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An EOG/EEG-Based Hybrid Brain-Computer Interface for Chess

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***Abstract*—Most user interfaces require motion; the motor-impaired therefore do not have many options to choose from. Electroencephalography (EEG) and the analysis of eye movement are two of the commonly proposed methods for enhancing the user experiences of the motor-impaired. In this paper, we propose an electrooculography (EOG)/EEG-based hybrid BCI that combines the strengths of EOG and EEG by using them simultaneously. We have shown the effectiveness of EOG/EEG-based hybrid BCIs by implementing the proposed interface and applying it to a chess game. Through this paper, we hope to provide improved interface systems for patients who have physical disabilities.**

***Index Terms*—electrooculography (EOG), electroencephalography (EEG), brain-computer interface (BCI), machine learning, supervised learning, evoked potential**

I. Introduction

Most modern application software has user interfaces that require motion to interact with; this leaves the motor-impaired and patients with debilitating diseases such as amyotrophic lateral sclerosis (ALS) with a lack of options to choose from. As such, research on new, innovative methods to help those patients has become more necessary and prevalent. One large group of such research uses electrooculography (EOG), which uses a group of electrodes for each eye to analyze eye movement by detecting the electric potential in the retina. A long history of studies on EOG has led to the development of hardware devices dedicated to the accurate capturing of EOG signals [1] [2]. EOG signals are particularly sensitive to eye blinks, which elicit higher potentials than other types of eye movement. As EOG signals are affected by the distance between the electrodes used for measurement and the eye, blinking evokes stronger potentials for the electrodes closer to the eye (Fig. 1). Therefore, it is possible to distinguish the four states of the blinking of only the left eye, the blinking of only the right eye, the blinking of both eyes, and not blinking by only using the electrode positions close to the eyes.

Another proposed technology is the brain-computer interface (BCI); previous research in the field of BCIs has created new paradigms with the development of several medical applications, such as brain-controlled wheelchairs or software that allows writing through non-physical means [3] [4]. Precise control in these applications is possible due to the underlying function of BCIs: mapping brain activity to some quantitative output to predict the user's intent.

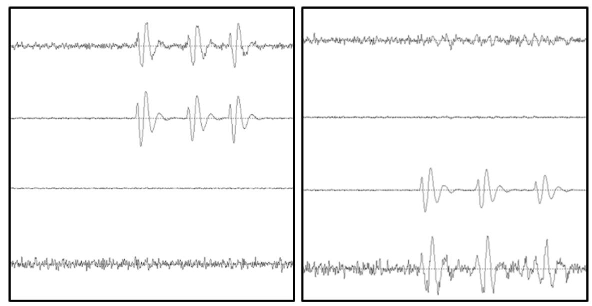

Fig. 1. The change in signals corresponding to the blinking of each eye. From top to bottom, the channels shown are Fp1, F7, F8, and Fp2.

One way to create this mapping is through electroencephalography (EEG), a method that measures electric neural signals. The most common variations of EEG include sensorimotor rhythm (SMR), steady state visually evoked potentials (SSVEP), and P300 [5]. SMR is a change in rhythmic neural activity within the sensorimotor cortex that corresponds to the execution or even the imagery of limb movement. SSVEP are potentials that naturally form within the occipital lobe when visually stimulated at a certain frequency. P300 signals are evoked within the parietal lobe when exposed to unexpected target visual stimuli with a low occurrence rate.

The widespread usage of EOG is inevitable when considering its clear strengths; EOG signals are extremely accurate, fast, and easy to analyze due to their large amplitude [6]. BCIs are also becoming more popular due to their high accuracy and their independence from any physical movement.

The purpose of this paper is to improve existing implementations of application software by enhancing the user experience of the motor-impaired. This was achieved with an EOG/EEG-based hybrid BCI that combines the strengths of the two aforementioned methods. Two hybrid BCIs were

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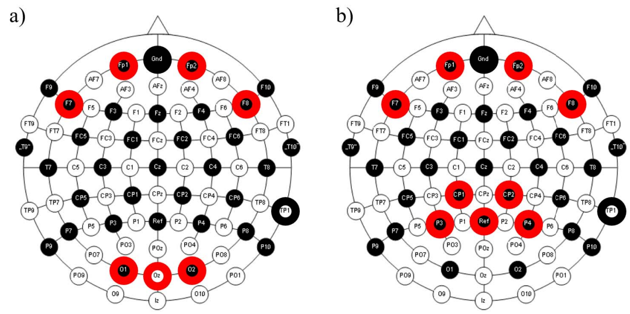

Fig. 2. a) The map of electrode positions for the EOG/SSVEP-based hybrid BCI and b) the map of electrode positions for the EOG/P300-based hybrid BCI. The ones highlighted in red represent the channels used in this paper. The ones highlighted in black represent the ground and reference electrodes.

