Classification of Mental Arithmetic and Resting-State Based on Ear-EEG

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Abstract—**Electroencephalography (EEG) has been mainly utilized for developing brain-computer interface (BCI) systems. In recent, use of Ear-EEG measured around the ears has been proposed to enhance the practicality of conventional EEG-based BCI systems. Most of BCI systems based on Ear-EEG have used exogenous BCI paradigms employing external stimuli. In this study, we investigated the feasibility of using Ear-EEG in developing an endogenous BCI system that uses self-modulated brain signals. EEG data was measured while subjects performed mental arithmetic (MA) and baseline (BL) task. EEG data analysis was performed after dividing the whole brain area into four regions of interest (frontal, central, occipital, and ear area) to compare their EEG characteristics and classification performance. Similar event-related (de)synchronization (ERD/ERS) patterns were observed between the four ROIs, and classification performance was insignificant between them, except occipital area (frontal: 72.6 %, central: 76.7 %, occipital: 82.6 % and ear: 75.6 %). From the results, we could confirm the possibility of using Ear-EEG for developing an endogenous BCI system.**

Keywords- electroencephalogram (EEG); brain-computerinter interface (BCI); Ear-EEG; mental arithmetic; endogenous BCI system;

I. INTRODUCTION

Brain-computer interface (BCI) systems can assist disabled people who cannot use their bodies to communicate with the external environment [1-3]. To date, electroencephalography (EEG) has been mainly applied to the development of BCI systems, compared to other brain imaging modalities, such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG), due to relatively low cost and easy set up. BCI systems based on conventional EEGs require the attachment of recording electrodes on the scalp with conductive gels for accurate signal measurements, which limits the application value of BCI systems in terms of practical use. In recent, to overcome the limitation of conventional EEG-based BCI systems, EEGs measured around the ears, called Ear-EEG, has been proposed that can allow unobtrusive EEG measurement [4-6].

Ear-EEG based BCI research mainly uses exogenous paradigms using external stimulus such as auditory steady-state response (ASSR) [7-9], steady-state visual evoked potential (SSVEP) [10] and event-related potential (ERP) [5]. However, endogenous paradigms based on self-modulated EEGs have rarely been studied for the development of BCI systems based on Ear-EEG. The aim of this study is to validate the feasibility of an endogenous paradigm in developing Ear-EEG-based BCI systems. To this end, EEG data was recorded while subjects were performing mental arithmetic (MA) and vocalization of English alphabet that was introduced as baseline (BL) task due to its low cognitive load. EEGs induced by MA were classified with those induced by BL task, and the performance of scalp-EEG and Ear-EEG was compared.

II. METHODS

A. Subjects

Seven healthy subjects participated in this study. All participants were between 21 and 31 years old (mean = 23.9, standard deviation = 3.07). They have no history of neurological or psychiatric diseases. The Institutional Review Board (IRB) of Kumoh National Institute of Technology reviewed and approved this study (no. 6250). All subjects signed a written consent after experimental procedures were explained.

B. Experimental procedures

Subjects were seated in a comfortable arm chair 1 m away from a 21-inch monitor. Thirty-one electrodes were used to measure EEG data (Brain Products, GmbH, Germany), twenty-five of which were attached on the scalp according to the international 10-20 system (Fp1-2, Fz, F3-4, 7-8, FC5-6, Cz, C3-4, CP1-2, T7-8, CP1-2, Pz, P3-4, 7-8, O1 and O2) while the others on the mastoids to measure Ear-EEG (Fig. 1). The EEG data was referenced to the FCz and collected with a sampling rate of 1000 Hz. The ground electrode was attached on the Fpz. The impedance was kept below 10 kΩ during the whole experiment. For the MA task, the subjects performed to continuously subtract a single-digit number (between 5 and 9) from a random three-digit number (e.g., 150 - 7) until a trial ended for 10 s. For the BL task, they imagined vocalization of English alphabet from A to Z with a 1 Hz speed for

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maintaining a low cognitive load state, which was assumed as baseline state, and thus BL was also used for resting state.

