# FREQUENCY RECOGNITION IN SSVEP-BASED BCI USING A HYBRID OF CANONICAL CORRELATION ANALYSIS AND POWER SPECTRAL DENSITY ANALYSIS

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**Abstract-** Brain-computer interface (BCI) provides a direct communication channel between human brain and external devices. Steady-state visual evoked potential (SSVEP) appears over occipital area of a brain when a subject is looking at repetitive visual stimuli with a specific frequency. Canonical correlation analysis (CCA) estimates the stimulus frequency from canonical correlations of pairs of canonical variables. Though CCA has been successfully applied to SSVEP recognition for BCI application, it makes an incorrect decision in case of using a short time window length (TW) because canonical variable of recorded signal may not match that of reference signals composed of sine-cosine waves. However, power spectrum of canonical variables has the largest sum of power at stimulus frequency band even with a short TW, comparing that of other frequencies. From this phenomenon, we propose a hybrid of CCA and PSDA. The proposed method uses power spectrum of canonical variable instead of canonical correlation. Experimental results show that the performance of the proposed algorithm is better than that of CCA when they have the same TW.

**Keywords-** Brain-computer interface (BCI), Electroencephalography (EEG), Steady-state visual evoked potential (SSVEP), Canonical correlation analysis (CCA), Power spectral density analysis (PSDA)

## I. INTRODUCTION

A brain-computer interface (BCI) system can be used for interpreting human thought and intention by analyzing brain activity and provides a direct connection between human brain and external devices such as a computer. There are two different methods depending on how to acquire a brain signal, i.e., invasive and non-invasive methods. Considerable researches have been focused on the electroencephalography (EEG), which is one of non-invasive methods, because EEG is cheaper and has more mobility than other non-invasive methods such as functional magnetic resonance imaging (fMRI) and magneto encephalography (MEG).

Another advantage of EEG is not to cause side effects by inserting electrode. Steady-state visual evoked potential (SSVEP) is one of the signals widely utilized in EEG-based BCI systems.

It is induced around the occipital lobe when a human is staring a flickering target with a specific frequency. SSVEP has a fundamental frequency, which is identical to the flickering or stimulus frequency, and its higher harmonics. SSVEP is very useful for EEG-based BCI systems because it requires very short training time and also guarantees a high signal-to-noise ratio (SNR) and a high information transfer rate (ITR).

The power spectral density analysis (PSDA) had been used for the frequency recognition of SSVEP. In the PSDA, the frequency corresponding to a peak of power spectrum is estimated at stimulus frequency. PSDA has a low computational cost and is simply implemented without a prior order selection step. However, PSDA is vulnerable to noise because PSDA only use of single channel EEG data.

In an attempt to solve this problem, in 2006, LIN et al. introduced a canonical correlation analysis (CCA)-based frequency recognition method, a multivariable statistical method, and showed thatthe performance of the frequency recognition based on CCA is better than that of PSDA. CCA maximizes canonical correlations of pairs of canonical variables corresponding EEG raw data and reference signal. Canonical variables are signals maximized each reference frequency component in raw EEG data.

For an SSVEP-based BCI system to be available to real-time applications, it is necessary to improve the performance of frequency recognition, having a short TW. In short TWs, the canonical variables include different frequency components from stimulus frequency.

However, sum of power, stimulus frequency band of canonical variables depending on EEG raw data, is greater than that of other frequencies. Using this phenomenon, we propose a new frequency recognition method which is a hybrid of CCA and PSDA.

## II. METHOD

**1.** Power Spectral Density Analysis (PSDA)

Power spectral density analysis (PSDA) had been used to recognize frequency of the SSVEP-based BCI before using CCA. PSDA is calculated from the discrete Fourier transform (DFT) and this method is

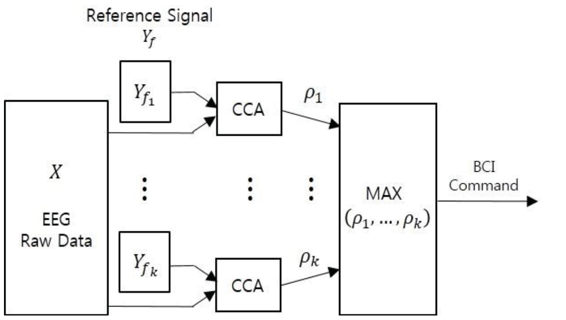


**Figure 1. An illustration of the CCA-based method for SSVEP frequency recognition**

able to estimate the flickering frequencyby searching the frequency of its peak. PSDA has a low computational cost because it makes use of the fast Fourier transform (FFT). However, there is a crucial disadvantage in this method. It is sensitive to noise because it utilizes only a single channel in frequency recognition.