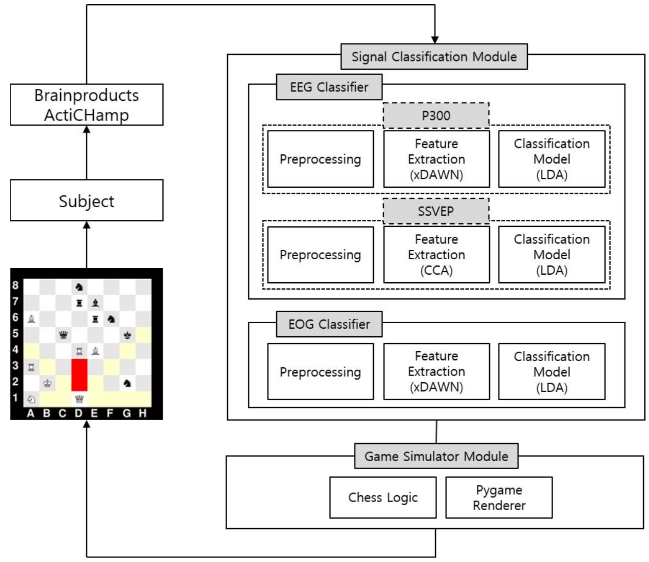

Fig. 3. The system architecture of the proposed EOG/EEG-based hybrid BCI system.

implemented; one used SSVEP for EEG signaling, while the other used P300 for EEG signaling. In order to study their effectiveness, the proposed EOG/EEG-based hybrid BCIs were implemented in a chess game, one of the most popular games of all time.

II. System Architecture

Brain Products' actiCHamp actiCAP was used to capture EOG/EEG signals from specific channels. The electrode positions Fp1, Fp2, F7, and F8 were used to capture EOG signals. For EEG signaling, O1, Oz, and O2 were used to capture SSVEP signals from the occipital lobe while P3, Pz, P4, CP1, and CP2 were used to capture P300 signals from the parietal lobe. For all of the aforementioned signaling methods, Fpz and Tp10 were used for the ground electrode and reference electrode, respectively (Fig. 2).

The hybrid BCI chess game proposed in this paper consists of two partitions: a signal classification module that analyzes EOG/EEG signals to understand the user's intentions and a game simulator module that plays the game according to the outputs provided by the signal classification module (Fig. 3). The signal classification module plays two important roles in the overall system; it filters and analyzes training data to create one classifier each for EOG and EEG, and it analyzes real-time signals with the model to understand the user's intent during the chess game. The game simulator module provides visual feedback on what it interprets to be the user's intent and dynamically moves a selected chess piece to its intended destination.

III. Signal Processing

Signal processing was done in the signal classification module. The signal processing procedure comprises signal preprocessing, feature extraction, and classification model training. A notch filter was used to first remove 60 Hz power-line artifacts from the raw data obtained by the actiCHamp actiCAP.

In EOG signal processing, a Butterworth band-pass filter was applied to extract signals of frequency 1-17 Hz. The xDAWN algorithm was used during feature extraction to increase the signal-to-noise ratio by enhancing evoked potentials [7]. In classification model training, linear discriminant analysis (LDA) was used to differentiate the EOG features by separating their corresponding values as much as possible [8]. The EOG classification model was capable of distinguishing three classes: blinking the left eye, blinking the right eye, and not blinking.

In EEG signal processing for SSVEP, a Butterworth band-pass filter was applied to extract signals of frequency 1-45 Hz. A canonical correlation analysis (CCA) was used to calculate the correlation coefficients of the EEG signals captured from the electrodes and the frequency of the flickering box [9]. LDA was used as a classifier to analyze whether the subject was looking at a box that was flickering at a frequency of 15 Hz.

