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A Comparison of Minimum Energy Combination and Canonical Correlation Analysis for SSVEP Detection

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Abstract—**Minimum energy combination (MEC) and canonical correlation analysis (CCA) are widely used for steady-state visual evoked potential (SSVEP) based brain computer interface (BCI), since both approaches have satisfactory performance. The purpose of this paper is to provide a guideline on choice of detection method, through comparison of the performance of the two approaches from simulation data and real SSVEP data. The experiment results show that CCA has lower deviation, higher accuracy and higher signal to noise ratio than MEC.**

I. INTRODUCTION

A brain computer interface (BCI) establishes a direct communication pathway between a human brain and an external device without using the normal output pathways of peripheral nerves and muscles. It recognizes the intent of the user through the electroencephalogram (EEG) signals which can be recorded from the surface of the scalp and translated into output commands that accomplish the desire of the user. Therefore, BCIs are particularly suited for elderly people or people with disabilities who are unable to communicate through any classical muscular control.

Many BCI systems have been widely reported in recent years [1]-[4]. A number of brain signals such as slow cortical potentials, mu and beta rhythms, P300 and steady-state visual evoked potential (SSVEP) are widely employed on a BCI system. Among them, SSVEP which is a resonance phenomenon arising mainly in the visual cortex when a person is focusing the visual attention on a light source flickering with a frequency above 4 Hz [5], has received widespread attention in recent decades since it is reliable and has high information transfer rate (ITR) compared to other brain features [6],[7].

Many signal processing methods have been applied to detect and process the SSVEP signal. For example, as a traditional method, power spectral density analysis (PSDA) has been widely used to detect SSVEP response. It is estimated from the user's brain signals within a time window and the peak is subsequently detected. The frequency which corresponds to the peak is the visual stimulus frequency. PSDA is very simple in principle, but it has drawbacks, such as low signal to noise ratio (SNR), parameter optimization and channel selection, which limit the practical application of the SSVEP-based BCI [8]. The multi-channel SSVEP detection methods which extract more information from brain signals can overcome these disadvantages and achieve higher detection accuracy. Recently, many algorithms are proposed to detect multi-channel SSVEP signals. Friman *et al.* [9] propose minimum energy combination (MEC) method, which combines multiple electrode signals to less number of channels in order to cancel noise as much as possible; it shows many advantages such as high detection accuracy, high SNR and no calibration data for noise estimation. Lin *et al.* [10] introduce canonical correlation analysis (CCA), which calculates the correlation between EEG signals and stimulus frequency also represents high performance. However, to the best of our knowledge, no paper made a comparison between MEC and CCA on SSVEP detection. This paper analyzed the simulation data and real EEG data with these two approaches respectively, and then evaluated the performance in terms of the detection accuracy. The results indicate that CCA has lower deviation, higher detection accuracy and higher SNR than MEC.

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II. METHODS

A. Minimum Energy Combination

Assuming that we have Ny electrodes, data length is Nt, the number of harmonics is Nh. Then EEG signal modeling can be described by the following formula:

$$Y = XA + B \tag{1}$$

The model is linear and contains two parts: the first part is the evoked SSVEP response which is composed of a number of sinusoids. A contains all the amplitudes for all electrode signals. X is SSVEP information matrix of size $Nt \times 2Nh$; the second part B is the noise, artifacts and all the information that are not relevant to the SSVEP response.

The different electrodes signals must be combined into a channel in order to extract discriminate features. A channel signal s is defined as a linear combination of each electrode signal y_i:

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw \tag{2}$$

Several sets of weights can be used to create several channels. S is the set of Ns channels.

$$S = YW \tag{3}$$

Minimum energy combination is derived from the principal component analysis (PCA). The noise signals can be canceled as much as possible by combining of the electrode signals. Firstly, remove any potential SSVEP components from all the electrode signals by using the orthogonal projection:

$$Y_1 = Y - X(X^T X)^{-1} X^T Y \tag{4}$$

Y_1 contains approximately only noise, artifacts and background activity.

The weight vector W which minimizes the variance of Y_1 can be found by optimizing:

$$\min \left\| Y_1 W \right\|^2 = \min W^T Y_1^T Y_1 W \tag{5}$$

which has the solution in the eigenvector that corresponds with the smallest eigenvalue of the covariance of Y_1. In order to increase the robustness, not only the eigenvector of the smallest eigenvalue but also those eigenvectors of the next largest eigenvalues are utilized here. About 10% of the variance of the date is included to construct the spatial filter.

The SSVEP signal power estimation is defined as follows:

$$\hat{P} = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \left\| X_k{}^T s_l \right\|^2 \tag{6}$$

EEG signals from multiple channels are calculated by the above steps and then the stimulus frequency corresponding to the maximum signal power is obtained. For more details, see [9], [11].

