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Original Article

Detection of Target Frequency from Multichannel SSVEP-Based BCI System using a Combined Approach of BSS-CCA

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Abstract *- This paper demonstrates the combined approach of Blind Source Separation (BSS) and Canonical Correlation Analysis (CCA) to detect the frequency component of a Steady-State Visual Evoked Potential (SSVEP). Accurate detection of the SSVEP frequency component is the most challenging task for developing the SSVEP-based brain-computer interface (BCI) system. Canonical Correlation Analysis (CCA) is the most widely and rigorously employed method to detect the SSVEP frequency component from multichannel recorded Electroencephalogram (EEG) signals. However, spontaneous EEG signals and artifacts often occurring while recording scalp-based EEG signals may deteriorate the detection accuracy of the SSVEP frequency component from the recorded EEG signal. This work investigates the BSS as a pre-processing technique to decorrelate the source signal (SSVEP) from the recorded mixed-signal (EEG) to improve the detection accuracy of the SSVEP-based BCI Inference system. This paper proposes second-order statistics-based BSS AMUSE algorithms as pre-processing methods for multichannel EEG signals. The CCA technique employs the pre-processed signal to detect the SSVEP frequency components from the recorded EEG signal. The obtained finding indicates that the proposed BSS-CCA method significantly improved the SSVEP detection accuracy compared to the standard CCA method. The authors have also observed that the selection of stimulus frequency also plays a vital role in improving the detection accuracy of the SSVEP BCI system. The analysis indicates that average detection accuracy is much higher when stimulus frequency is in the range of the alpha band (8Hz – 16Hz) compared to stimulus frequency beyond the alpha band (above 16Hz) using both CCA and BSS-CCA approaches.*

Keywords *- Brain-Computer Inference (BCI), Blind Source Separation (BSS), Canonical Correlation Analysis (CCA), Electroencephalography (EEG), Steady-State Visual Evoked Potential (SSVEP).*

1. Introduction

Brain-Computer Interface (BCI) is a communication system that enables users to communicate with an external device via a thought process [1, 2]. Different thoughts generate electrical potentials over the scalp's surface and are recorded with sensors placed over the scalp. A physiological signal related to electrical potential in response to thought is called an Electroencephalogram (EEG) signal [3]. The BCI based on the EEG signal has been the most challenging and exciting research topic for a decade. The human brain's neural activity, recorded non-invasively, is sufficient to control an external machine if advanced signal analysis and feature extraction methods are combined with machine learning techniques. Many EEG-based paradigms, such as motor imagery, P300, and SSVEP, have recently been used to design BCI inference systems [4, 5]. Nowadays, SSVEP-based BCI Inference systems have become a more popular choice as compared to other BCI paradigms due to high Information Transmission Rate (ITR), high Signal-to-Noise Ratio (SNR), and minimal training time [4]. SSVEP is an evoked signal induced into the occipital region of the brain when the subject focuses their attention on a visual stimulus flickering at a specific frequency [5-8].

An SSVEP-based BCI system is depicted in Figure 1. This type of BCI system allows the subject to control the different applications, i.e., the movement of the electric wheelchair and the direction of the cursor on the computer screen [6]. Each generated command is associated with a repetitive visual stimulus flashing at a distinctive frequency. Several stimuli are presented before the users, who select the command by focusing on the corresponding stimulus. When the users focus on the visual stimulus [7], the signal appears in a recorded EEG signal with the same frequency as the stimulus's fundamental flicker frequency and its harmonics, along with the spontaneous EEG signal and artifacts.

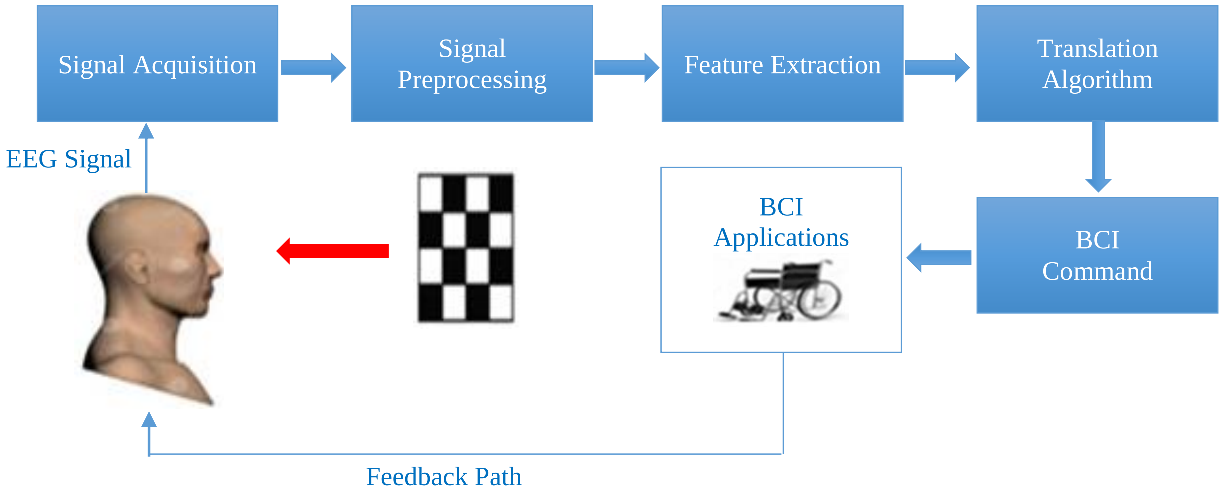

Fig. 1 SSVEP BCI system

Researchers have recently suggested that artifacts and spontaneous EEG signals may degrade the performance of the SSVEP BCI Inference system [8]. Consequently, many methods were employed to pre-process the recorded EEG signals to develop the SSVEP BCI inference system [9]. Among them, the most common practice is filtering methods: FIR bandpass and IIR bandpass filter [5-9]. Besides the classical approach, spatial filtering [9] and decomposition techniques such as the wavelet filter bank approach and empirical mode decomposition [10, 11] method have also been used to a large extent.