In EEG signal processing for P300, a Butterworth band-pass filter was applied to extract signals of frequency 1-20 Hz. Similarly to EOG signal processing, feature extraction and construction of the classification model used the xDAWN algorithm and LDA, respectively. P300 signals were captured when the subject was looking at a box that randomly flickered with a low probability to utilize the oddball paradigm [10].

IV. Subject Training

Subject training was held before each game simulation in order to gather data from the user. Each subject was required to participate in two training stages, the EOG training stage and the EEG training stage, for the creation of personal classification models for their EOG and EEG signals.

A. EOG training stage

Each subject completed 10 consecutive trials of EOG training. A single trial consisted of one left blinking training and one right blinking training, with each blinking training

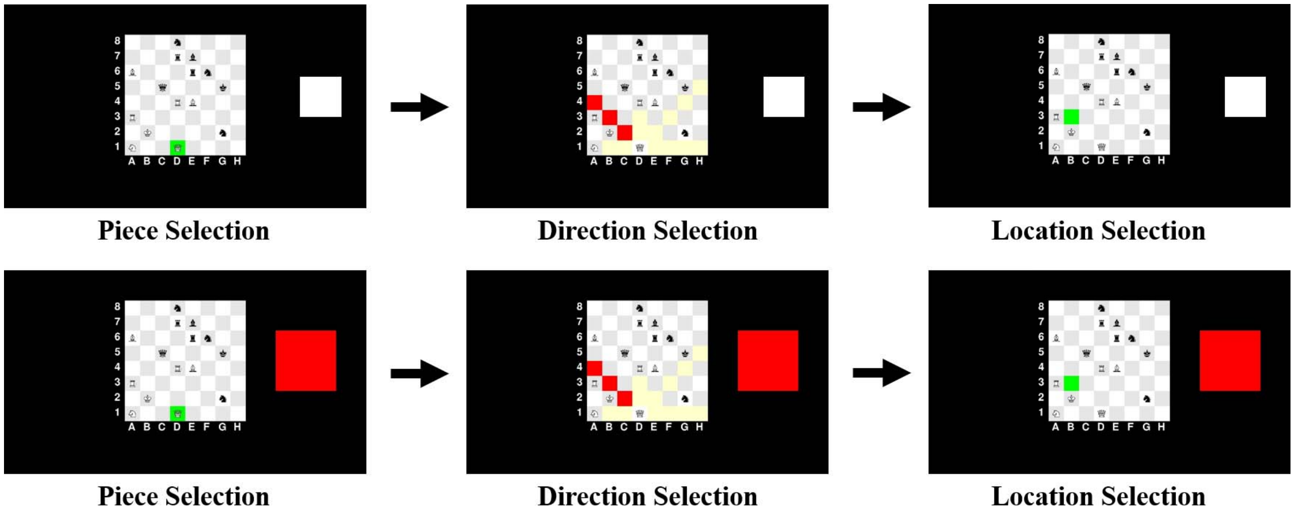

Fig. 4. Screenshots of the game simulator module's graphical user interface using P300 (top) or SSVEP (bottom) during the experiment. In order to move a chess piece to the desired location, the subject went through the following steps: piece selection, direction selection, and location selection. To confirm the selection using P300, the subjects were instructed to gaze at the location where the white box would appear. To confirm the selection using SSVEP, the subjects were instructed to gaze at the red box, which was constantly flickering at a frequency of 15 Hz throughout the experiment.

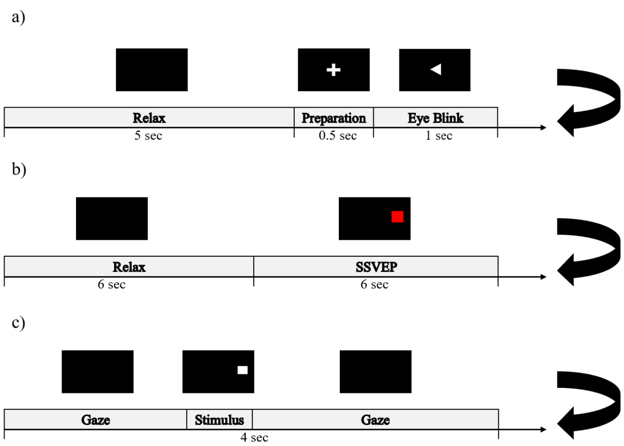

Fig. 5. a) The components of each EOG blinking training. b) The components of each SSVEP EEG recording trial. c) The components of each P300 EEG recording trial

