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BCI Implementation with Short-Time SSVEP Using Canonical Correlation Analysis

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Abstract:

Recently developed effective methods for detection commands of steady-state visual evoked potential (SSVEP)-based brain–computer interface (BCI) that need calibration for visual stimuli, which cause more time and fatigue prior to the use, as the number of commands increases. This paper develops a novel unsupervised method based on canonical correlation analysis (CCA) for accurate detection of stimulus frequency. Canonical correlation analysis (CCA) is commonly used to recognize the frequency of steady state visual evoked potential (SSVEP) for the implementation of brain computer interface (BCI). The performance of CCA is degraded when lower data length is used. On the other hand, BCI implementation becomes more effective when it uses lower data length i.e. lower calibration time. This paper presents a CCA based approach to enhance the frequency recognition accuracy of short-time SSVEP signal. To decrease the calibration time, a shorter data is concatenated to increase the data length for better fit of using CCA. The multiset CCA (MsetCCA) is employed to derive the reference signal from the training set and then traditional CCA is used to recognize the frequency of short-time SSVEP. The performance of the proposed method is evaluated using publicly available dataset. The experimental results show that the newly introduced method performs better than the recently developed algorithms.

Keywords —**Brain computer interface (BCI), canonical correlation analysis (CCA), steady state visual evoked potential (SSVEP).**

I. INTRODUCTION

The cause of disability can be a genetic disorder, congenital illness, accident, or unknown. Disabilities have different symptoms and levels of severity. One of the major problems is the inability to move, which results in dependence on mobility equipment for assistance in everyday life. So far, many assistive devices have been developed. Yet, they cannot cover all levels of disabilities, especially for severely paralyzed patients who completely lose movement and communication abilities [1]. As a result, they require advanced assistive technology, through employing biomedical signals to directly interface with the machine or device [2].

A brain–computer interface (BCI) is an emerging human-computer interaction (HCI) technology used to communicate between the human brain and computers [3, 4]. A BCI can create a replacement or alternative pathway connection between the brain and prostheses or assistive devices for spinal cord injury (SCI), stroke, and amyotrophic lateral sclerosis (ALS) (also known as neuro-prosthetics. Generally, the three main parts of a BCI consist of (1) brain signals and data acquisition, (2) a feature extraction and classification algorithm, and (3) command translation and applications. A non-invasive BCI [2] is a popular technique for research and development.

Currently, the research interest on BCI has increased for its application in neuroscience, signal processing, machine learning, clinical rehabilitee etc. [5]. It takes brain signals, analyze them, and translate them into commands to operate external device for executing intended action. The brain signal obtained by electroencephalography (EEG) is widely used for BCI implementation. BCI converts EEG signals generated from the brain activity on the scalp into control command using machine learning technique [6]. Steady state visual evoked potential (SSVEP) is a popular BCI system that can be recognized through detecting the dominant frequency components of the recorded EEG signals [7]. SSVEP is an EEG signal, captured after introducing the subject or user to flickering type of visual stimuli. EEG arrangement cost is low, portable and safe, user just have to wear a special electro cap on the scalp in which electrodes are placed.

The performance of SSVEP-based BCIs depends on three key factors: (i) stimulus presentation, (ii) multiple target coding, and (iii) target identification. The presentation of flickering stimulus needs to be steady such that the elicited SSVEP signals are robust and reliable for exact target identification. Efficient detection of target frequency plays an important role in SSVEP-based BCIs. Flickering of liquid crystal display (LCD), LED (light-emitting diode), CRT (cathode ray tube) with a constant frequency is used to generate SSVEP-based command for BCI implementation [8].

In SSVEP-based BCI user are asked to gaze a particular frequencies. Canonical correlation analysis (CCA) has been widely used in the frequency detection of SSVEP-based BCIs [9]. CCA used artificially generated sine-cosine reference signal set for detecting target frequency. CCA finds the maximum correlation between the test SSVEP and stimulating signals to identify the frequency of SSVEP signal. The performance of CCA is very much depended on the length of SSVEP data. Inherently, it increases the calibration time of the subject, whereas, the minimization of calibration time is an open problem in SSVEP based BCI implementation. In this paper, we introduced a method to enhance frequency recognition method with shorter data length. The selected data is concatenated by itself to obtain the length of data suitable for CCA. The analyzing SSVEP signal is pre-filtered and reference signals are obtained by applying MsetCCA on the training set of the data. The CCA is used with thus obtained reference signals to recognize the frequency of SSVEP.