B. Canonical Correlation Analysis

CCA is generally used for finding the correlations between two sets of multi-dimensional variables. It seeks a pair of linear combinations, called canonical variables, for two sets, such that the correlation between the two canonical variables is maximized. Then it finds a second pair, which is uncorrelated with the first pair of canonical variables but has a second highest correlation. The process continues until the number of pairs of canonical variables equals the number of variables in the smallest set. The coefficients describe the correlation relation of the two sets. CCA is used to detect SSVEP frequency. Only the largest coefficient is considered. A variable in one set is the recorded multiple electrode signals Y and the second set is SSVEP information matrix X. Consider their linear combinations $x=X^T W_x$ and $y=Y^T W_y$ respectively, W_x and W_y which can be found by CCA maximize the correlation between x and y, by solving the following problem:

$$\begin{aligned} \max \rho(x, y) &= \frac{E\left[x^T y\right]}{\sqrt{E\left[x^T x\right] E\left[y^T y\right]}} \\ &= \frac{E\left[W_x{}^T X Y^T W_y\right]}{\sqrt{E\left[W_x{}^T X X^T W_x\right] E\left[W_y{}^T Y Y^T W_y\right]}} \end{aligned} \tag{7}$$

The maximum of ρ with respect to W_x and W_y is the maximum canonical correlation. The frequency corresponding to the largest coefficient is the one of SSVEP [10], [12].

III. RESULTS

A. Simulation

We studied the anti-noise capability of the two approaches through simulation. First, six sinusoidal waveforms were generated to simulate the SSVEP of 6 channels at each of the 8 stimulation frequencies 8 Hz, 9 Hz, 10 Hz, 11 Hz, 12 Hz, 13 Hz, 14 Hz and 15 Hz. Gaussian white noises (SNR from -10dB to -20dB) were added to the sinusoidal signals and then noise contaminated signals were obtained. The sampling rate was 256 Hz and the signal window length L were 1s, 2s, 4s and 8s respectively. MEC and CCA were applied on every 50 segments of the window length. The analysis was repeated 10 times. Finally, average recognition accuracy was obtained at different combinations with SNR and window length L. The SNR is defined as

$$SNR = 10\log_{10} \frac{P_{signal}}{P_{noise}} = 10\log_{10} \frac{\left(A/\sqrt{2}\right)^2}{\sigma^2} \tag{8}$$

where P is power, A denotes the amplitude of the sine wave and σ^2 is the variance of the noise [10].

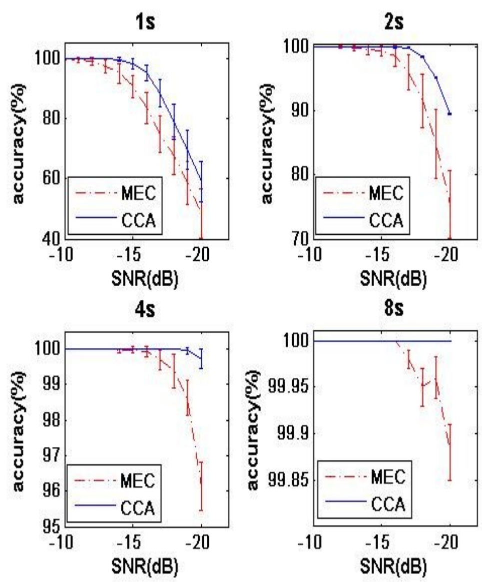

Fig. 1 Simulation accuracy and standard deviation with respect to different SNR for various data length using the two methods. The error bars represent standard deviations.

Fig.1 shows the average recognition accuracies of two methods at different SNR and window length, from which we can see that CCA has higher accuracy and smaller standard deviation than MEC with any window length (for the 2s window length figure, standard deviation of CCA is not obvious because of the large scale). Furthermore, the performance of CCA is more insensitive to the change of SNR than that of MEC. Therefore, CCA has better robustness than MEC.

TABLE I
AVERAGE ACCURACY OF SIMULATION DATA

Window length	MEC	CCA
1s	83.22%	91.97%
2s	95.01%	98.44%
4s	99.44%	99.97%
8s	99.98%	100%

TABLE I summarizes the average accuracy obtained by MEC and CCA for all SNR. From the table, it can be observed that when the window length is 1s, the accuracy of CCA is 8.75% higher than MEC. When the window length is 8s, the accuracy of CCA is 100%.

In order to evaluate the effects of different detection methods as well as SNR on the recognition rate, two factors analysis of variance (ANOVA) was performed. The significance level was 0.05. When window length are 1s and 2s respectively, the p value for both factors are very small ($p<0.05$), indicating that SNR and detection methods significantly influence on the recognition accuracy. However, there is no significant difference for different SNR and different detection method on the detection accuracy when window length are 4s and 8s respectively ($p>0.05$). In general, shorter window length will achieve higher ITR in the online BCI system. Therefore, CCA has better performance than MEC.