Furthermore, Blind Source Separation (BSS) [12-16] is another efficient and extensively used technique to minimize artifacts and to separate the source signal from the recorded EEG signal. The central part of the SSVEP-based BCI system is feature extraction, by which the SSVEP frequency component is extracted from recorded EEG signals. The Power Spectral Analysis (PSA) [17] is the most widely and commonly used method to extract the SSVEP frequency components from recorded raw EEG signals [19-22]. In addition to this, Canonical Correlation Analysis (CCA) is another efficient and powerful technique to recognize the SSVEP frequency component from the multichannel EEG signals [17]. Recently, a different version of CCA has been developed to optimize the detection accuracy of the SSVEP signal [19, 20].

After the literature survey, it was found that various spatial filtering [13, 22-24] techniques have been employed before the feature extraction from the multichannel SSVEP BCI system. The feature extraction from the multichannel recordings directly influences the detection accuracy because the multichannel EEG signals are correlated [23-24]. Blind Source Separation (BSS) [23] is an advanced signal processing method to mix the independent sources at the sensor point or decorrelate the recorded EEG signal [13]. The performance of BSS, along with CCA, is a new method for detecting SSVEP from the multichannel EEG signals. Regarding the research gap, there are two approaches to handle the SSVEP-based BCI inference system: single-channel and multiple-channel [25-27]. The objective of the BCI researcher is to develop a BCI inference system to decode the user's intention [28]. It consists of an EEG data acquisition system, a Preprocessing method, Feature extraction, and classification, followed by a control interface [6-9] shown in Figure 1. As a researcher, the paper's objective is to propose a preprocessing method to enhance detection accuracy considering the approach of multiple channels.

Canonical Correlation Analysis (CCA) [11, 12] is the most widely and rigorously employed method to detect the SSVEP frequency component from multichannel recorded Electroencephalogram (EEG) signals. However, spontaneous EEG signals and artifacts often occurring while recording scalp-based EEG signals may deteriorate the detection accuracy of the SSVEP frequency component from the recorded EEG signal.

Blind Source Separation (BSS) [15, 16] is the most important technique for analyzing the multichannel EEG recording to get the independent brain signals mixed at the sensor point. It finds the signal components, assuming the independent components equal the number of sensors employed to record the brain signals. This work investigates the BSS as a pre-processing technique to decorrelate the source signal (SSVEP) from the recorded mixed-signal (EEG) to improve the detection accuracy of the SSVEP-based BCI Inference system. This paper proposes second-order statistics-based BSS AMUSE algorithms [23, 24] to pre-process multichannel EEG signals. Based on the above literature survey, the authors consider the multiple recordings of EEG data for SSVEP detection. This paper sets the following objectives: How detection accuracy depends on the selection of these three parameters: Number of harmonics (L), Number of channels (CH), and Length of data (Tw) if one has multiple channels of EEG signal available to detect SSVEP-based command. Therefore, the primary challenge is to detect the presence of the SSVEP frequency component from the recorded EEG signal with higher accuracy to improve the performance of the SSVEP BCI inference system.

There is a need to investigate the effectiveness of the hybrid approach in detecting the SSVEP frequency component from the EEG signals. Also, an efficient signal processing technique is required for pre-processing and feature extraction of recorded EEG signals. This paper studies and finds the effectiveness of the BSS and CCA hybrid method for extracting the SSVEP signal with higher accuracy from the recorded EEG signal.

As far as the authors know, nobody has analyzed the RIKEN dataset. Many labs have machines to acquire the EEG signal for SSVEP detection. They have performed CCA and AMUSE separately to find the detection accuracy for stimulus frequency in the alpha band. As per the reported results, the proposed methods achieve better detection accuracy for stimulus frequency in the alpha band. The entire paper is organized into five sections. Section 2 describes the proposed methodology used to detect the SSVEP frequency components. A brief description of the dataset is explained in Section 3, while Section 4 describes the various methods, followed by the results, discussions, and conclusions in Section 5.

2. Proposed Method

The proposed method for detecting the SSVEP frequency component from a multichannel EEG signal is depicted in Figure 2. The acquired scalp-based EEG signal is filtered using an FIR Bandpass filter with a cut-off frequency of 1Hz-30Hz. The filtered signal is pre-processed using the Blind Source Separation (BSS) based AMUSE algorithm. This pre-processed signal is further applied as an input signal to the feature extraction unit.

CCA is a feature-extraction method to find the correlation coefficients as a feature vector between the reference sine-cosine signal and the pre-processed EEG signal. The maximum correlation coefficients over the stimulus frequency and uncorrelated EEG signal indicate the corresponding SSVEP signal frequency. Finally, the detected SSVEP frequency component is used as a command to communicate and control the external device in the SSVEP-based BCI system.