II. METHODS AND DATA

Normally, EEG signals are spontaneous brain potentials and event-related potentials (ERPs) to generate BCI commands. Event-related desynchronization (ERD) or synchronization (ERS) occurs from mental imagery paradigms, such as motor and speech imagination [10, 11]. Moreover, time- and phase-lock phenomena happen from an external stimulus through the sensory nerve and, especially, the visual system that usually applies different stimulus patterns or paradigms to activate neurons of the visual cortex at the occipital lobe. EEG signals are measured using visual stimulation as visual evoked potentials (VEPs). VEPs can be divided into two types, based on different techniques of visual stimulus: (1) transient VEP or P300 [12] and (2) steady-state visual evoked potential (SSVEP) [13]. The SSVEP is a brain signal, which has steady periodic to visual stimulation, with a specific frequency. When the optic nerve is stimulated at a frequency in the range of 3.5–75 Hz, the brain generates an electrical signal of the same frequency or multiple frequencies; this can be stimulated by a light-emitting diode (LED), image on a liquid crystal display (LCD), animation, or pattern image [14]. A SSVEP-based BCI is widely used for electric wheelchairs. Previously, many researchers demonstrated that SSVEP achieves high accuracy, high information transfer rate (ITR), and less time for user training than other BCI techniques [15]. However, SSVEP-based BCI systems have the following weaknesses: (1) users can experience visual fatigue from focusing and attending flicker stimulus patterns over an extended period of time, and (2) the SSVEP response is still unclear for some users who can perform with low or high visual stimulus pattern flickering frequency. Both are challenging for practical applications, and many research groups have attempted to investigate methods for improving SSVEP-based BCIs.

The standard CCA has been widely used in the frequency detection of the SSVEP signal in BCI systems. Usually longer length (about 4s) of SSVEP is used to apply traditional CCA to achieve effective accuracy. We are proposing a new method based on standard CCA and MsetCCA that uses shorter time window (TW) up to 1s for implementing short-time SSVEP based BCIs. The calibration dataset and single-trial test data are denoted by $X \in R^{K \times C \times N \times M}$ and $\hat{X} \in R^{C \times N}$ respectively; where, K is the number of stimuli, C is the number of channel, N is the number of sampling point, M is the number of trial. The calibration dataset means capturing of EEG signal for every guess of visual stimuli for every stimulus frequency.

The goal is to recognize the target frequency. Take the target identification as $\hat{X} \in R^{C \times N}$ and set it to one of K classes f_k, where k=1,2,…., K. Class f_k corresponds to the stimulus frequency $f_k \in \{f_1, f_2, \ldots, f_k\}$. Unsupervised and supervised methods can be used to compute f_k as $\rho_k = p(\hat{X}, Y_k)$ and $\rho_k = p(\hat{X}, Z)$ respectively. Here, Y_k is an artificially generated reference signal that models SSVEPs elicited by the k^{th} stimulus and Z is the reference signals derived from training set.

In SSVEP based BCI, the method's goal is to find the maximum ρ_k to optimize the accuracy of the target identification.

A. Standard CCA Method

Canonical correlation analysis (CCA) is a statistical method which is used to measure the underlying correlation between two sets of multidimensional variables. Consider X is a single trial-test data and Y is stimulus set and their linear combination is $x = X^T w_x$ and $y = Y^T w_y$. CCA finds the weight vectors w_x and w_y such that the correlation between linear combination x and y will be maximum by evolving the following problem.

$$\rho(x, y) = \max_{w_x, w_y} \frac{E[xy^T]}{\sqrt{E[xx^T]E[yy^T]}} \quad (1)$$

The maximum of correlation coefficient ρ with respect to w_x and w_y is the maximum canonical correlation.