consisting of the following sequence of screens: 5 seconds of a blank screen, 0.5 second of a white cross, and 1 second of an arrow pointing either left or right depending on which blinking training it was (Fig. 5). When a blank screen appeared on the monitor, the subject was expected to rest. When a cross appeared, the subject was informed to prepare to blink. When an arrow pointing either left or right was shown on the screen, the subject was instructed to perform a single blink of their corresponding eye. EOG data was collected throughout the entire process.

B. SSVEP training stage

Each subject completed 10 consecutive trials consisting of a 6-second SSVEP signal recording period and a 6-second resting period. During the resting period, a blank screen was displayed, and the subject was expected to rest. When a red box flickering at a frequency of 15 Hz appeared on the right side of the screen, the subject was instructed to gaze at the flickering box. EEG data was collected from the last 4 seconds of each resting period and each SSVEP signal recording period.

C. P300 training stage

Each subject completed 80 consecutive trials, all 4 seconds long. For each trial, the subject was required to fix their eyesight at a location where a box was expected to appear briefly. EEG data was collected throughout all 4-second trials.

V. Chess Game Procedure

To move a chess piece in the game simulation module, subjects were required to complete three steps in order: the piece selection step, the direction selection step, and the location selection step. Subjects chose a piece to move in the piece selection step, a direction in the direction selection step, and how far to go in the selected direction in the location selection step (Fig. 4).

The subject's intent was analyzed by the signal classification module through EOG/EEG signaling, which consequently alerted the game simulator module about how to change the graphical user interface (GUI) to provide the correct visual feedback to the subject. EOG was used to rotate through the possible choices of the selection in question. EEG was used to confirm selections for each step. For SSVEP, the subject was required to look at the flickering box located on the right side

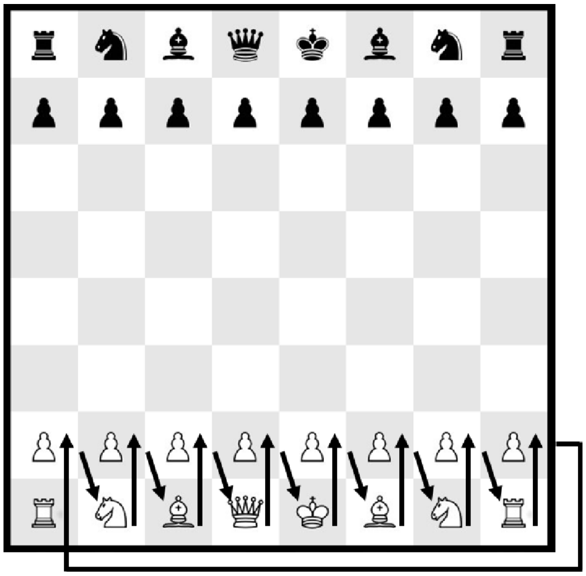

Fig. 6. An example of the implicit hierarchy enforced by the game simulator module. The arrows represent the sequence of rotation by right bilnking through the possible chess pieces. The sequence for left blinking rotation is in the opposite direction of the arrows shown.

of the GUI to confirm a selection. If the signal classification module detected three consecutive SSVEP signals, the signal classification module alerted the game simulator module to lock in the subjects choice and move on to the next step. For P300, the subject was required to look at a location on the screen specified by the instructor where a box was expected to randomly appear briefly every few seconds. The signal classification module alerted the game simulator module when it detected at least three P300 signals out of the four most recent stimuli from the subject.

A. Piece selection

When the subject first entered the simulation, the game simulation module first highlighted all chess pieces the subject can move in red for a few seconds. The game simulation module is designed to create an implicit hierarchy for these pieces; pieces on columns to the right are of higher rank than pieces on columns to the left. Within each column, pieces on a higher row are of higher rank than pieces on a lower row. Subsequently, the game simulation module highlights the uppermost and rightmost piece, or the highest ranked piece in the hierarchy, in green by default. The subject was able to highlight another piece instead by blinking left or right. Blinking left changed the highlighted piece to the previous piece according to the implicit hierarchy, while blinking right changed it to the next piece. The hierarchy is also cyclic. If the currently selected piece is the highest ranked piece and the subject blinks right, the lowest ranked piece is highlighted. Likewise, if the currently selected piece is the lowest ranked piece and the subject blinks left, the highest ranked piece is highlighted. In this way, the subject was able to rotate through all the possible chess pieces by blinking. Figure 6 serves as a visual aid on the details of the piece selection step. Once the subject was pleased with their choice, they were instructed to look at the flickering box to confirm their selection.

