac.kr) * Corresponding author

Abstract: This paper presents the development of a wearable wireless interface based on brain activity and eye movement. A low-cost electroencephalogram (EEG) headset to read human intention is combined with a custom-built eye-gaze tracker to track eye movement. This wireless, wearable interface addresses limitations in previous hybrid interfaces by restoring freedom of movement. The proposed interface allows users to find an electronic item of interest by gazing at it and turn it on by concentrating. We examine the potential of the proposed interface to fit into our daily life through our experimental scenario. The experimental scenario simulates finding and turning on devices.

Keywords: Electroencephalogram (EEG), Eye tracking, Hybrid brain-computer interface, Wearable interface.

1. INTRODUCTION

Brain computer interfaces (BCIs) have drawn enormous interest and advanced considerably over the past decade [1]. However, using BCI system in our daily life still faces severe challenges. As an approach to realize real-world usability, hybrid BCI has emerged [2, 3]. Hybrid BCI systems are systems combining at least one BCI system with other systems. Combining systems helps hybrid BCI improve accuracy, overcome disadvantages of each system, or increase the number of commands. Among the many possible combinations, we focus on combining EEG-based BCI with eye-gaze tracking.

EEG-based BCI systems are convenient due to being non-invasive and therefore safe. Current commercial offerings [4] help verify the practical feasibility of simple EEG-based BCI protocols. Although simple EEG-based BCI has disadvantages like limited control capacity, it requires no intensive training and is comfortable.

Eye-gaze tracking technologies have advanced [5, 6] and are easy to use. In addition, eye-gaze tracking is a natural expression of a user's attention and interest.

Combining the two protocols helps to achieve controllability and robustness for daily life applications.

Although previous work has been conducted, the work severely limited the movement of the user and did not consider wireless communication for real-world scenarios [7, 8, 9]. Thus, our goal is to present a wearable hybrid interface system composed of EEG-based BCI and eye tracking. Furthermore, we examine the potential of our interface through test scenarios comparable to daily life.

2. INTERFACE DESIGN

2.1 Hardware

Our interface consists of two pieces of hardware for the purposes of selection and pointing.

We used an Emotive Epoc headset for selection. The headset consists of fourteen electrode channels to detect EEG signals, two references (CMS/DRL) around the sensorimotor cortex, and a gyro sensor. The headset applies notch filter at 50 Hz and 60 Hz and band-pass filter between 0.2 - 45 Hz to the raw signals. Then, the filtered signals are converted by a 14-bit resolution AD converter. The application of the headset as a reliable recoding system has been studied in previous work [3].

For the purpose of pointing, we used a custom-built wearable eye-gaze tracking system. As shown in Fig. 1, the custom built eye-gaze tracker has two cameras and a translucent acrylic panel. The acrylic panel is mirror coated to reflect the eye while still allowing the user to see through it.

We attached one of the cameras on the frame looking forward so to capture the scene as seen by the user.

In addition, we located the other camera inside the glass frame pointing toward the acrylic panel to capture reflected images of the eye. An infrared (IR) band-pass filter is installed on the camera and four small IR LEDs are located around the mirror pointing toward the user's eye.

Both of the cameras send captured images to a PC wirelessly.

The total cost of building the eye tracking interface was less than $300USD.

2.2 Software

Our software for the interface processes the EEG signals along with gyro data as well as eye images and forward-facing images for selecting a device and pointing at a device, respectively.

To select an object, we used a simple EEG-based BCI

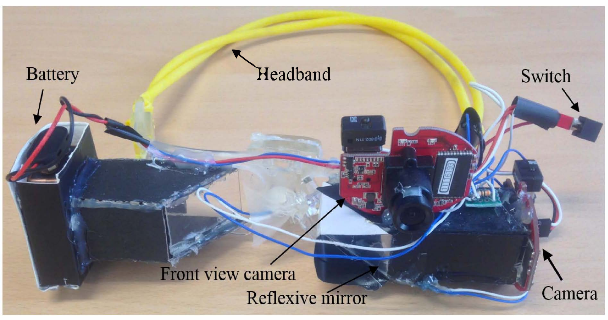

Fig. 1 A custom-built wearable eye tracking system

protocol that discriminates concentration states from non-concentration states. We regarded the discrimination problem as a binary classification problem. To solve the binary classification problem, we extracted classification features from the two classes using spatial filters which were built by the Common Spatial Patterns (CSP) algorithm [10]. During preprocessing, the EEG signals were band-pass filtered between 8 and 30 Hz which has been shown to be important [11, 12] and a sliding window of 2 s with 0.25 s increments was applied.