B. *Real SSVEP Data*

To further evaluate the performance of CCA and MEC, SSVEP-based BCI system was designed and offline analyses were performed. Six subjects (age 24~28) took part in the experiment. They were seated in a comfortable chair in front of the visual stimulator about 60 cm. EEG signals were recorded from the scalp via 6 standard EEG electrodes by amplifier (g.USBamp, Guger Technologies, Graz, Austria). The signal locations were P3, P4, Pz, O1, O2 and Oz according to international 10-20 system. AFz and FCz were used for the reference and ground respectively. The sampling rate was 256 HZ. A LCD visual stimulator had 8 flickers with frequencies described previously in our simulation, which was designed according to [13]. In each trial, subjects were requested to gaze at one of 8 targets for 8s in turn and there were 4s interval between trials. 6 trials EEG data were recorded for each flicker then totally there were 48 trials.

Fig.2 presents the performance of these two methods for each subject. We can see from this figure that the accuracies of s1 and s5 are less than 50%, which indicate that their SSVEP signals were very weak; the accuracies of s2 and s4 are more than 90%. In totally, CCA has higher accuracy than MEC for each subject.

Fig.3 shows average accuracy for all subjects of MEC and CCA with different window length, which indicates that CCA has higher accuracy than MEC. The accuracy is improved when window length becomes longer.

ANOVA was performed to evaluate the effects of window length and frequency detection method. The significance level was 0.05. The results show that both window length and frequency detection methods have significantly influence on the detection accuracy ($p<0.01$). For the average accuracy with all subjects and window length, CCA is 6.02% higher than MEC. The experiment results agree with the simulation one, which indicates that CCA has better performance than MEC.

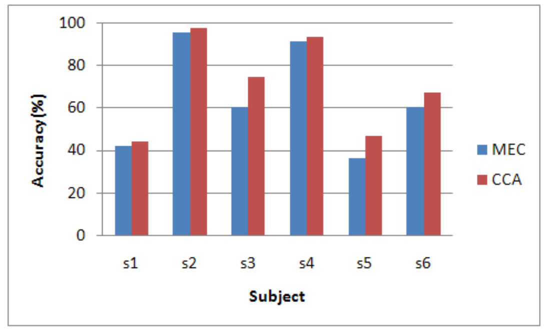

Fig. 2 Average accuracy for each subject using two methods. The blue bars and red bars represent the results of the CCA and MEC approaches respectively.

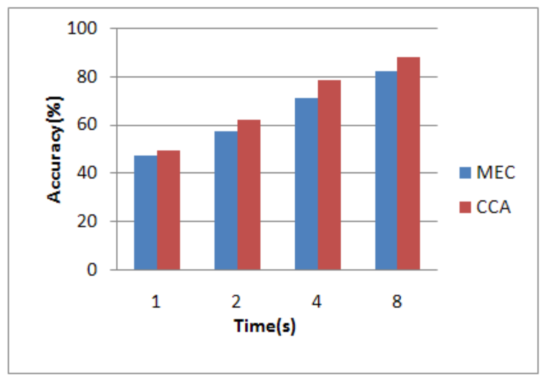

Fig. 3 Average accuracy for each window length using the two methods. The blue bars and red bars represent the results of the CCA and MEC approaches respectively.

IV. DISCUSSION AND CONCLUSION

This work compared the performance of CCA and MEC which are the good detection methods on multi-channel SSVEP-based BCI. The results show that CCA has lower deviation, higher detection accuracy and more insensitive to the change of SNR than MEC.

MEC can enhance SSVEP signal and cancel nuisance signals by forming combinations of the electrode signals. With the CCA, the weights vector Wx which maximizes canonical correlation can improves the SNR of the combined electrode signals. To demonstrate which method has higher SNR, a 8s, 13 Hz SSVEP data set was analyzed using the two approaches respectively. Fig.4 shows that the power spectral from canonical variant x given by CCA and combining electrode signals given by MEC. It indicates that CCA has a higher SNR than MEC. Furthermore, the spectral density of the MEC shows larger second harmonic components. The higher SNR is the possible reason that CCA has higher detection accuracy than MEC.

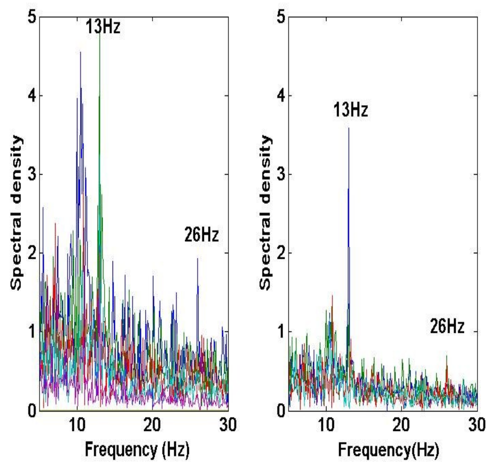

Fig. 4. (a) The spectral density of combined signals by MEC. (b) The spectral density of canonical variant x using the CCA.

The future work will focus on the aspects as follows: theoretical analysis will be performed to find out the relationship between MEC and CCA; different combinations of electrodes will be investigated to find out the optimal selection; the higher accuracy method of SSVEP-based BCI than CCA will be developed.

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