To recognize the frequency of the SSVEP signal, CCA calculates the canonical correlation ρ between the multichannel EEG test signal X and the reference signals set Y at each stimulus frequency. In SSVEP detection, the reference signals of f_k frequency $Y_k \in R^{2H \times N}$ are set as

$$Y_k = \begin{bmatrix} \sin(2\pi f_k n) \\ \cos(2\pi f_k n) \\ \vdots \\ \sin(2\pi H f_n n) \\ \cos(2\pi H f_n n) \end{bmatrix}, n = \left[\frac{1}{F_s}, \frac{2}{F_s}, \cdots \frac{N}{F_s}\right] \quad (2)$$

Where F_s is the sampling rate and H is the number of harmonics. The frequency with the maximal correlation ρ_k will be selected as the frequency of the SSVEPs signal and is generated by

$$\tau = \arg\max_k \rho_k, k = 1,2,\ldots,K \quad (3)$$

B. Standard CCA Method

The raw SSVEP data is pre-filtered between ranges of frequency 6 - 120 Hz. Then to reduce the calibration time, short-time SSVEP signal with 0.25s to 1.0s is taken from the recorded signal. The standard CCA method usually uses 4s of TW for SSVEP frequency detection to obtain effective accuracy as it is suitable for long length. The recognition performance with shorter length of data is reasonably lower, whereas, the lower calibration time is more effective for BCI implementation with SSVEP. Hence, the proposed method is aimed to enhance the frequency recognition accuracy with lower data length. In this method the shorter time window (TW) from 0.25s to 1s is used for frequency recognition. Instead of directly using standard CCA on short-length signal we increase the length of the signal.

To mitigate the limitation of CCA regarding the data length, the data of the selected shorter time window is concatenated repeatedly to make its length up to the required size. Thus the length the any shorter TW is made to the equivalent of 4s. After increasing the length of the short-time SSVEP signal then reference signals are derived from training set using MsetCCA [9]. Then standard CCA is applied on the test set together with the reference signals derived by using MsetCCA. The proposed method can be described by the following algorithm:

1. Take the trial of length TW (for 0.25s to 1.0s).
2. Copy (concatenate) the signal of TW multiple times to make the length equivalent to 4s.
3. Derive reference signal using MsetCCA.
4. Recognize the frequency of SSVEP signal using standard CCA.

Thus increasing the length of the short-time SSVEP signal enhances the frequency recognition accuracy.

C. Data Description

We are using publicly available dataset collected from M. Nakanishi [16]. There were 12 target visual stimuli (6×6 cm each) as shown in Fig. 2. The visual stimuli were represented on a 27-inch LCD monitor (ASUS VG278) of resolution 1280×800 pixels with refresh rate 60Hz. The horizontal and vertical intervals between two neighboring stimuli were 5cm and 1.5cm. The visual stimuli were arranged and tagged with different frequencies $(f_0 = 9.25Hz, \Delta f = 0.5Hz)$ to implement a 4×3 matrix as a virtual keypad of phone. The stimulus program was developed under MATLAB using Toolbox extensions. The healthy subjects were participated and seated in a comfort chair at a distance of 60cm in front of the LCD monitor. For each subject, the experiment consisted of 15 blocks. In each block, subjects were asked to gaze at one of the visual stimuli indicated by the stimulus program in a random order for 4s and complete 12 trials corresponding to all 12 targets.

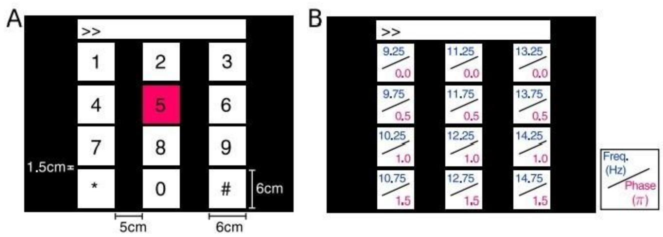


Fig. 1. Stimulus designed of the 12-target BCI system. (A) Virtual keypad of a phone-dialig program for user interface. (B) Frequency and phase values specified for each target. The red square in (A) is the virtual cue indicating a target symbol 5 in the experiment [16].

At the position of the target stimulus a red square will appear for 1s in each trial. Subjects were asked to switch their gaze to the target within the duration of 1s. Then, all stimuli simultaneously started to flicker for 4s on the monitor. During the stimulation period subjects were asked to avoid eye blink to reduce physiological artifacts. Data epochs consisting eight-channel of SSVEPs were extracted according to event triggers generated by the stimulus program. All data epochs were down-sampled to 256Hz and then band-pass filtered between the ranges of frequency 6 - 80 Hz using an infinite impulse response (IIR) filter. By The Zero-phase forward and reverse IIR filter implemented by using the filtfilt() function in MATLAB. The data epochs were extracted in [0.135s (0.135+d)s], by considering a latency delay in the visual system, where the time 0 indicated stimulus onset and d represented the data length used in the offline analysis. The 135-ms delay was selected towards the maximum classification accuracy.