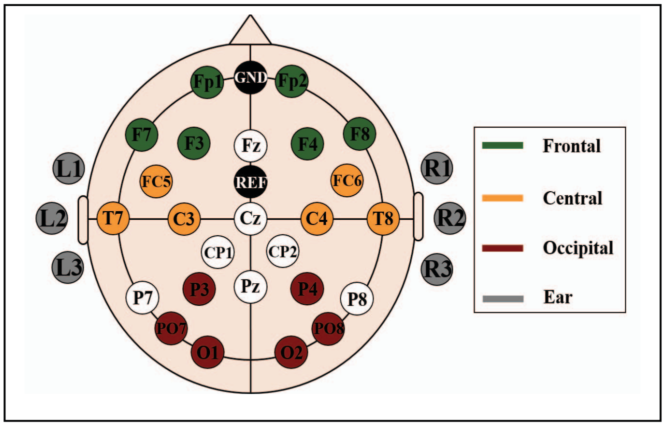

Figure 1. Electrode positions used for recording EEG data. The brain area is divided into four clusters that are frontal, central, occipital, and ear area.

Fig. 2 presents the experimental paradigm used for recording EEGs for a single session. Each session started with an initial resting state in which a blank was first displayed for 5 s, which was followed by resting state where the word 'ABC' and asterisk fixation were presented together. The subjects imagined vocalization of English alphabet for 10 s while focusing on the asterisk that was used as a fixation mark to prevent sever ocular movements. As mentioned above, note that the subjects performed internal vocalization of English alphabet during both BL task and resting state. A single trial was comprised of a task presentation with 5 s, followed by a fixation with 10 s, and variable resting periods (10 - 15 s). At the task presentation state, a MA problem or 'ABC' word was displayed on the screen. After 5 s, the task period started by presenting a black fixation cross for 10 s, during which the subjects performed either MA or BL according to an instruction presented by the monitor. It followed by resting state after each task period. A short beep sound (300 ms) was presented at every screen transition. The experiment consisted of five sessions. Each session consisted of 10 repetitions for MA and BL in a random order. After each session, there was a break for several minutes.

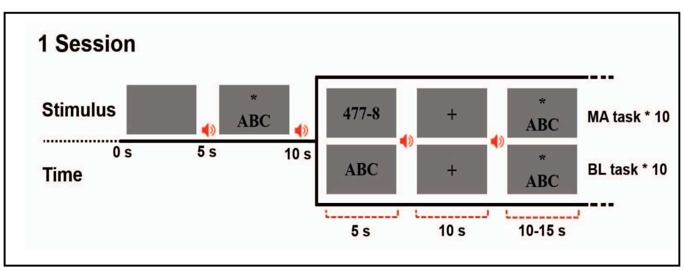

Figure 2. One session of the experimental paradigm used in this study

C. *Data Analysis*

The EEG signals were down sampled from 1000 to 200 Hz, and band-pass filtered in the range of 1 - 50 Hz with a fourth-order Butterworth filter. Before main analysis, we first divided brain areas into four regions of interest (ROIs) that are frontal, central, occipital, and ear areas to compare their EEG characteristics and classification performance. The 24 electrodes out of 31 electrodes were used to cluster each brain area including each 6 electrodes: frontal (Fp1-2, F3-4, 7-8), central (FC5-6, C3-4, T7-8), occipital (P3-4, PO7-8, O1-2), and ear area (R1-3, L1-3). Independent component analysis (ICA)-based weight adjusted second-order blind identification (iWASOBI) method was used for removing eye blink and movement artifact.

Event-related (de)synchronization (ERD/ERS) of each ROI was analyzed for MA and BL task from 1 – 50 Hz, for which EEG data between -2 and 0.5 s based on task onset was used for baseline correction.

To inspect classification accuracy, we extracted EEG features of two tasks between -2 and 10 s from stimulus onset, for which common spatial pattern (CSP) algorithm was applied to the preprocessed EEG data. To find subject-dependent band-pass used for CSP, the signed squared biserial correlation coefficients were used. The subject-dependent single pass band showing the highest *r-value* was determined using heuristic method, and was used for CSP. EEG features were calculated as the variance of CSP-filtered data. A ten-fold cross-validation was performed ten times to estimate classification accuracy using shrinkage linear discriminant analysis (sLDA; the BBCI toolbox) [12-13]. We performed the classification for each ROI, and statistical analysis was performed using the Friedman test between the four ROIs in terms of classification accuracy to compare the classification performance between the ROIs.

III. Results

A. *ERD/ERS map*

Fig. 3 shows ERD/ERS pattern maps of representative channels for each brain area during MA and BL. The x-axis indicates the time from -2 to 10 s based on task onset, and y-axis indicates the frequency range between 1 to 50 Hz. A cue sign for each task is marked with a vertical dashed line (t = 0 s). The ERD/ERS maps show significant increase in alpha band and decrease in beta and gamma bands for the four representative channels during MA. During BL, ERS pattern is observed in most frequency bands. This difference between MA and BL can be used for classifying the two conditions.