**2.** Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is a multivariate statistical method seeking a pair of maximizing correlation between $x$ and $y$ . Here, $x$ and $y$ , called canonical variables, are each linear combination of two sets of random variables $X$ and $Y$ . The relationship between $x$ , $y$ and $X$ and $Y$ are given by

$$x = X^T W_x \,, \;\; y = Y^T W_y \,, \qquad (1)$$

where $W_x$ and $W_y$ are weighting vectors which project $X$ and $Y$ onto these vectors. Canonical correlation $\rho$ is a maximum correlation coefficient between the canonical variables $x$ and $y$ and can be found from the covariance matrices of $X$ and $Y$ which is given by

$$C = \begin{bmatrix} C_{xx} & C_{xy} \\ C_{yx} & C_{yy} \end{bmatrix} = E\left[ \begin{pmatrix} X \\ Y \end{pmatrix} \begin{pmatrix} X \\ Y \end{pmatrix}^T \right] .(2)$$

$\rho^2$ , $W_x$ , and $W_y$ are obtained by calculating the eigenvalues and eigenvectors such as

$$\begin{cases} C_{xx}^{-1} C_{xy} C_{yy}^{-1} C_{yx} W_x = \rho^2 W_x \\ C_{yy}^{-1} C_{yx} C_{xx}^{-1} C_{xy} W_y = \rho^2 W_y \end{cases} , \qquad (3)$$

where the eigenvalues $\rho^2$ are the squaredcanonical correlations and the eigenvectors $W_x$ and $W_y$ are the normalized canonical correlation basis vectors.

In SSVEP recognition using CCA, signal $X$ is generally the set of raw EEG data and signals $Y$ means the set of reference signals which have same length as $X$ . The reference signals $Y_{f_k}$ are defined as the flickering frequencies $f_k$ and the number of harmonics $N_h$ .

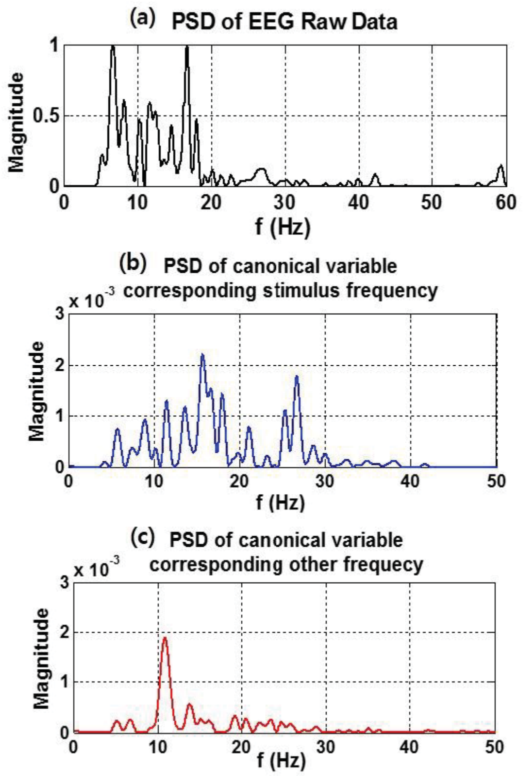


**Figure 2. (a). Power spectral density of EEG raw data, (b), (c). Power spectral density of canonical variables in the short time window length (TW). (The stimulus frequency is 16 Hz, other frequency is 10.6 Hz and TW is 1 sec.)**

$$Y_{f_k} = \begin{pmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ \vdots \\ \sin(2\pi N_h f_k t) \\ \cos(2\pi N_h f_k t) \end{pmatrix} \qquad \textbf{(4)}$$

**Fig. 1 illustrates an overall system using CCA for frequency recognition of the SSVEP-based BCI.**

CCA provides a multi-channel optimization for signal-to-noise ratio (SNR) improvement. However, CCA is difficult to be applied to the real-time interactive BCI system based on SSVEP as it is likely to encounter over fitting from reference signals.