III. Experimental Results

Canonical correlation analysis (CCA) is a popular statistical method for analyzing brain signals. CCA is widely used in SSVEP target detection. CCA can assess the relationship between the data to be examined with the previously defined reference (sinusoidal signals at flickering frequencies), in order to find the canonical correlation values. The maximum target of the correlation coefficient was selected to identify the target frequency of brain signals used to generate commands for the BCI, in order to control devices or make decisions about answer choices.

In this study, the proposed method is evaluated using public dataset [16]. The results are compared with standard CCA and MsetCCA method to validate its effectiveness for short-time SSVEP frequency recognition. To make short-time SSVEP we use maximum of 1.0s duration of SSVEP signal from available length of 4s. To implement CCA and MsetCCA, the short-time SSVEP signal is used directly, whereas, the length is increased (by concatenation) to apply the proposed method. The original dataset is pre-filtered within the range 6 – 120 Hz. The frequency recognition accuracy of various time windows (0.25s to 1s) for each subject is shown in Fig. 2. Table I shows the accuracy each subject for 1.0s and their average. It is noticed from Fig. 2 and Table I that proposed method achieved better recognition accuracy of all subjects for 1s.

In addition, BCI classification accuracy is also evaluated by information transfer rate (ITR). The

ITR is one of the most used techniques to measure the performance of BCI system. The ITR is defined as [17, 18].

$$ITR=\left(\log_2 K+P\log_2 P+(1-P)\log_2\left[\frac{1-P}{K-1}\right]\right)\times\left(\frac{60}{T}\right) \qquad (4)$$

where P is the classification accuracy, K is the number of class and T is the average time for a selection (seconds/selection).

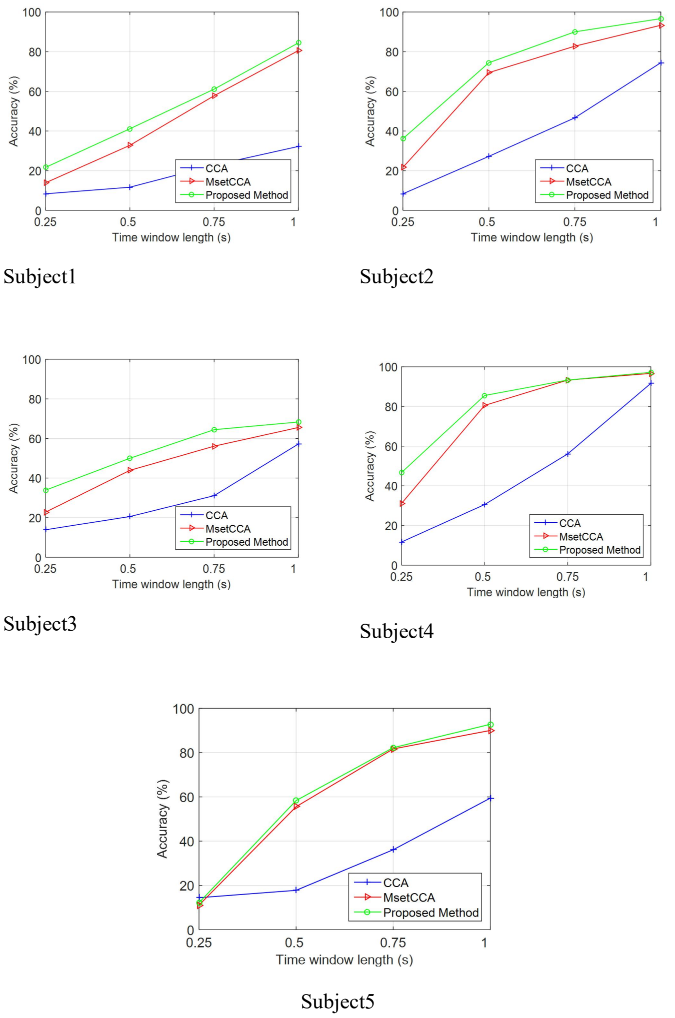


Fig. 2: Comparison of frequency recognition accuracy of proposed method with standard CCA and MsetCCA for different subjects

Here target gazing time is 0.25s to 1.0s and gaze shifting time is 0.25s. Here, the classification performances using different T are illustrated. ITR comparison for individual subject between standard CCA, MsetCCA and proposed method with different data length from 0.25s to 1.0s is shown Fig. 3. Table II shows the ITR comparison among standard CCA, MsetCCA and proposed method for 1.0s. Fig. 3 and Table II collectively illustrate the superiority of the proposed method compared to standard CCA and MsetCCA in term of ITR. The proposed method is performing better than standard CCA and MsetCCA for both recognition accuracy and information transfer.