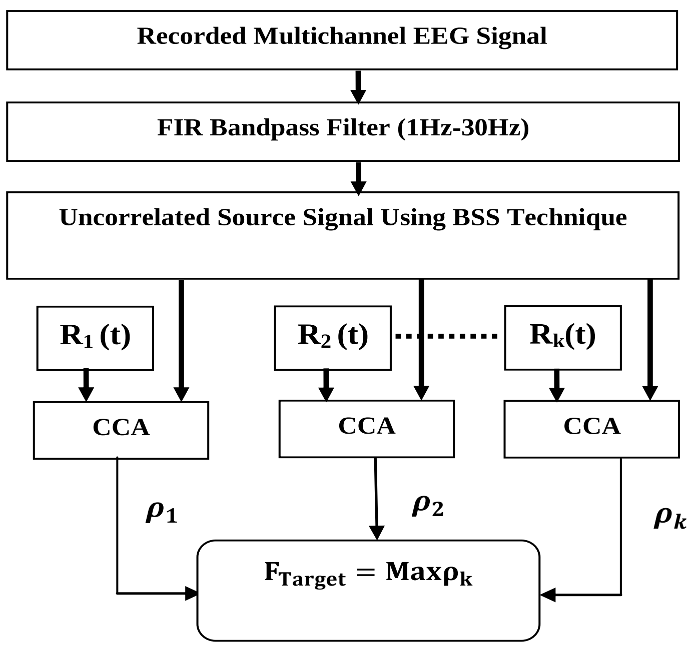

Fig. 2 Proposed methodology

3. Experimental Paradigm and Data Set

The proposed method is evaluated on a publicly available online dataset, RIKEN-LABSP, provided by Hovgim Bakardjian. The dataset consists of four healthy subjects. The recorded EEG signal is captured using checkerboard pattern visual stimulation at 8 Hz, 14 Hz, and 28 Hz. These stimulus frequencies are used for experimental purposes. Each trial lasted 15 seconds and was repeated five times at each stimulus frequency. The EEG signals are documented by placing 128 electrodes on the scalp's surface using a 10-20 electrode positioning system depicted in Figure 3 [26]. Dataset-related information is given in Table 1. The EEG signals are recorded at a 256 Hz sampling frequency. The SSVEP signal is found to be prominent in the occipital region. Therefore, the EEG signal recorded at P3, O1, O2, O3, Oz, P2, P4, P7, and P8are selected for further analysis.

Table 1. SSVEP dataset used in this study for experimental purpose

Dataset	No. of subjects	No. of trials	No. of channels	Data length	No. of stimulus frequencies	Stimulus Frequencies
RIKEN LABS	4	60	128	15s	3	8, 14 and 28Hz

