Toward Exoskeleton Control based on Steady State Visual Evoked Potentials

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***Abstract*—Brain-machine interfaces (BMIs) are systems that establish a direct connection between the human brain and a machine. These systems are applicable to neuro-rehabilitation. In this study, we propose a method of finding optimal threshold of canonical correlation analysis (CCA) based steady state visual evoked potentials (SSVEPs) classification for detecting resting state and reducing misclassification. As a result, we successfully found optimal threshold for the best performance. This result shows the possibility of SSVEP based exoskeleton online control with a proposed method.**

Keywords-Brain Machine Interfaces; Electroencephalogram; Exoskeleton; Steady State Visual Evoked Potential (SSVEP)

I. INTRODUCTION

Brain-machine interfaces (BMIs) are communication systems in which the user's intention is conveyed to the external world without involving the normal output pathways of peripheral nerves and muscles [1]. For patients suffering from a high spinal cord injury (SCI), BMI can be used for device control such as wheelchair [2], robot arm and lower limb exoskeleton.

To meet this end, BMI have to be adjustable under real world conditions. This means it has to work whenever the user wants control. In BMI studies, electroencephalography (EEG) is a good method under real world. EEG is the only noninvasive method of recording brain activity that involves sensors light enough to allow uninhibited movement and has sufficient time resolution to record brain activity on the time scale of natural motor behavior. And, SSVEP is the one of the most commonly used modalities. It has advantages of high signal-to-noise ratio (SNR) and information transfer rate (ITR). Also, this is an inherent response of the brain, therefore very little training is required to enable a user to operate the BMI.

In case of wearable exoskeleton control, measured EEG always contains noise like a movement artifact. Therefore, method which holds robust signals against movement artifact is needed in order to control external devices. Also, each subject has different brain response to visual stimulus. CCA can be applicable efficiently in these conditions. This method can extract frequency information including harmonic frequency associated with the SSVEP [3].

In this paper, we propose a method for finding optimal threshold of CCA based SSVEP classification for detecting resting state and reducing misclassification. The result of offline experiment shows the feasibility of SSVEP based wearable exoskeleton online control.

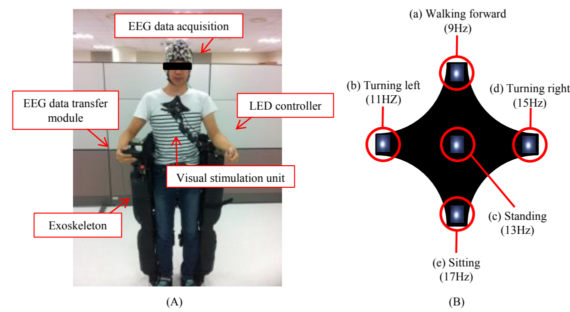

Figure 1. (A) Components of BMI based eskeleton system. (B) Visual stimulation unit with intuitive interfaces: walking (a), turning left (b), standing (c), turning right (d) and sitting (e) flickers with 9Hz, 11Hz, 13Hz, 15Hz and 17Hz respectively.

II. MATERIALS AND METHODS

A. Experimental Environment

Three subjects with no history of neurological disease participated in this experiment after giving informed consent. Our system mainly consists of a wireless EEG system (MOVE system, Brain Products GmbH), a visual stimulation unit, a LED controller (Atmega128) and a robotic exoskeleton (REX, REX Bionics Ltd.). This exoskeleton has advantage of self-balancing. It has the programmed motions like walking, turning, sitting, standing and shuffling. Also this enables a person to move by a joystick and a remote controller (Fig. 1 (A)).

B. Visual Stimulation Unit

We designed a visual stimulation unit using an arm stand (IK-208, Ilkwang Inc.) with five light emitting diodes (LEDs). Each LEDs had a command for walking forward, turning left, standing, turning right and sitting (Fig. 1 (B)). We have considered power reduction when frequency increased, second harmonic frequency and adjacent visual stimulus LEDs. Hence, we operated the LEDs in 9Hz, 11Hz, 13Hz and 17Hz respectively.

