

Canonical Correlation Analysis and Its Extension for SSVEP-based BCI Detection: A Systematic Review

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Abstract: SSVEP-based Brain-Computer Interfaces (BCIs) utilize steady-state visual evoked potentials, which are brain responses triggered by visual stimuli flickering at specific frequencies. Users can focus on these stimuli, allowing the system to interpret their intent based on the brain's electrical activity. This technology has applications in communication for individuals with disabilities, gaming, and neuro-feedback, offering an ultimate means of interaction through thought alone. In this study, systematic literature review was conducted to identify analytical methods for SSVEP spellers with PRISMA method from the eligibility criteria. CCA and its extension become gold-standar method that give excellent performances for SSVEP recognition and signal classification. Some unques features also found such as MsetCCA, FB-CCA, MF-CCA, TW-CCA, CP-CCA, IIS-CCA, TT-CCA and RLS-CCA. Therefore, we have various options for choosing the best method for recognizing SSVEP from EEG signals based BCI.

Keywords: Brain computer interface; CCA analysis; Electroencephalography; steady-state visual evoked potential; Systematic literature review.

Introduction

The development an effective algorithm for SSVEP-based BCI is of considerable important in recognizing the SSVEP frequency with high accuracy and a short time window. Thus, a high-performance BCI applications will be developed. Nowadays, various approaches have been introduced to recognize the SSVEP frequency. Among such methods, the canonical correlation analysis (CCA)-based recognition method has been widely used to spell targets due to its efficiency reported in the literature. Lin *et al.* introduced the standard CCA method which uses sinusoidal signals as reference signals and first proposed for SSVEP detection without calibration (Lin et al., 2007; Y. Zhang, Yin, et al., 2018). Therefore, the exploration of the CCA method needs to be done considering that the extensions of this method are very diverse. One of the efforts so that we

can obtain solid and comprehensive information is a systematic literature review study, which is highly recommended.

SLR is a systematic and explicit method to identify, select, extract, and synthesize the available scientific information from the studies (Landschaft et al., 2024; Putro et al., 2023; Sulaeman et al., 2022; Trifu et al., 2022). Thus, it is a good recommendation. for a specific review of the CCA methods and their extension. In this present SLR, We discussed the CCA methods and their extension based on eligibility criteria. Based on the search and knowledge of authors, the study of the CCA and its extension using SLR has never been done. In addition, the Boolean algorithm used in database searches using Publish or Perish (PoP) gave excellent results when using Google Scholar as the data source. because of the maximum limit of 1000 meta-databases. Therefore, this research can provide consideration for

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Example: Susilawati, S., Doyan, A., Muliyadi, L., & Hakim, S. (2019). Growth of tin oxide thin film by aluminum and fluorine doping using spin coating Sol-Gel techniques. *Jurnal Penelitian Pendidikan IPA*, 1(1), 1-4. <https://doi.org/10.29303/jppipa.v1i1.264>

researchers among academics or practitioners in applying CCA and its extension for SSVEP recognition and classification.

In the field of SSVEP signal processing, CCA and its extensions have advanced significantly. Therefore, the purpose of this study is to systematically identify CCA analysis and its extensions so that we can follow the latest developments and also apply the latest extensions for research on this topic, especially in the field of electroencephalography.

Method

Protocol

Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method was chosen in the present systematic review. It consists of well-defined stages, developed and described eligibility criteria of an information source, literature search strategy, literature selection process, and data synthesis on selected literature (Moher et al., 2015)(Ortiz-Martínez et al., 2019). We used these steps as a review strategy in finding the significance of CCA methods of SSVEP-based BCI from EEG signals. Therefore, this systematic approach includes identified and discussed SSVEP-based BCI through parameters referring to analytical methods based CCA and its extended results.

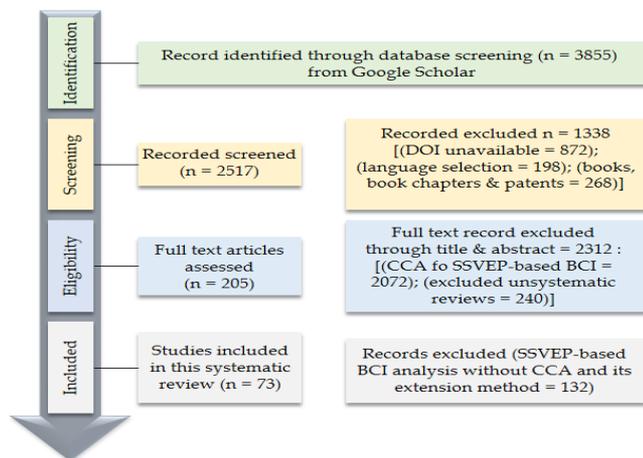


Figure 1. Schematic diagram of SLR with PRISMA method.