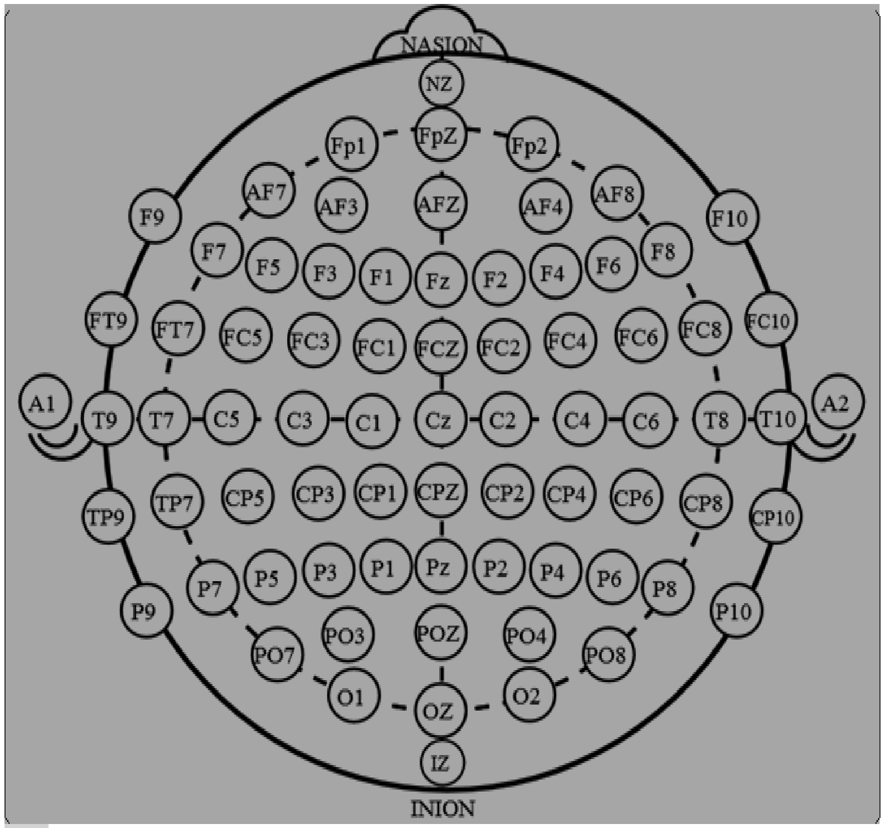

Fig. 3 Sensor layout of the recorded EEG signal

4. Methods

4.1. BSS as a Filtering Technique

Blind Source Separation (BSS) is a technique to extract the meaningful information buried within the recorded EEG signal [18, 19]. This technique mainly applies to a system containing multiple sources and sensors, as depicted in Figure 2. The objective of the BSS technique is to reject the artifacts and separate the acquired signal into temporally uncorrelated or independent components [23]. The SSVEP signals are generally embedded into EEG-recorded signals containing noise and artifacts. Therefore, applying the BSS to reject the artifacts appears natural, enhancing the detection accuracy of SSVEP signals. Generally, BSS can be performed based on characteristics such as non-Gaussianity, non-stationarity, and time correlation [23]. In this paper, we have assumed that the recorded EEG signal is time-correlated. Therefore, time de-correlation via the BSS method was required according to the time structure of the acquired EEG Signal. The Block diagram of the BSS approach to decorrelate the informative signal (SSVEP) from the multichannel EEG recorded signal is depicted in Figure 4. The source signal is composed of a finite number of components given by $\boldsymbol{S(t)} = [\boldsymbol{S_1(t)} \dots \dots \boldsymbol{S_n(t)}]$; where 't' is the discrete time index, n is the number of components. The acquired EEG Signal by the EEG sensor is given by;

$$\bar{X} = H\bar{S} + Q, \qquad (1)$$

Where

$$X^k = [x_1^1 \dots \dots \dots \dots \dots \dots x_N^K] \qquad (2)$$

$\mathbf{X^k}$ denotes the acquired EEG signal from the K^{th} channel, where K=1……M, where M represents the number of channels and N represents the number of samples in each channel. The term H is a mixing matrix and is the independent source. Q is uncorrelated white noise. The main objective of the BSS algorithm is to obtain the unmixing matrix (W), which is the inverse of the mixing matrix (H). The rhythmic information is also correlated when multiple channels of the EEG signal are acquired for a particular application. A second-order statistics-based BSS AMUSE algorithm is proposed as a pre-processing method to extract the source signal, which is assumed to be an SSVEP signal that is buried in the acquired multichannel recorded EEG signal

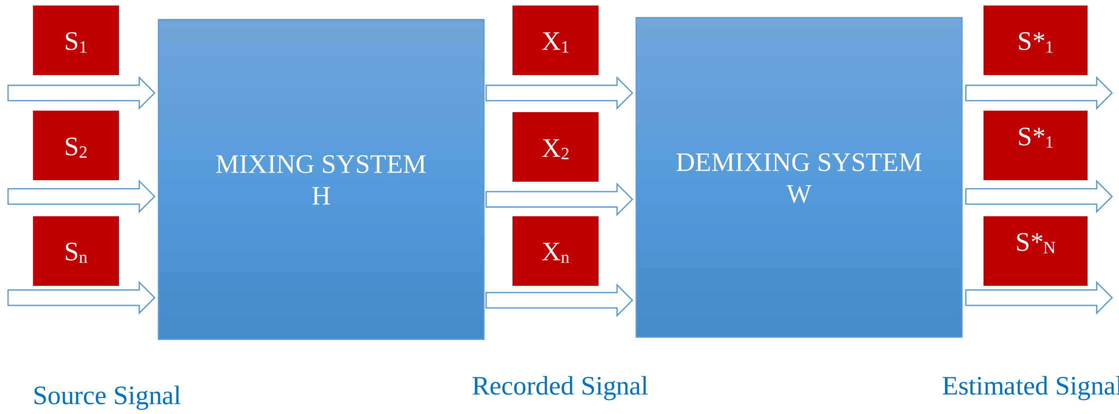

Fig. 4 Block diagram of AMUSE-based source separation

4.2. AMUSE-Based Source Separation Algorithm

The AMUSE algorithm uses a straightforward principle, where the estimated components are spatiotemporally uncorrelated and less complex, where the components are arranged according to the decreasing Eigenvalues of the covariance matrix [20, 21]. The AMUSE algorithm is performed in two steps using the principle component analysis. First, the eigenvalue decomposition is employed on the covariance matrix of the recorded EEG signals [19]. Second, the singular value decomposition is applied to the time-lagged covariance matrix of the whitened signal. The detailed descriptions of the AMUSE algorithm, which is performed in two steps, are given below:

Step-1: The whitening data using the eigenvalue decomposition is given below [21, 22]:

$$Z(n) = \o\, X'(n); \tag{3}$$

where $\emptyset = \mathbf{R}_{\mathbf{X}}^{-\frac{1}{2}}$ is the whitening matrix of the

Covariance matrix

$$R_{XX} = E\{X'(n)X'^{T}(n)\} \tag{4}$$

Where $\mathbf{R}_{\mathbf{XX}}$ is a covariance matrix, $\mathbf{X}'(\mathbf{n})$ is raw EEG signal.