To find an optimal classifier that separates concentration and non-concentration states, we used a linear kernel Support Vector Machines (SVM) algorithm [13]. SVM was applied due to its good generalization properties [14].

One of the conditions for accurate classification is noise free EEG acquisition because the noise in EEG signals can confuse the classifier as it categorizes the acquired signals into each class. However, our goal was to develop a wearable interface usable in daily life and it is possible that this movement will generate EEG signal noise. To minimize influence of movement-induced noise, we used a gyro sensor. When a person is moving, the variance of data from the gyro sensor is much larger than data from a person who is stationary. Therefore, by applying a threshold to the variance, we are able to determine whether the EEG data should be analyzed.

To estimate where the user is looking and identify a device, our eye-gaze tracking system analyzes the eye and forward-facing images. We applied a standard image processing algorithm based on open source software [15, 16] to the received eye images for estimating pupil's center coordinates. Our system extracts points which form a contour between the pupil and iris. Because the system uses IR images, extracting these points is done using a predefined threshold. After extraction of the contour points, the system fits a circle

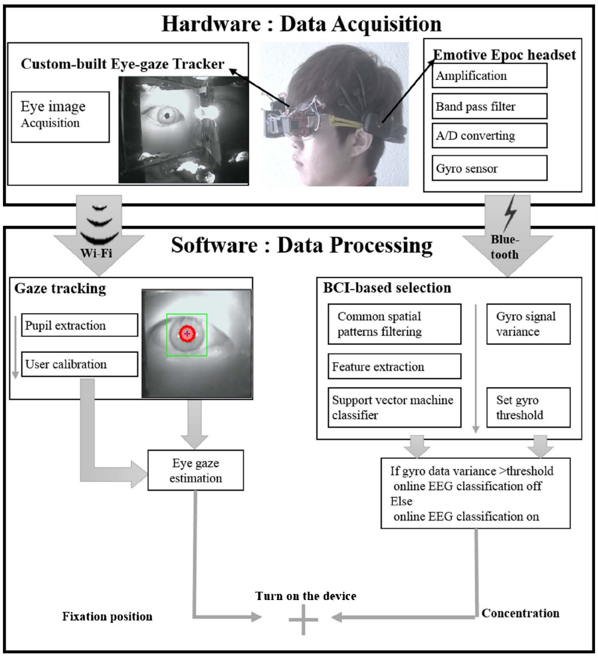

Fig. 2. Data flow of the suggested interface

using these points and estimates center coordinates of the circle. The center coordinates are the estimated pupil center. Finally, with the estimated coordinates and forward-facing image, the system identifies a device that a user is looking at.

The .NET framework was used to integrate the different software components of the system. We also developed a windows application for performance evaluation.

2.3 Integrated System

The suggested interface hybridizes the eye-gaze tracking system and EEG recording system with the signal processing software for the two systems. Fig.2 shows the data flow of the interface.

Our interface works wirelessly. Therefore, a user can freely move around wearing our interface as long as the user is within the range of wireless communication. While the user moves around with the interface, the EEG headset and eye tracking system records and captures required data and sends the data to the software on the computer.

Then, the software processes the eye and forward-facing images to identify the electric device of interest as well as processes the EEG signals to turn on the device. The EEG signals are analyzed only if the data is recorded under the right conditions.

3. Experiment

3.1 Subjects

Four healthy subjects (age 28.25 ± 3.95 (mean ± SD)) volunteered for our experiments. We fully informed them about the purpose of the experiments. Additionally, they were asked to search and select a designated object naturally as fast as they could.

3.2 Experimental Setup

In our experimental environment, we simulated a room where a person sits on a sofa and finds devices such as a coffee machine, laptop, or other electric device to turn on.

To control the distance to each object, we installed a reference point and placed a chair at a distance of 4.15 m from the point. Five electronic devices were deployed in different locations. Each device had a different width and distance from the reference point.

We measured the width of each object based on the device's incidence angle as measured from the reference point. Each device was labelled by a number from one to five.

3.3 Calibration and Classifier Training Procedure

Before the experimental task began, each subject trained the EEG classifier and calibrated the eye tracking system.