B. Direction selection

In the direction selection step, the game simulation module highlighted in yellow all possible directions the selected chess piece can move in, and then highlighted in red one of the directions. Similarly, the subject was able to highlight another direction in red instead by blinking left or right and finalize their choice by looking at the flickering box.

C. Location selection

In the final location selection step, the game simulation module highlighted in green the location closest to the selected chess piece in the selected direction. The subject was able to highlight another piece instead by blinking left or right. Blinking left highlighted the location that was one tile further away from the selected piece, while blinking right highlighted the location that was one tile closer to the selected piece. The choice was again finalized by looking at the flickering box.

VI. Experimental Protocol

A. Subjects

Five naive subjects participated in this experiment. All subjects were healthy male college students aged between 21 and 24. All subjects had no prior experience with EOG and EEG.

B. Experimental procedures

Each subject was requested to sit comfortably in front of a display monitor, which was used for training and to display the GUI for the game simulator module of the hybrid BCI. The subjects were recommended to avoid blinking during the EEG training process and movement in general.

After subject training, the training data was used in two ways: cross-validation and construction of the subject's personal classification model. The data was first used to create a classification model for each subject that was subsequently used during the chess game simulation. After experimentation with the chess game simulation was complete, the training data was also used for leave-one-out cross-validation, a cross-validation method by which a single epoch from the training data is tested on a classification model produced with the remaining data, to measure the accuracies of the EOG and EEG classifications.

In chess game simulation, each subject was given a chess board of a certain state that complied with the rules of chess (Fig. 7). Before the piece selection step, each subject was instructed to move a certain piece to a specific location provided by the instructor. Each subject was asked to move five chess pieces in a single experiment.

To evaluate the effectiveness of SSVEP and P300 within our system, the game simulator module was also implemented such that it maintained an internal timer that measured the time

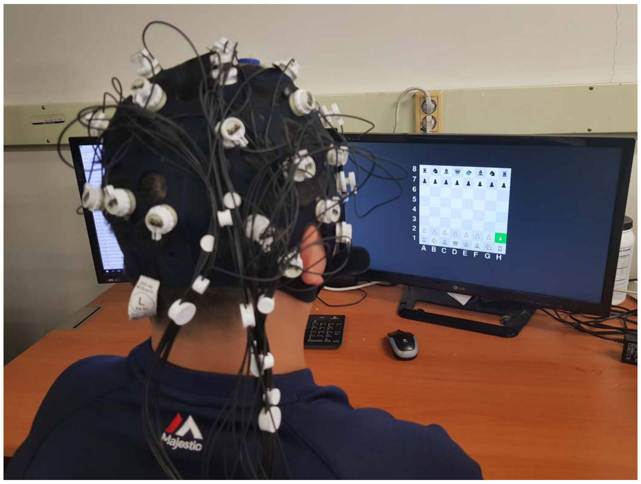

Fig. 7. A participant during the experiment.

passed since the last EOG signal. This timer ran throughout all selection steps (piece selection, direction selection, and location selection). If the timer passed 30 seconds, signifying the fact that 30 seconds had passed since the last eye blink, the game simulator module automatically assumed that the subject had made his decision but had not been able to confirm his selection. Subsequently, the game simulator module automatically moved on to the next step and displayed a ”No SSVEP/P300 Signal Detected” sign on the other monitor. The instructor of the experiment counted how many times such an automatic shift had occurred to evaluate the accuracy of SSVEP and P300 within our chess game.

VII. Results

Table I and Table II show the cross-validation results for the five subjects on both the EOG and the EEG data. Despite the fact that the EOG classification differentiates three classes, it showed higher accuracy than the EEG classifier, which differentiates two classes. Furthermore, by capturing EOG signals during one-second time windows, EOG takes significantly less time to gather a single epoch compared to methods using EEG such as SSVEP, P300, and SMR [9] [11] [12].