C. Data Acquisiton and Preprocessing

The EEG data were acquired using a wireless interface with 8 Ag/AgCl electrodes (PO7, PO3, PO, PO4, PO8, O1, Oz, and O2) on the occipital area according to 10/20 international system. The reference electrode was mounted on the FCz and the ground

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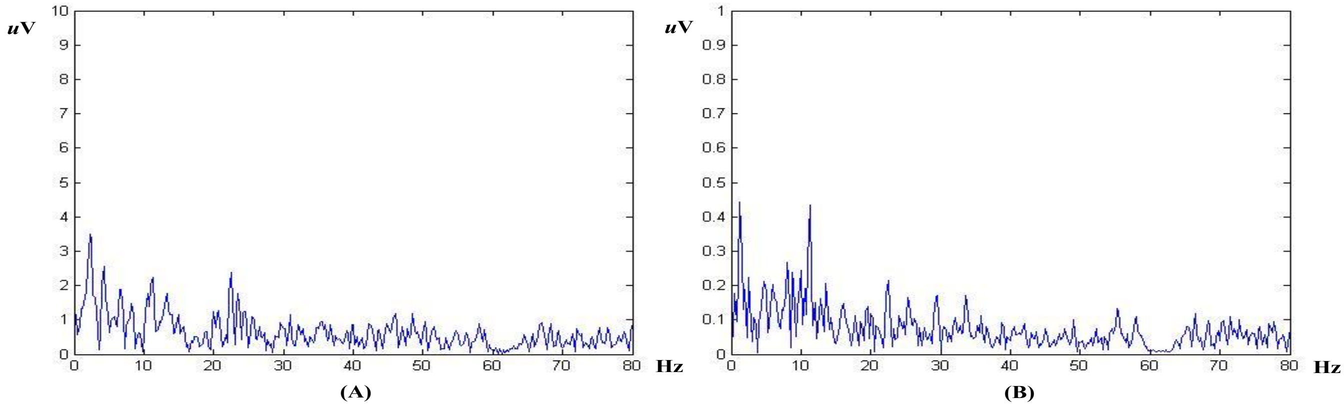

Figure 2. (A) FFT plot of the EEG data before adjusting CCA. (B) FFT plot of the EEG data multiplied with the weight after CCA when 11Hz visual stimuli is given. (B) has higher correlation with 11Hz signal and second harmonic frequency 22Hz than (A).

electrode was mounted on Fpz. The sampling rate was 1000 Hz. All impedances were maintained below 10kΩ. A 60 Hz notch filter was applied. Then, the data were bandpass filtered in the (0.1-100Hz) range using a second order Butterworth filter.

D. Signal Processing

CCA is a multivariable statistical method used when there are two sets of data. It finds a pair of linear combinations such that the correlation between two canonical variables is maximized. We made one data set from the EEG data and other five data sets using the reference signals (e.g. $[\sin(2\cdot\pi\cdot f_i\cdot t), \cos(2\cdot\pi\cdot f_i\cdot t), \sin(2\cdot\pi\cdot (2\cdot f_i)\cdot t), \cos(2\cdot\pi\cdot (2\cdot f_i)\cdot t)]$, where i is the number of stimulus frequency) which have the same length with EEG data. Then, we calculated the maximum correlation between EEG data set with each five predefined data set. CCA method always finds the maximum of correlation with respect to each weight of data sets. The optimal threshold was fixed to the number which is subtraction from the mean of maximum correlation among the correctly classified data set after discarding misclassified data set to standard deviation of them.

E. Experimental Procedure

In our experiment, subjects gazed the corresponding LED stimuli which was ordered by random auditory cue while standing on exoskeleton. First, a random command was presented, and then the start beep sound was given 3 s later. Subjects looked at the corresponding LED during 5 s. Each command was presented ten times. The number of total trials were fifty. After that, we extracted the data from 5.3 s to 7.3 s. The segmented data was then used for input data of CCA.

III. Results

The CCA-based classifier achieved high accuracy in our experiment. Fig. 2 shows that the FFT plot of EEG data before adjusting CCA and FFT plot of EEG data multiplied with weights after CCA. In the latter case, it shows higher correlation with first harmonic frequency as well as second harmonic frequency than former case. The results are shown in Table 1. The average number of the correct detection in 50 commands is 48.67±2.3. In case of S2 subject, four misclassification were occurred. But after adjusting optimal threshold, the number of misclassification was reduced to one. Accuracy was calculated by dividing the number of correctly classified command into the total number of classified command.

Table 1. Optimal Threshold and Accuracy

Subject	T_9	T_{11}	T_{13}	T_{15}	T_{17}	Accuracy (%)
S1	0.199	0.238	0.273	0.245	0.261	100
S2	0.14	0.138	0.142	0.158	0.145	97.5
S3	0.178	0.205	0.227	0.253	0.182	100

IV. Discussion and Conclusion

The misclassified command may potentially be dangerous to the users who controlling the exoskeleton. In this paper, we propose a method of finding optimal threshold of CCA based SSVEP classification for detection of resting state and decrease of misclassification. The results show the high accuracy of SSVEP classification. This means the proposed method can minimize malfunction of exoskeleton.

In our future works, we will demonstrate the possibility of SSVEP based exoskeleton online control with acquired optimal threshold through a goal-oriented online task

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