For the eye-gaze tracker, subjects performed a typical nine point-calibration procedure. Following this, subjects carried out an EEG calibration procedure. We asked subjects to not move during the calibration

TABLE I
EYE CALIBRATION ERROR AND
BCI CLASSIFICATION ACCURACY

Subjects	Eye calibration error(SD) (cm)	BCI classification Accuracy(SD) (%)
Subject01	0.65(0.30)	92.00(2.29)
Subject02	0.54(0.31)	85.68(3.19)
Subject03	0.50(0.25)	86.45(2.25)
Subject04	0.42(0.12)	88.25(3.61)
Mean	0.53	88.10
SD	0.09	2.81

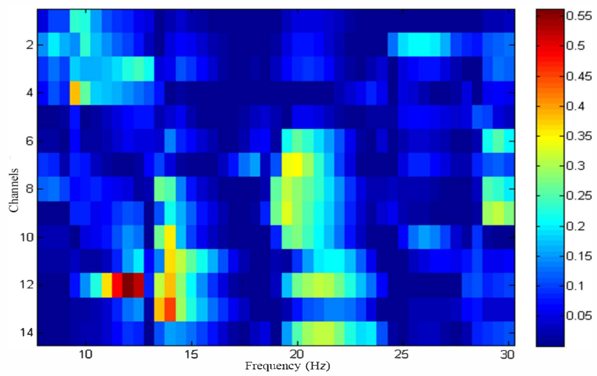

Fig. 3 Fisher's ratio of power spectral density between two mental states from subject01.

procedures to minimize the influence of noise. During the EEG classifier training, subjects were shown two different words, "Concentration" and "Rest" in random order. Each word appeared on the computer screen for 5 s. The subjects tried to focus their attention if they saw "Concentration" on the screen. On the other hand, if "Rest" appeared on the screen, they simply relaxed. Each word appeared five times and 2 s of preparation time was given to each subject between words. The EEG training procedure took 1 min and 8 s. Each participant repeated the EEG training three times to collect data with the corresponding label to train the SVM classifier. The gyro data was collected simultaneously with the EEG signals. The software used the gyro data to define a threshold to determine the appropriate condition to turn on the EEG classifier.

Table 1 presents the eye tracker calibration error and BCI classification accuracy of four subjects. Fig.3 shows the fisher's ratio of power spectral density between the two mental states from subject01. The color spectrum used ranges from blue to red, where red indicates a large difference between the two states.

3.4 Target Acquisition Task

After performing the calibration procedure, a subject wearing our interface sat in a chair and looked at the reference point. During the experiment, our system randomly chose a label number from one to five and announced it through a speaker. Then, the subject searched for the designated device by checking the label

TABLE II
PARAMETER AND SUCCESS RATE OF EACH OBJECT

Objects	^{a}D (cm)	^{b}W (cm)	Success rate (%)
Object01	94.0	65.5	100.0
Object02	130.0	59.5	100.0
Object03	304.0	36.5	100.0
Object04	310.0	27.5	97.5
Object05	600.0	16.0	82.5
		Mean	96.0
		SD	7.62

^{a}D = distance from reference point, ^{b}W = width

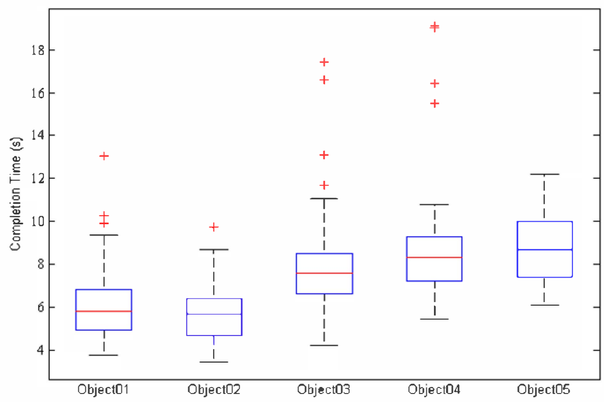

Fig. 4 Boxplot of completion time.

and looked at the center of the object. By looking at the object, the pointing step was completed. To turn on the device using EEG signals, the subject concentrated his/her attention on the device for 1 s. A trial was composed of the pointing and selecting procedures. If a selection occurred, the subject was informed by via a beep sound. The trial was successful only if the selection occurred while the gaze estimation points were located inside the object's boundary.

A trial had a 20 s time limit and a session consisted of ten trials. A specific sound announced the end of a trial. After a trial was completed, a 5 s interval was given to the subject to look at the reference point again. Each subject repeated the experiment for a total of ten sessions.

3.5 Experimental Result

During the experiments, we measured the total time to complete a trial. Fig.4 shows the boxplot of the completion time. Because the subjects looked at the reference point when a trial began, the completion time includes the searching, pointing, and selecting times. The average completion time across objects was 7.79 s (SD = 1.80 s). Table 2 shows the parameters and the selection success rate for each object.

4. DISCUSSION AND CONCLUSION

We proposed a wearable interface composed of an EEG-based BCI and eye-gaze tracking system. With the eye-gaze tracker, users could easily pinpoint an object of interest and through focusing, could turn on the selected device using the EEG-based BCI protocol. This is an intuitive and natural way to read the user's intentions.