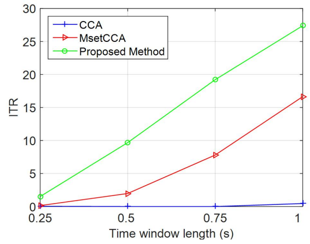
TABLE I
FREQUENCY RECOGNITION ACCURACY FOR EACH SUBJECT WITH 1.0S DURATION

Subject	***CCA (%)***	***MsetCCA (%)***	***Proposed Method (%)***
Subject 1	32.22	80.55	84.44
Subject 2	74.44	93.33	96.66
Subject 3	57.22	65.55	68.33
Subject 4	91.66	96.66	97.22
Subject 5	59.44	90.00	92.77
Average Accuracy	63.00	85.22	87.88

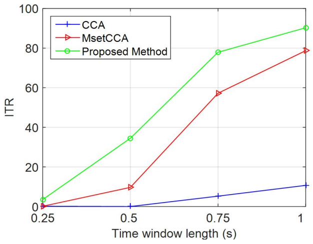
IV. Discussion and Conclusions

The frequency recognition performance of short-time SSVEP is studied here. A quantitative analysis CCA based target identification methods for short-time SSVEP-based BCIs is illustrated. The aim is to improve the classification accuracy of short-time SSVEP for BCI implementation. The length of pre-filtered (6 – 120Hz) short-time signal is artificially increased to fit for applying CCA. The proposed method produces better recognition accuracy than standard CCA and MsetCCA. Fig. 3 shows that the proposed method exhibits higher ITR than standard CCA and MsetCCA. To improve the recognition accuracy of the proposed method, the short-time data of multichannel SSVEP is reformed to increase its length. The underlying assumption of making such modification is that the CCA method works better for higher length of data, whereas, the selected short-time SSVEP is not adequate in term of length for standard CCA. The comparisons in terms of recognition and ITR among standard CCA, MsetCCA and proposed method of short-time SSVEP of all subjects obtained with different time window from 0.25s to 1.0s are illustrated. In both comparisons, proposed method achieves higher performance than standard CCA and MsetCCA method for all TWs.

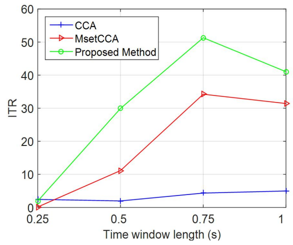
A novel method for frequency recognition of short-time SSVEP signals is introduced here. It is observed that the performance of the proposed method is better than that of the standard CCA and MsetCCA for a wide range of the length of short-time SSVEP signals.



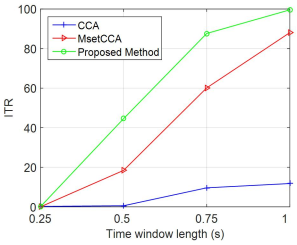
Subject1



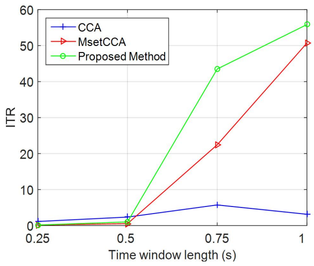
Subject2



Subject3



Subject4



Subject5

Fig. 3: Comparison ITR of proposed method with standard CCA and MsetCCA for different subjects

TABLE III
ITR COMPARISON OF EACH SUBJECT FOR 1S DURATION

Subject	*CCA*	*MsetCCA*	*Proposed Method*
Subject 1	0.45	16.64	27.39
Subject 2	10.68	78.71	90.28
Subject 3	4.97	31.42	41.05
Subject 4	11.78	88.06	99.58
Subject 5	3.13	50.70	55.85
Average ITR	6.20	53.11	62.83

The underlying contention of improved performance of proposed method is that the artificial increase (by concatenation) of short-time SSVEP dataset works better for frequency recognition than directly using short-time SSVEP dataset using CCA based approach. The experimental demonstrates that the proposed method outperforms the standard CCA and MsetCCA method of recognition accuracy also information transfer rate (ITR) for short-time SSVEP based BCIs implementation. At the same time, the method is more suitable to implement BCI with lower calibration time.

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