**3.** Proposed Algorithm

For on-line BCI system, we need to improve speed and performance of frequency recognition. PSDA and CCA are known as popular methods. But PSDA is easily influenced by noise because it uses information from single channel.

In case of CCA, it determines wrong BCI command in case of using a short TW because CCA puts reference signal as pre-constructed sine-cosine waves.

**Table 1.** A comparison of the recognition accuracies (%) with 1 sec to 2.5 sec time window length (TW)

| TW | 1sec | | 1.5sec | | 2sec | | 2.5sec | |
|---|---|---|---|---|---|---|---|---|
| Method | CCA | Proposed algorithm | CCA | Proposed algorithm | CCA | Proposed algorithm | CCA | Proposed algorithm |
| Accuracy | 55% | **80%** | 71.25% | **88.75%** | 77.5% | **96.25%** | 87.5% | **100%** |

Also, a standard CCA decides the BCI command by comparing the canonical correlations between pairs of canonical variables, $x$ and $y$. When it has not enough TW, canonical variable includes some different frequency components such as Fig. 2(b).

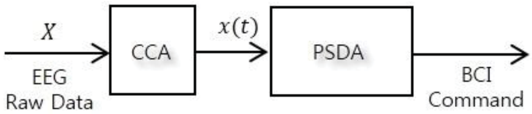


**Figure 3. The block diagram of the proposed method for SSVEP frequency recognition**

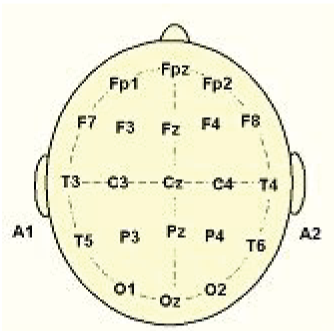


**Figure 4. The experimental paradigm, (a) electrode placement**

However, sum of power of canonical variables corresponding to stimulus frequency is greater than that of other frequencies (Fig. 2(b) and (c)).

Therefore, we propose a hybrid of CCA and PSDA to improve the performance even when a short TW is used for frequency recognition. The proposed method applies the canonical variables to PSDA. Fig.3 represents the overall proposed method.

## III. EXPERIMENTS

**1.** Experimental Paradigms

In this study, EEG data was recorded at 1000 Hz sampling rate with band-pass filter of 5 Hz-60 Hz and downsampling to 125 Hz was finally performed. Only six channels were used foranalysis and extracted electrodes were P3, Pz, P4, O1, Oz and O2 around the occipital regions.

The ground and reference electrodes were each Fz and both ear lobes, A1 and A2 (Fig. 4). Also, we considered third harmonics, it meant the number of harmonics $N_h$ is three. The LCD screen had two flickering targets like fig. 5 and each flickering frequency of targets on the screen was 16 Hz and 10.6 Hz. A subject stared at one of two targets for 5 seconds and it was repeated 10 times in each run. The subject performed total 4 runs for each stimulus frequency (total 80 trials, 40 trials corresponding to the two stimulus frequencies, respectively).

**Figure 5. The experimental paradigm, (b) stimulus placement**

**2.** Experimental Results

We compared the results obtained by two recognition methods that are CCA and proposed algorithm. Table 1 summarizes the recognition accuracies. As shown in Table 1, the proposed recognition method achieved higher accuracies for one subject when the system had same time window length (TW). Fig. 6 shows a power spectral density of the canonical variable $x$ with different TWs, 1, 1.5, 2 and 2.5 s when flickering frequency is 16 Hz.

## CONCLUSION

We proposed a hybrid frequency recognition method combining two popular methods of CCA and PSDA for frequency recognition in SSVEP-based BCI system. By using the canonical variables, we attained higher accuracies than that of standard CCA which compares the canonical correlations. The performance difference gets higher when the time-window length becomes short. As a further research, it is needed to confirm the enhanced performances on more subjects and to study anon-line SSVEP-based BCI system.

## ACKNOWLEDGEMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2012R1A1A2008555).

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