Step-2: Estimation of separating matrix W with SVD [19, 20]

The SVD is used on the time-delayed covariance matrix of the whitened signal.

$$R_Z = E\{Z(n)Z^{T}(n-1)\} = USV^{T} \tag{5}$$

S is the diagonal of decreasing singular values, and U and V are the Eigenvector matrices. The separating matrix is estimated as follows [20]:

$$W = U^{T}\o \tag{6}$$

The independent components are computed as follows:

$$Y = WX \tag{7}$$

4.3. Canonical Correlation Analysis (CCA)

The CCA is fundamentally a multivariate statistical approach used to determine the association between two datasets [15-17, 25]. Its key strength is to find the pair of linear transforms such that when transformations are applied, the new set of variables will have a maximum transformation. For example, assume P and Q are two datasets, $\boldsymbol{\theta}_{\mathbf{P}}$ **and** $\boldsymbol{\theta}_{\mathbf{Q}}$ are the canonical variants. After the linear transformation, the new sets of variables can be given as $\bar{\mathbf{P}} = \boldsymbol{\theta}_{\mathbf{P}}\mathbf{P}^{\mathbf{T}}$ and

$\bar{\mathbf{Q}} = \boldsymbol{\theta}_{\mathbf{Q}}\mathbf{Q}^{\mathbf{T}}$. The primary function of the CCA algorithm is to determine the weight-vector $\boldsymbol{\theta}_{\mathbf{P}}$ and $\boldsymbol{\theta}_{\mathbf{Q}}$ and their correlation can be given as,

$$\rho = \max(\theta_P, \theta_Q)\frac{E[\bar{P}\bar{Q}^{T}]}{\sqrt{E[\bar{P}\bar{P}^{T}]E[\bar{Q}\bar{Q}^{T}]}} \tag{8}$$

$$\rho = \max(\theta_P, \theta_Q)\frac{\theta_P C_{PQ}\theta_Q}{\sqrt{\theta_P C_{PP} W_x{}^{T}\theta_Q C_{QQ}\theta_Q{}^{T}}} \tag{9}$$

Where ρ denotes the correlation coefficient between the datasets P and Q, which can be maximized by maximizing Z. Lin et al., in 2007, were the first to propose the CCA technique towards detecting SSVEP signals in BCI applications [14]. As per this technique, among the extracted correlation coefficients for all stimulus frequencies, the SSVEP frequency is the maximum correlation coefficient [25].

The mathematical modeling to determine the SSVEP signal using the CCA technique can be described as follows. Assume that ‘K’ denotes the number of target frequencies in the SSVEP-based BCI system, and let X denote the EEG signal recorded from the ith channel, which consists of 'n' samples in each channel. The recorded EEG signal is whitened using AMUSE algorithm to minimize the artifacts and spontaneous EEG signal. Assume that R_K denotes the reference signal at the k^{th} stimulus frequency $\mathbf{f_k}$ (k=1, 2…..k) and comprises sine-cosine function, then R_K can be given by,

$$R_k = \begin{bmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ . \\ . \\ . \\ sin(2\pi N_H f_k t) \\ \cos(2\pi N_H f_k t) \end{bmatrix}, t = \frac{1}{f_s}, \frac{2}{f_s}, \dots\dots.. \frac{k}{f_s} \quad (10)$$

In this study, the number of harmonics is considered as 1. To recognize the SSVEP frequency, the canonical correlation between the reference signal at each stimulus frequency and the uncorrelated EEG signal by the AMUSE algorithm is calculated using CCA. Finally, the maximum correlation between the reference signal at each stimulus frequency and the uncorrelated EEG signal is selected as a frequency of the SSVEP signal.

5. Result

This paper compares the proposed BSS-CCA method with the standard CCA method to confirm its effectiveness in recognizing SSVEP frequency. The EEG signal was recorded at the stimulus frequencies of 8, 14, and 28Hz by placing 128 electrodes at different locations on the scalp of the brain.

Since the SSVEP signals are more prominent in the brain's occipital and parietal scalp area, only eight channels, namely P3, O1, O2, O3, Oz, P2, P4, P7, and P8, are used for further analysis of the EEG signal.

As the number of harmonics H needs to be pre-defined for CCA, we first investigate the effect of varying harmonics on the accuracy of frequency recognition.

Figure 5 depicts the raw EEG signal acquired from the scalp of the brain by placing the sensor at locations P3, O1, Oz, O2, P2, P4, P8, and P7. The uncorrelated signal is shown in Figure 6 after applying the AMUSE algorithm over the selected multiple channels of the EEG signal.

As the number of harmonics L needs to be pre-defined for CCA, we first investigate the effect of varying harmonics on the accuracy of frequency recognition.

Table 2 shows the effect of averaged recognition accuracy obtained using CCA and AMUSE-CCA methods with several harmonics varied from 1 to 4 at various window lengths.

The obtained result revealed that the CCA and BSS-CCA methods yielded higher accuracies at L=2 to 4 than L=1. However, no significant accuracy changes were observed for both methods, increasing L from 2 to 4. Therefore, L=2 is chosen for further investigation for the standard-CCA and AMUSE-CCA methods.