There was a group which studied an alternative interface implemented using only EEG [17]. The group tested their interface using two-dimensional targets for acquisition tasks. The average selection time for healthy a subject acquiring a diagonal target was 7.99 s (SD = 2.71 s). In contrast to our study, all of the targets used to test the group's interface were located on a computer screen. Therefore, the group's completion time did not include target searching time. In addition, the distances between the reference point and targets were much longer in our experimental setup.

Although our interface is a prototype, the experimental results supported the potential of our interface.

The hardware design can be transformed to use other BCI protocols such as P300 and steady state visually evoked potential in future work [18, 19].

REFERENCES

[1] G. Dornhege, J. del R. Millan, T. Hinterberger, D. J. McFarland, and K.-R. Muller, *Toward brain-computer interfacing. Cambridge*, MA: MIT Press, 2007.

[2] G. Pfurtscheller, et al., "The hybrid BCI," *Front Neurosci.*, vol. 4, no. 30, Apr. 2010.

[3] Choi, B. and Jo, S., "A low-cost EEG system-based brain-computer interface for humanoid robot navigation and recognition", *PLoS ONE*, Vol. 8, No. 9, 2013.

[4] P. Brunner, L. Blanchi, C. Guger, F. Cincotti, and G. Shalk, "Current trends in hardware and software for brain-computer interfaces (BCIs)," *J. Neural Eng.,* vol. 8, Apr. 2011.

[5] R. J. K. Jacob, and K. S. Karn, "Eye tracking in human-computer interaction and usability research: ready to deliver the promises," *Mind*, 2003.

[6] R. Vertegaal, "A Fitts law comparison of eye tracking and manual input in the selection of visual targets," *in Proc. Int. Conf. Multimodal Interact. (ICMI)*, 2008, pp. 241-248

[7] T. O. Zander, M. Gaertner, C. Kothe, and R. Vilimek, "Combining eye gaze input with a brain–computer interface for touchless human–computer interaction," *Int. J. of Human-Comput. Interact.*, vol. 27, no. 1, pp. 38-51, Dec. 2010

[8] M. Kim, and S. Jo, "Hybrid EEG and eye movement interface to multi-directional target selection," *35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 763-766, 2013

[9] B. Kim, M. Kim, and S. Jo, "Quadcopter flight control using a low-cost hybrid interface with EEG-based classification and eye tracking," *Comput. Biol. Med.*, vo. 51, pp. 82-92, 2014

[10] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal Spatial Filtering of Single Trial EEG During Imagined Hand Movement," *IEEE Trans Rehabil Eng.*, vol. 8, no. 4, pp. 441-446, , Dec. 2000

[11] E. Kandel, J. Schwartz, and T. Jessell, *Principles of Neural Science*, 4th ed., McGraw-Hill, 2001, pp. 916

[12] D. Purves, et al, *Neuroscience 3rd Ed.*, Sinauer Associates, Inc., Sunderland, Massachusetts, USA, 2004, pp. 668-670.

[13] O. Chapelle, "Training a Support Vector Machine in the Primal," *Neural Computation*, vol.19, no. 5, pp.1155-1178, May. 2007

[14] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, and B. Arnaldi, "A Review of Classification Algorithms for EEG-based Brain-Computer Interfaces," *J. Neural Eng.*, vol. 4, no. 2, pp. R1-R13, Jun. 2007..

[15] D. Li, J. Babcock, and D.J. Parkhurst, "OpenEyes: a low-cost head-mounted eye-tracking solution," *in Proc. Symp. Eye Tracking Res. & Applicat. (ETRA)*, New York, NY, 2006, pp. 95-100

[16] J. San Agustin, et al., "Evaluation of a low-cost open-source gaze tracker," *in Proc. Symp. Eye-Tracking Res. & Applicat. (ETRA)*, New York, NY, USA, 2010, pp. 77-80

[17] E. A. Felton, R. G. Radwin, J. A. Wilson, and J. C. Williams "Evaluation of a modified Fitts law brain-computer interface target acquisition task in able and motor disabled individuals," *J. Neural Eng.*, vol. 6, no. 5, Aug. 2009.

[18] [25] J. Park, K.E. Kim, and S. Jo, "A POMDP approach to P300-based brain-computer interfaces," *in Proc. Int. Conf. Intell. User Interfaces (IUI),* 2010, pp. 1-10

[19] G.R. Müller, R. Scherer, C. Brauneis, and G. Pfurtscheller, "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *J. Neural Eng.*, vol. 2, no. 4, Dec. 2005