Development of an "Eyes-Closed" Brain-Computer Interface System for Communication of Patients with Oculomotor Impairment

Chang-Hee Han, Han-Jeong Hwang, Jeong-hwan Lim and Chang-Hwan Im*

*Abstract***—The goal of this study was to develop a new steady-state visual evoked potential (SSVEP)-based BCI system, which can be applied to disabled individuals with impaired oculomotor function. The developed BCI system allows users to express their binary intentions without needing to open their eyes. To present visual stimuli, we used a pair of glasses with two LEDs flickering at different frequencies. EEG spectral patterns were classified in real time while participants were attending to one of the presented visual stimuli with their eyes closed. Through offline experiments performed with 11 healthy participants, we confirmed that SSVEP responses could be modulated by visual selective attention to a specific light stimulus penetrating through the eyelids, and could be classified with accuracy high enough for use in a practical BCI system. After customizing the parameters of the proposed SSVEP-based BCI paradigm based on the offline analysis results, binary intentions of five healthy participants and one locked-in state patient were classified online. The average ITR of the online experiments reached to 10.83 bits/min with an average accuracy of 95.3 %. An online experiment applied to a patient with ALS showed a classification accuracy of 80 % and an ITR of 2.78 bits/min, demonstrating the practical feasibility of our BCI paradigm.**

I. INTRODUCTION

Many patients suffering from severe neuromuscular diseases such as amyotrophic lateral sclerosis (ALS), brainstem stroke, multiple sclerosis, and spinal cord injury have difficulty communicating with other people. Brain–computer interfaces (BCIs) are non-muscular communication methods that help such individuals interact with the outside world using brain activity [1]. In BCI studies, one of the most widely used electroencephalography (EEG) potentials is steady-state visual evoked potential (SSVEP), which is a periodic neural response elicited by a certain visual stimulus flickering at a specific frequency. Since BCI systems based on SSVEP can provide a high information transfer rate (ITR) and do not require extensive training procedures, a variety of SSVEP-based BCI systems have been developed and applied to such activities as controlling an electric apparatus [2], playing a 3D game [3], operating an electrical prosthesis [4], controlling an avatar in a virtual reality environment [5], and mentally spelling words [6]-[8].

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The conventional SSVEP-based BCI systems commonly require the basic assumption that the users have normal oculomotor function and thus are able to maintain an open gaze at a given visual stimulus consistently. In practice, however, it has been reported that some patients suffering from serious neuromuscular disorders have difficulty controlling their eyes [9]-[11]. In particular, many patients with ALS have oculomotor impairments [12]-[13] causing abnormal visual perception [14]. According to studies by Okuda et al [9] and Averbuch-Heller et al [11], some ALS patients have abnormal eye movements with prominent gaze impairments. A study by Averbuch-Heller et al [11], for instance, described an ALS patient with normal corrected visual acuity who could move his eyes horizontally but had

difficulty opening his eyes and moving them upward. These patients would not be able to open their eyes continuously to

gaze at one of the target visual stimuli.

The main goal of the present study was to develop a new SSVEP-based BCI system that can be used for classifying binary intentions of individuals who have impaired oculomotor function. In this study, we implemented a visual stimulation system using a pair of glasses and LEDs attached to the glasses. EEG signals were measured while participants were selectively concentrating on either the left or right LED flickering at different frequencies with their eyes closed. Preliminary offline experiments were conducted with 11 healthy participants to confirm that distinct SSVEP responses could be recorded from the 'eyes-closed' participants. After customizing parameters based on the results of preliminary offline experiments, the binary intentions of five healthy participants and one ALS patient were classified in real time.