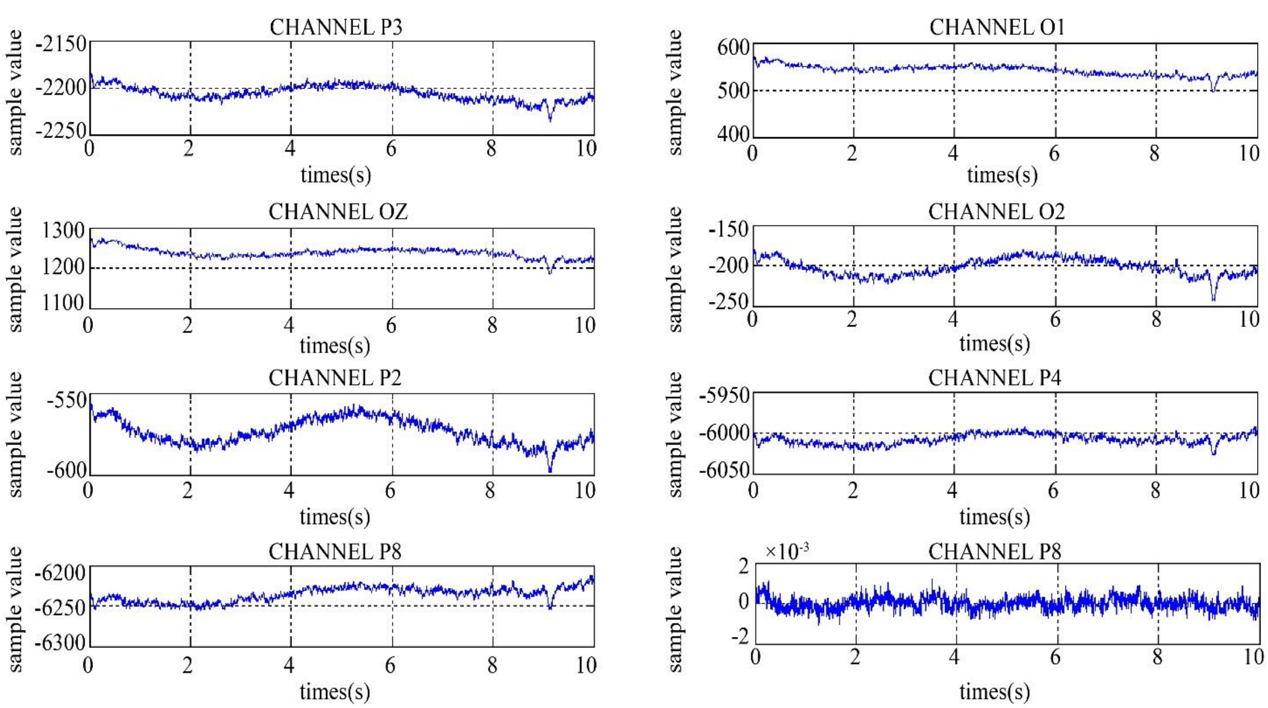

Fig. 5 Recorded EEG signal by placing the electrode at P3, O1, O2, O3, OZ, P2, P4, P7 and P8 position

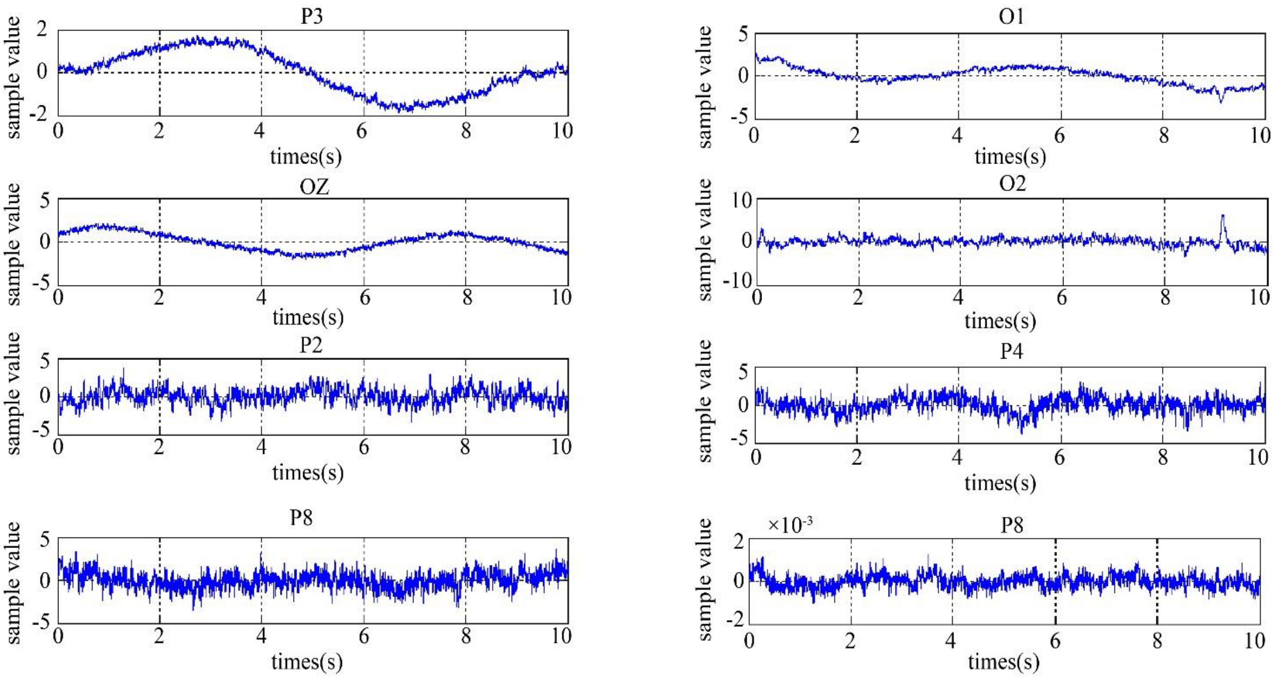

Fig. 6 The whitened signal obtained using the AMUSE method, respectively

Table 2. SSVEP detection accuracy of AMUSE-CCA and CCA methods with increasing number of harmonics and time window lengths (TWs)

Method	No. of Harmonics	Time Window Lengths (TWs)			
		1sec	2sec	3sec	4sec
CCA	L=1	48.33	58.33	60.00	63.33
	L=2	45.00	58.33	63.33	65.00
	L=3	43.33	60.00	60.00	63.33
	L=4	41.66	58.33	60.00	61.66
AMUSE-CCA	L=1	46.66	60.00	60.00	61.66
	L=2	43.33	61.66	63.33	63.33
	L=3	43.33	60.00	60.00	60.00
	L=4	41.66	56.66	58.33	58.33

As we know, the detection accuracy of SSVEP frequency over multichannel EEG signals also depends on the number of channels selected.