To evaluate the accuracy of the two EEG methods during our chess game simulation, accuracy was calculated with the 15 EEG confirmations each subject was required to make to move the 5 chess pieces during the experiment (each chess piece requires 3 EEG confirmations, one for each of the piece selection, direction selection, and location selection steps). For SSVEP, 2 out of 5 subjects (subjects 2 and 5) were able to successfully move all 5 chess pieces to the desired location provided by the instructor, not making any errors in their SSVEP confirmations. Subjects 1 and 4 both had one unintended confirmation before they made their selections, therefore each successfully making 14 SSVEP confirmations. Subject 3 had the worst performance out of the five subjects with 3 failed SSVEP confirmations, all unintended confirmations.

In chess game simulation using P300, none of the subjects were able to move all 5 chess pieces to the desired location provided by the instrutor. In most cases, the classification model misjudged the intent of the subject as they were selecting the chess piece, direction, and final destination. All the subjects experienced at least 3 unintended P300 confirmations, with one subject even experiencing 6 unintended confirmations before they made a selection.

None of the subjects had an automatic shift occur during their experiments.

VIII. Discussion

Despite the relatively low accuracy seen for the single trial based cross-validation of P300 data, we expected the accuracy to rise when cross-validating with multiple sequences of data as seen in previously conducted research [7]. However, as seen in the results, the hybrid BCI that used P300 for its EEG method is not applicable due to its poor performance. This may be due to interference between EOG and P300 data, as signals that affect the electrodes for EOG also affects those for P300 and vice versa. Nevertheless, the results show the clear viability and superiority of the EOG/SSVEP-based hybrid BCI compared to its P300 counterpart. We have therefore shown the effectiveness of EOG/EEG-based hybrid BCIs by applying the proposed interface to a chess game.

Unlike EEG, which requires high concentration from the user in order to gather appropriate data for training, EOG was preferred by the participants due to its simplicity. A survey

TABLE I
Cross-validation results of each subject for the EOG and SSVEP classifications.

Subject Number	Cross-Validation Results (%)	
	EOG (3 class)	*SSVEP (2 class)*
Subject 1	94.2	88.0
Subject 2	97.5	93.0
Subject 3	97.5	76.0
Subject 4	95.8	86.0
Subject 5	96.7	86.0
AVG	***96.3***	***85.8***
STD	***1.38***	***6.18***

TABLE II
A single trial based cross-validation results of each subject for the EOG and P300 classifications.

Subject Number	Cross-Validation Results (%)	
	EOG (3 class)	*P300 (2 class)*
Subject 1	95.8	69.4
Subject 2	94.2	68.1
Subject 3	96.7	70.0
Subject 4	92.5	68.8
Subject 5	96.7	62.5
AVG	***95.2***	***67.8***
STD	***1.81***	***3.02***

to the participants of our experiment found that most of the subjects felt less fatigue training for EOG than EEG. The subjects cited our recommendation to not blink while staring at the flickering box as the main reason behind the exhaustion for EEG. On the other hand, subjects could freely blink their eyes while resting during EOG training and only had to perform specific blinks for a comparatively short amount of time.

However, both EOG and SSVEP are limited on the number of classes they can distinguish. Therefore, the proposed EOG/EEG-based hybrid BCI is not sufficient for complicated tasks such as typing, as performing such tasks requires the differentiation of many classes. Further research will attempt to tackle this problem by combining the proposed hybrid BCI with other BCI techniques to create a user interface with even more degrees of freedom for the motor-impaired. Another possibility is to find a way to separate EEG and EOG signals by lessening the effects of interference between them, which would allow for the simultaneous usage of EOG and P300. If such a way were to be found, comparing the accuracy of this paper's proposed EOG/SSVEP-based hybrid BCI with that of an improved EOG/P300-based hybrid BCI may be conducted for further research.

With our interface's combination of EOG and EEG for detecting the user's intent, we have successfully reached our goal of simulating a chess game without using any body movement besides blinking. The effectiveness of our interface suggests that controlling systems with a diverse range of complex actions is possible with a hybrid approach. Through this paper, we hope to provide improved interface systems for patients who are motor-impaired.

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