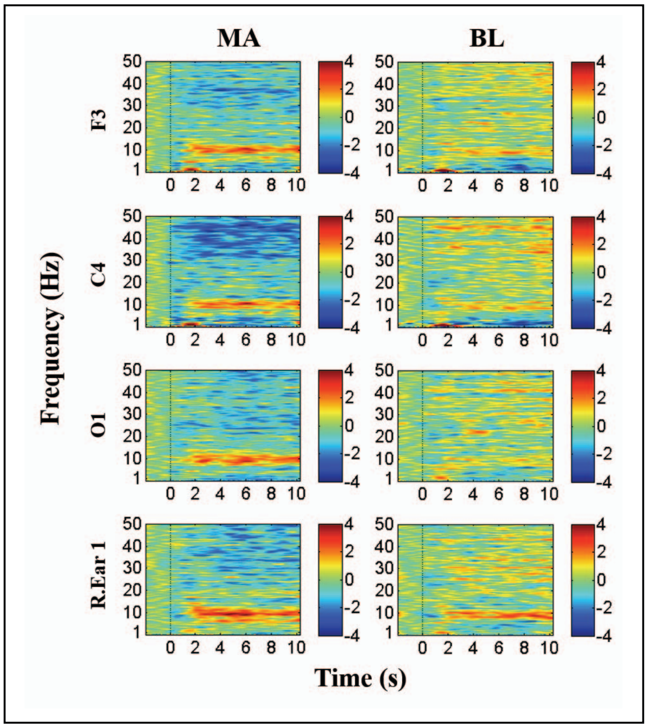

Figure 3. ERD/ERS maps of representative channels of each ROI during MA and BL

B. Classification accuracy

In Fig. 4, average classification accuracies are shown for the four ROIs and the whole area excluding 6 ear electrodes (denoted as 'Scalp' in Fig. 4). The mean accuracies of the whole scalp, frontal, central, occipital and ear area are 88.9, 72.6, 76.7, 82.6 and 75.6 %, respectively. Friedman test shows no significant difference between the four ROIs (p = 0.3659). Note that the whole area ('Scalp') was not included for this statistical test. The post-hoc analysis revealed that the classification accuracy of occipital area is significantly higher than the other three ROIs, but no significant different between the three ROIs (Frontal vs. Central vs. Ear).

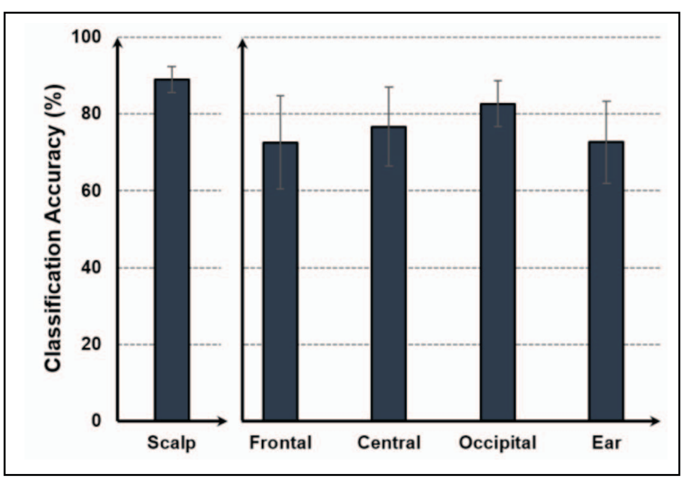

Figure 4. Mean classification accuracies of four ROIs and the whole scalp area ('Scalp') excluding six locations of Ear-EEG

IV. Conclusion

This study aims to develop an Ear-EEG based endogenous BCI system by discriminating brain responses induced by MA and BL. Brain responses (ERD/ERS) measured around the ears were similar to those measured from the other brain areas. In particular, strong ERS pattern in alpha frequency band was observed across all ROIs, which is consistent with a previous study that reported alpha activity increase during high cognitive task [14]. The mean classification accuracy using Ear-EEG was 75.6 %, and it was not significantly difference between other brain areas, except occipital area. From the analysis results, we confirmed the feasibility of using endogenous paradigm for developing an Ear-EEG based BCI systems, but more experiments should be performed with more subjects to generalize our results.

Acknowledgment

This research was supported by Business for Cooperative R&D between Industry, Academy, and Research Institute funded Korea Small and Medium Business Administration in 2016 (Grans No. S2380249)

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