II. MATERIALS AND METHODS

A. Design of a Visual Stimulation System

In order to present flickering visual stimuli to eyes-closed participants, we implemented a new visual stimulation system using a pair of glasses, LEDs, and an LED controller. We first made two LED channels composed of four square, multi-chip, high-flux LEDs. Then, each LED channel was attached to the inside of each lens of eyeglasses utilizing Velcro fasteners as shown in Fig. 1(a). Each LED channel attached at the lateral side of each eye flickered at different frequency. The locations of the LED channels could be readily adjusted depending on each participant's eye position. To control the LED channels, an LED controller was fabricated using a TMS320F2812 chip (Texas Instruments Inc., USA). The flickering frequency of each LED channel could be easily adjusted using in-house software developed by the authors. In this study, a frequency band of $7 - 17$ Hz was empirically selected as the stimulation frequency band, different combinations of two stimulation

Fig. 3. The classification accuracy for each participant with respect to varying analysis window sizes and average classification accuracy for all participants (black bold line).

frequencies were determined for each participant through the preliminary experiment [15]. Table I shows the selected optimal pair of flickering frequencies for each participant.

B. Experimental Procedures

Offline experiments were conducted with healthy 11 participants (P1-P11) to verify whether the SSVEP responses modulated by selective attention to a specific flickering light stimulus penetrating through the eyelids could be classified with accuracy high enough to be used in practical BCI systems. The participants were required to gaze at either the left or right LED for 10 s with their eyes closed. This procedure was repeated 100 times to obtain 50 epochs of SSVEP responses for each of the 'left' and 'right' trials.

To verify whether the proposed paradigm could be used for a practical BCI system, we conducted online experiments with 5 out of the 11 healthy participants (P7-P11). For the online experiments, two electrodes showing the highest classification accuracies were selected for each participant based on the offline analysis results (See Table 2 for the selected electrodes). Fig. 2 shows the online experimental paradigm. At the beginning of each trial, instructions were presented through the speakers in front of the participant, indicating which visual stimulus the participant should gaze at ("left" or "right"). Two seconds later, a pure tone was presented to the participants to indicate that they should begin concentrating on the designated visual stimulus for a certain

TABLE II. RESULTS OF ONLINE EXPERIMENTS WITH RESPECT TO THE PARTICIPANT OF OVERVER EXTERNMENTS WE DIFFERENT TIME PERIODS..

Participants	Electrodes	Classification Accuracy (%)			
		2 _s	3 _s	4s	5 _s
P7	PO ₂ , O ₂	80.0	100.0	93.3	100.0
P ₈	Oz, O ₂	80.0	80.0	93.3	90.0
P ₉	POz, PO ₂	96.7	96.7	100.0	100.0
P ₁₀	Oz. 01	73.3	83.3	96.7	93.3
P11	POz, PO ₂	76.7	90.0	93.3	96.7
Mean $(\%)$		81.3	90.0	95.3	96.0
ITR (bits/min)		9.21	10.62	10.83	9.09

Fig. 2. A schematic diagram of the experimental paradigm used for online experiments.

period.

We tested four time periods $(2, 3, 4, \text{ and } 5 \text{ s})$ to investigate changes in the performance of our BCI paradigm. While the participants were focusing on either visual stimulus, EEG signals were recorded and analyzed in real time. The classification results were provided to the participants ("Correct" or "Wrong") via the speakers right after the recording period. An experimental session consisting of 10 trials (five for left stimulus and five for right stimulus) was repeated three times for each of four different time periods.

Another online experiment was conducted with an ALS patient (male, 43 years old). The patient was completely locked-in state and could only control his eyes horizontally, but the movement speed was extremely slow. Before the experiment, we selected two stimulation frequencies, 6 Hz for the left stimulus and 7 Hz for the right stimulus. To verify the practicality of the developed 'eyes-closed' SSVEP-based BCI system, we attempted to communicate with the patient using our BCI system. We asked ten different questions related to the patient, e.g., Are you older than 30?, and the patient answered 'yes' or 'no' using the developed 'eyes-closed' SSVEP-based BCI system. At the mean time, the right and left LED stimuli were assigned to 'yes' and 'no' responses, respectively. The time period for each question was set to 6 s.