Therefore, we also investigate the effect of varying the number of channels on recognizing SSVEP frequency components for L=2. Table 3 summarizes the average detection accuracy obtained by the BSS-CCA and CCA methods at various window lengths for the harmonics L=2.

Table 3. The SSVEP detection accuracy using BSS-CCA and standard CCA methods. Here, the number of HARMONICS, L=2.

Method	No. of Channels (CH)	Time window lengths (TWs)			
		1 sec	2 sec	3 sec	4 sec
CCA	4	41.66	48.33	56.66	61.66
	6	45.00	55.00	65.00	63.33
	8	48.33	58.33	61.67	66.67
AMUSE-CCA	4	43.33	50.00	58.33	63.33
	6	46.67	56.67	66.67	65.00
	8	50.00	60.00	63.33	68.33

The results indicated that the average detection accuracy increased with the increasing number of channels. Thus, the number of channels selected for further analysis of the SSVEP EEG signal was set to 8. Figure 7 shows the subject-wise accuracy using CCA and AMUSE-CCA methods for the number of channels C=8 and number of harmonics L=2 at different Time-Windows lengths (TWs) 1 to 4 s. The reported results indicate that the AMUSE-CCA method yields higher accuracy than the standard CCA method at various time windows for all the subjects.

Table 4. Average SSVEP detection accuracy of all the subjects using CCA and BSS-CCA at various time window lengths of 1 to 4 seconds using the standard CCA and BSS-CCA methods. Here, the number of channels CH =8 and the number of harmonics L = 2.

TW(S)	Accuracy (%)	
	CCA	AMUSE-CCA
1	48.33	55.00
2	58.33	65.00
3	61.66	68.33
4	66.66	73.33

Furthermore, the average detection accuracy of all the subjects at different Time Window lengths (TWs) of 1 to 4 s is given in Table 4. The reported results show that the average detection accuracy for all the subjects at various Time Windows (TWs) lengths of 1 to 4s was found to be 48.33, 58.33, 61.66, and 66.66 %, respectively, using the CCA technique. In contrast, using the BSS-CCA method, it is 55.00, 65.00, 68.33, and 73.33 %, corresponding to the same window length. In this paper, the authors also investigate the effect of the selection of stimulus frequency on the detection accuracy of SSVEP frequency.

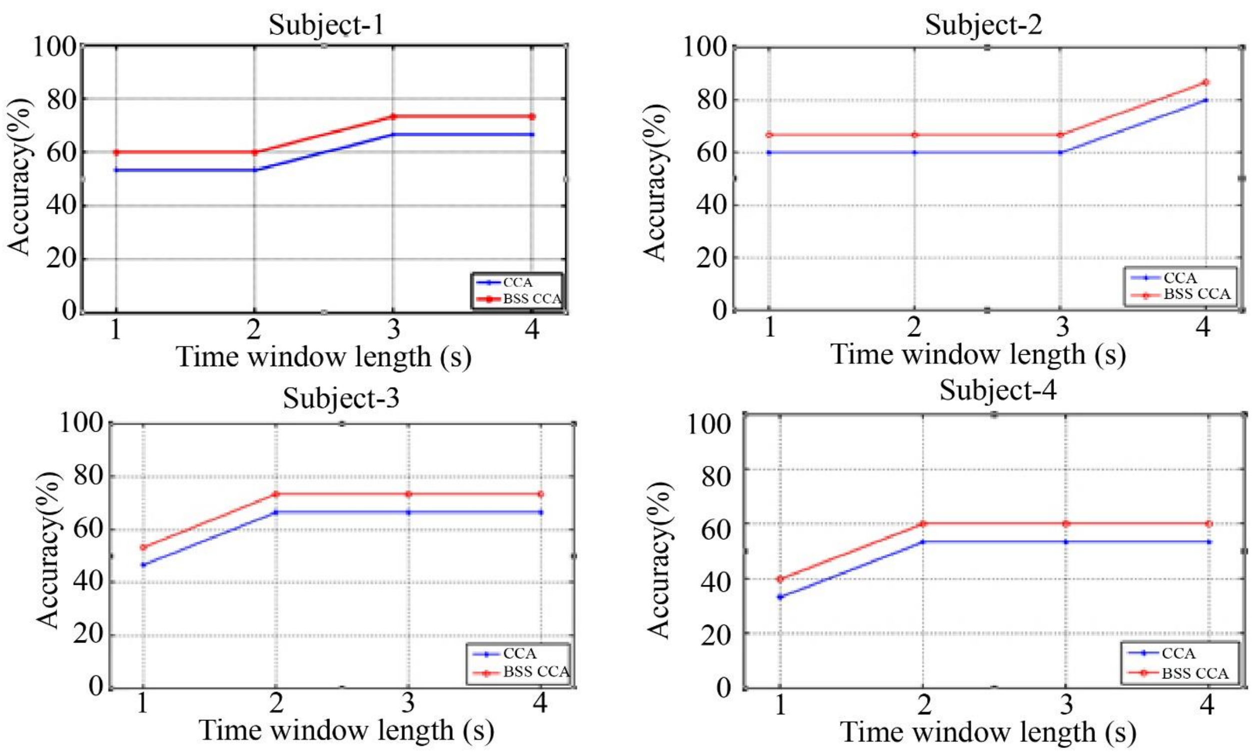

Fig. 7 Detection accuracy of subjects 1, 2, 3 & 4 for the window length of 1 sec - 4 sec. m CH=8 and L=2

