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Developing an Online SSVEP based BCI System Using Ear-EEG

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*Abstract*— The purpose of this study aims to (1) merge two online signal processing algorithms, filter bank CCA and CCA with training dataset, to (2) demonstrate an online SSVEP-based BCI system using Ear-EEG. Our previous studies have shown the aspect that the Ear-EEG is capable to collect SSVEPs. Even in a well control laboratory environment, however, the low signal to noise ratio of acquired SSVEPs makes related applications hard to implement. In the other hand, filter bank- and CCA with training data set based online target detection algorithms have shown the significant performance improvement in terms of the accuracy and ITR in our previous studies. By using optimal parameters for the filter bank CCA and CCA with training data, we assume the Ear-EEG can be used in an SSVEP-based BCI system. Two subjects participated this SSVEP-based BCI experiment using customized, lightweight, 6 channels earpieces for acquiring SSVEPs from ear canal and auricle. Their task was to input four directions by gazing coded and different phase visual stimulus. The offline classification results showed proposed detection algorithm can reach the accuracy of XX% and XX ITR using 4 sec-long SSVEPs acquired from earpieces. In the online experiment, both subject successfully completed the task of manipulating a 4 targets BCI system with XX ITR and the accuracy of XX%. The result suggested that the ability of using proposed merged algorithm and Ear-EEG to perform the SSVEP-based BCI applications. This study might lead an alternative path to implement practical real-world applications.

# INTRODUCTION

Steady-state visual evoked potential (SSVEP)-based brain computer interface (BCI) systems have gained a lot of attentions due to the high information transfer rate (ITR) and requires almost no training [1]. In most of the applications and fundamental studies, placing electrodes on the top of the occipital site seems reasonable since it’s the closed spot to visual cortex and it’s signal to noise ratio (SNR) is relatively high. However, constrains of gel usage and long time skin preparation make this paradigm unreliable in most real-world applications.

Several efforts have been made in order to overcome the constrains. Mike et al. [2]. proposed dry and noncontact electroencephalogram (EEG) sensors to acquire SSVEPs without gel usage from hair-covered area on scalp. The electrodes featuring custom integrated, high-impedance analog front-end, fingered contact posts, and active buffering circuitry successfully demonstrated real-world application, i.e. no gel usage. Lin et al. [3] proposed dry polymer form electrodes fabricated by electrically conductive polymer covered by a conductive fabric suggested an alternative approach to long-term acquire EEGs from non-hair-covered area. Similar effort were also made in Huang et al. [4], as they proposed an active comb-shaped dry electrode avoiding signal attenuation and phase distortion. In sum, dry or non-contact sensors introduced a good solution to overcome the challenges including gel usage and long-time preparation. However, for the ventilator users who suffered quadriparetic surgery, it is not easy to collect SSVEPs from occipital site when they were lying on the bed. Therefore, an alternative approach to perform the data collection is crucial. Recently, Ear-EEG has been evaluated and demonstrated that both auditory and visual evoked responses are possible to be collected in ears across a population of subjects [5]. Low SNR, however, makes the online implementation remaining a challenge. To our best knowledge, no studies have shown online applications using this technology in BCI fields.

Performance of SSVEP-based BCIs depends on the three factors including stimulus presentation, multiple target coding, and target identification algorithm [8: Nakanishi et al., 2014 (IJNS)]. In previous studies, frequency or phase information have been generally used to modulate multiple visual stimuli with discriminability [13: Wang et a., 2008]. Our recent studies demonstrated the efficiency of the hybrid frequency and phase coding methods to maximize the differentiation of each visual stimulus [8: Nakanishi et al., 2014; 10: Chen et al., 2014]. To realize high performance, the target identification method also plays an important role. The canonical correlation analysis (CCA)-based method has been widely used to detect SSVEPs tagged with frequency coding [14: Lin et al., 2007; 15: Bin et al., 2009]. However, misclassification can be caused by the interference from the spontaneous EEG activities [16: Wang et al., 2014]. To reduce the effect of the spontaneous EEG signals, the extended CCA-based method, which incorporates pre-recorded individual calibration data, has been proposed [16: Wang et al., 2014]. In addition, this method has shown better performance in hybrid frequency and phase coding than the standard CCA-based method [8: Nakanishi et al., 2014; 10: Chen et al., 2014]. To optimize the performance of an online SSVEP-based BCI, therefore, aforementioned issues should be addressd.

This study aimed to explore the feasibility of an online SSVEP-based BCI using Ear-EEG signals. Using four visual stimuli tagged with all different frequencies (8Hz, 9Hz, 10Hz, and 11Hz) and phases (0, 0.5, , and 1.5), this study demonstrated the possibility of using Ear-EEG to perform an online BCI system even with low SNR.