D. EEG Data Recording and Analysis

The EEG signals were recorded using eight electrodes (POz, PO1, PO2, PO3, PO4, Oz, O1, and O2) attached to the participants' scalps according to the international 10-20 system. In the online experiment performed with an ALS patent, only three electrodes (Oz, O1 and O2) were used to simplify the experimental procedures.

In the offline analyses, we tested three different types of feature vectors: spectral powers at stimulation frequencies, denoted as H1; those at the second harmonic frequencies ($2 \times$ stimulation frequencies), denoted as H2; and the arithmetic sum of H1 and H2, denoted as H1+H2. To select two optimal electrodes and an optimal feature type for online experiments, the classification accuracies were evaluated for each electrode and each feature type. Ten different analysis window sizes (1-10 s with a step of 1 s) were tested to evaluate the influence of analysis time periods on the classification accuracy. We used a simple classification algorithm that searches for the frequency with the largest SSVEP amplitudes (H1, H2, or $H1+H2$).

In the online experiments, we used the same classification strategy as in the offline experiments.

III. RESULTS

A. Offline Analysis Results

Fig. 3 shows the changes in classification accuracy for each participant with respect to different analysis window sizes when the optimal feature type and the best electrode were used. The average classification accuracy was 74.8% when the analysis window size was 1 s, and it exceeded 90% when the analysis window size was longer than 4 s, demonstrating that the SSVEP responses obtained under eyes-closed condition can be classified with high accuracy.

B. Online Experimental Results

Table II shows the results of online experiments performed with the five healthy participants with respect to different time periods. The time listed in the second row in the table is that allotted for gazing at each designated stimulus. As shown in the table, the average classification accuracy increased as the time period increased (2 s: 81.3%, 3 s: 90.0%, 4 s: 95.3%, and 5 s: 96.0%). It is worthwhile to note that the average classification accuracy was 81.3% even when the time period was only 2 s, demonstrating that our paradigm could be used for a BCI system requiring quick responses. The highest average ITR was obtained when the given time period was 4 s, suggesting that the trade-off between classification accuracy and ITR should be carefully considered.

The ALS patient correctly answered 8 out of the 10 questions (80 % accuracy) and the ITR was 2.78 bits/min. Although the number of questions was relatively small, our results are meaningful in that the proposed 'eyes-closed' BCI paradigm could be used for the locked-in patient.

IV. DISCUSSION

Some patients suffering from severe neuromuscular diseases have difficulty controlling their eyes [9]-[11]. Since these patients have difficulty gazing at specific visual stimuli or keeping their eyes open for a long time, they are unable to use the typical SSVEP-based BCI systems. In the present study, we introduced a new SSVEP-based BCI paradigm, which can be used for disabled individuals with impaired oculomotor function. In order to provide visual stimulation to these 'eyes-closed' individuals, we implemented a visual stimulation system with two LEDs flickering at different frequencies in a pair of glasses. The results of our offline and online experiments demonstrated the feasibility of our proposed paradigm.

In this study, we used a conventional frequency detection method based on FFT to identify the user's intentions. Recently, several researchers proposed new target detection algorithms, such as canonical correlation analysis (CCA) and phase-constrained CCA (p-CCA) [16, 17]. It has been proven that the novel target identification methods based on CCA could increase the overall performance of SSVEP-based BCI systems. In our future studies, we will apply the CCA-based target detection methods to our BCI system.

In the previous studies, some BCI paradigms using other senses were proposed for communication of patients who have impaired oculomotor function. In Müller-Putz *et al*'s study

[18], steady-state somatosensory evoked potential (SSSEP) was used for classifying binary intentions. The reported online classification accuracy was between 53.5% and 88.1%. Also, in a study by Kim *et al* [19], a paradigm based on steady-state auditory evoked potential (SSAEP) was proposed and showed an average classification accuracy of 71.4%. Despite that both methods were applied only to healthy participants, the ITRs of the two studies were 3.45 bits min⁻¹ and 0.819 bits min⁻¹, respectively, which is relatively low compared to ours (the average ITR was 10.83 bits min^{-1} for healthy participants).

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