Table 5. Average detection accuracy of all subject for C=8, L=2, stimulus frequency 8 Hz, 14 Hz

TW(S)	Average accuracy (%)	
	CCA	**AMUSE-CCA**
1	70.00	80.00
2	87.50	95.00
3	90.00	95.00
4	95	97.50

To demonstrate the impact of the choice of stimulus frequency, the authors find that the stimulus. Frequency falling in the alpha band achieves more detection accuracy. Table 5 shows the average detection accuracy of all subjects for different window lengths (1 sec -4 sec) for stimulus frequencies of 8 Hz and 14 Hz. At the same time, all other parameters (Number of channels CH and number of harmonics L) remain the same, with CH=8 and L=2.

The results show that using the CCA technique, the average detection accuracy for all subjects at various Time Windows (TWs) lengths of 1 to 4s are 70.00, 87.50, 90.00, and 95.00%, respectively. In contrast, using the BSS-CCA method, it is 80.00, 95.00, 95.00, and 97.50 %. Considering that the authors compare the result with other researchers' work , the proposed hybrid approach has better results than CCA and AMUSE for stimulus frequency in the alpha band. However, the dataset is not the same. From the reported results, the authors understand that the hybrid approach has better results than separately applied CCA and AMUSE methods for stimulus frequency in the alpha band. When one considers the number of channels to acquire the EEG signal, placing many channels for accurate detection of the SSVEP signal is paramount. The sensors are so closely placed that the influence of correlativeness has separate importance. BSS is a key concept to address the multiple channels case and find decor-related/independent components from the mixed signal. The real-time application of the BCI inference system depends on fast decisions and the algorithm. The algorithm takes less time to provide the decision. Keep in mind that the second-order statistics-based BSS algorithm is proposed to enhance the detection accuracy of the CCA-based algorithm. The performance of the hybrid approach is evaluated with three parameters: the number of channels C, the length of data, and the number of harmonics (L). At the same time, this paper considers the stimulus frequency. If the frequency falls in the alpha and beta bands, AMUSE-based CCA performs better than the simple CCA-based method. If the stimulus frequency falls in the upper beta band, the average detection accuracy falls significantly, as shown in Table 4. The limitation of this study is that the limited dataset is available for the flickering frequency above 26 Hz.

There is a need to explore the proposed method over a larger number of datasets, considering the stimulus frequency above 26 Hz. In the Future, the authors will try to address this limitation through their experiment. The proposed method, AMUSE CCA, has better results for stimulus frequency in the alpha band because the second-order statistics-based BSS algorithms consider that the mixed data at sensor points are correlated. By applying the AMUSE algorithm, one can make the mixed sensor signal uncorrelated and independent. Also, it is required to be decorated to find the independent signal. After that, the authors applied CCA as a feature extraction technique to find the detection accuracy.

Furthermore, the authors have reported that the SSVEP frequency is mixed due to a slow frequency stimulus signal having better detection accuracy if one can apply AMUSE CCA. On the other hand, this paper reports that the SSVEP signal generated inside the brain due to a fast stimulus frequency does not have better results. There is a need to explore the dynamics of the brain with slow frequency stimulus signals and fast stimulus signals, as well as how adaptable the existing BSS algorithm is in a fast-changing environment of signal mixing. The reported result clearly shows that the selection of stimulus frequency also plays a vital role in optimizing the performance of the SSVEP-based BCI system. Due to the high stimulus frequency above 20 Hz (in the recorded dataset, it is 28 Hz), the SSVEP frequency response is not as good as the corresponding low stimulus frequency. The detection accuracy for higher stimulus frequencies differs from that for lower ones. This result indicates further exploration of more stimulus frequencies in the upper range. This analysis and reported results conclude that the selection of stimulus frequency also plays a vital role in optimizing the performance of SSVEP-based BCI systems.

6. Conclusions and Future Work

This paperwork finds that the SSVEP recognition accuracy could be significantly improved using the BSS-CCA method compared to the standard CCA method for low stimulus frequency. The results reveal that blind source separation as a signal pre-processing technique is uncorrelated with the recorded multiple-channel EEG signal.

Therefore, it can enhance the recognition accuracy of SSVEP signals buried in the recorded EEG signals. The selection of the number of channels to improve the recognition accuracy of SSVEP is also presented. In addition, the authors have also investigated the choice of stimulus frequency, which also plays a vital role in improving the detection accuracy of SSVEP signals. Using both CCA and BSS-CCA methods, the authors reported that detection accuracy is enhanced at low stimulus frequency compared to high frequency (above 20 Hz). There is a need to develop further automatic channel selection algorithms for analyzing multichannel EEG recordings. Also, we need to explore and validate the effectiveness of the proposed method for the new dataset.

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