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(b)

Fig1. Four targets layout of proposed visual stimulus. Top was used to show subject’s input. When the training starts, each target was flickering at coded frequency and phase. A red square is the cue that appears for XX mini seconds to assistant subjects to gaze on it. In online experiment, the red square appears for xx mini seconds to indicate the decision by the system.

# Method

## A. EEG Recording

The visual stimulus is consisted of four coded targets rendering on a 27-inch screen with resolution of 1024800, as shown in Fig. 1. Each target is a 7cm7cm square flickering at white and black contrast. The phase and frequency was also coded in each target. For instance, top target was flickering at 9Hz with phase of 0 degree. The detailed coding info can be found in [8][10][11].



Fig. 4. SSVEPs of raw data (top), power spectrum(middle), and SNR(bottom) from occipital site (black), left ear (blue), and right ear (right) when a subject was gazing at 9Hz visual stimulus.

Two subjects (1 males and 1 female, average XX years old) with normal eyesight participated training and online experiment. They both signed consent form before running the experiment. One of them had experienced using SSVEP-based system while the other one is naive.

The earpiece is a customized 3D printing device with six-conduct mental connectors, as shown in Fig. 2(a). It can collect 4 channel data in canal and two channel data from auricle. All of the electrodes were connected to the cable of amplifier.

In order to have a ground truth, eight channels around occipital site following 10-20 system were simultaneously recorded. All channels were reference to forehead. The amplifier was Biosemi ActiveTwo EEG system (Biosemi, Inc.).

## B. Offline experiment

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This study performed an offline classification of SSVEPs. The recorded EEG data were first divided into 4s-long epochs according to event triggers generated by the stimulus program, and down-sampled to 256Hz. All data epochs were referenced to an electrode located at forehead area. In this study, the extended CCA-based method which combined filter bank approach and individual template-based approach to identify a target stimulus [9: Chen et al., in revision; 8: Nakanishi et al., 2014; 16: Wang et al., 2014]. The procedure of the method is as follows: (1) decomposing individual template signals and test data to sub-band signals, (2) calculating correlation coefficients between decomposed template signals and test data after spatial filtering as feature values, (3) calculating a weighted sum of squares of the correlation values as final feature values, and (4) identifying target based on the feature values. The accuracy and simulated ITR were estimated by ten-fold cross validation.

## D. Online Experiment



(a) (b)

Fig. 5. (a) Classification accuracy and (b) simulated ITR using Ear-EEG with different data length.

This is online.

# Results

## A. Offline Analysis

Fig. 3 shows channel correlation of six earpiece’s channels among different targets from subject2 Fig. 3(a) and subject 1 Fig. 3(b). The error bar indicates the standard error among six earpiece channels across all targets. As we can see that there was no significant difference among channels. This indicates the difference of SSVEPs collected from each earpiece are similar. Therefore we average the SSVEPs for the further analysis.

Fig. 4 shows the averaged SSVEPs collected from occipital (black), left ear (blue), and right ear (red) of one subject gazing at 9Hz visual stimulus. The amplitude from ear SSVEPs are obviously smaller than the SSVEPs acquired from occipital over visual cortex. In power spectrum density, as shown in Fig. 4(b), the dominant peak are all located in 9Hz, and second harmonic also appears in occipital and left/right ears. In general, both subjects have second harmonics and almost no further harmonics so the optimal parameter for the filter bank are 2. These parameters would be used for the simulated online and online analysis. Note that, interference noise also appears in ear SSVEPs (marked as “+”), as addressed in the [12].

## B. Simulated Online and Online Analysis

This study first used leave-one-out cross-validation to estimate the BCI performance, as shown in Fig. 5. The accuracy reaches ~80% for both subjects. The results suggest that accuracy increased as longer testing data used.

Table I shows the online results for two subjects. Both subjects completed online task, in which inputs the four directions three times. Ideally, the input length should be 12. This result suggests that the Ear-EEG can indeed to demonstrate the SSVEP-based BCI applications.

# Conclusions and Discussions

## Challenges including easy-of-use and user friendly play important roles in BCI field. Studies have proposed many approaches in order to overcome the problems by developing practical BCI systems in real-world applications. Dry electrodes, non-contact sensors demonstrate one possibility of overcoming the problems in practical BCI systems. Alternatively, Ear-EEG featuring the un-seen, easy-of-use, and continuously monitoring opens another path to increase the usage in BCI systems. This paper proposed a new algorithm to implement an SSVEP-based BCI system using Ear-EEG. The offline training analysis is used to find the best parameters i.e. sub-band and number of harmonics for the further online experiment. The empirical results show the accuracy can reach XX% and ITR can reach XX bits/min.

Appendix

Appendixes should appear before the acknowledgment.

Acknowledgment

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