Eligibility Criteria

The eligibility criteria consist of inclusion and exclusion criteria. In this present SLR, the inclusion criteria were: (1) articles that reported CCA method and its extended for SSVEP-based BCI from EEG signals; (2) published articles in 2018 until 2024; (3) articles that have comprehensive related information about CCA method and its extended for SSVEP-based BCI detection. Besides, the exclusion criteria were: (1) review articles types; (2) books and book chapters; (3) patents; (4) articles published in a language other than English; (5)

articles without Digital Object Identifiers (DOI); and (6) unrelated topics by abstract checking.

Search strategy and selection process

The database was searched by using Publish or Perish (PoP) software with Google Scholar data sources to obtain information of the articles published in 2018-2024. The search technique of PoP used the Boolean algorithm as keywords format to search the meta-data. The keywords format is “Canonical Correlation Analysis” AND “electroencephalography” AND “steady-state visual evoked potential” AND “brain-computer interface”. We obtained 3855 meta-data and collected with Mendeley Version 1.19.4 software to management and selection process as explained in Figure ... based on eligibility criteria. Finally, 73 articles were selected and presented in Table 1.

Synthesis of result

The synthesis of the results focused on discussing the empirical trends. The data is presented without meta-analysis because it lacks sufficient statistical information. In addition, the search process resulted in several variation data types such as patents, books, and website. Therefore, it does not support to conducted meta-analysis.

Result and Discussion

A systematic review was conducted using 3855 meta-data from PoP software, following the processes depicted in Figure 1. The data was reduced to 2517 after excluding several meta-data based on DOI unavailability, non-English language, books, book chapters, and patents. Afterwards, 205 articles were selected based on eligibility criteria using Mendeley software. Finally, 73 articles were selected to be studied further in this SLR, which are shown in Table 1.

In the present SLR, we want to examine feature extraction for the SSVEP method in more depth, especially in relation to CCA and its extensions. As a conventional multivariate statistical analysis, CCA was first introduced by Lin et al. (2007) to decode SSVEP frequencies from multiple electrodes with high efficiency. Thus, it aroused the interest of many researchers (Wei et al., 2019). Here we will explain in detail the CCA method and its extensions based on our exploration via meta-data obtained from PoP.

CCA Method

CCA is a multivariable statistical approach that aims to investigate the underlying connection between two sets of random variables. It looks for two weight vectors that maximize the correlation between two variables (Tanaka et al., 2013)(Wei et al., 2019). Given

two dimensional variables X and Y, their respective linear combinations may be expressed as $x = X^T W_x$ and $y = Y^T W_y$. This method finds the two weight matrices W_x dan W_y , by maximizing the correlation ρ between the two combinations as express:

$$\rho = \arg \max_{W_x, W_y} \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}}$$

$$= \arg \max_{W_x, W_y} \frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_x]} \sqrt{E[W_y^T Y Y^T W_y]}} \quad (1)$$

where ρ is a one-dimensional vector with components sorted in decreasing order, and E represents mathematical expectation. SSVEP-based BCIs employs the first columns of W_x and W_y , which correspond to the maximum value in ρ , as spatial filters. CCA has two input signals for SSVEP-based BCI applications, the input X is a single-trial testing signal, whereas the input Y is a reference signal that can be either a specific frequency sine-cosine reference signal or an individual template signal (IT-CCA) yielded by averaging training signals across multiple trials.

The sine and cosine reference signals (Y_n) of the n -th simulation frequency (f_n) and its harmonics are used as the sine and cosine reference signals in the conventional CCA method.

$$Y_n = \begin{pmatrix} \sin(2\pi \times 1 \times f_n t) \\ \cos(2\pi \times 1 \times f_n t) \\ \vdots \\ \sin(2\pi \times N_h \times f_n t) \\ \cos(2\pi \times N_h \times f_n t) \end{pmatrix}, t = \frac{1}{f_s}, \frac{2}{f_s}, \dots, \frac{N_s}{f_s} \quad (2)$$

Where the number of harmonics used for the CCA analysis is indicated by N_h . Then, f_s is the sampling rate, and N_s denotes the number of time samples. The CCA technique computes the correlation coefficients ρ_n between the multi-channel EEG data X and the reference signals Y_n at the n -th stimulus frequency in order to

determine the SSVEP target. The maximum correlation coefficients ρ_n are chosen in the following manner to determine the SSVEP target:

$$T = \max \rho_n, n = 1, 2, \dots, N_f \quad (3)$$

In our findings, the CCA feature extraction method was utilized for SSVEP response analysis and fatigue rate evaluation in normal subjects (Keihani et al., 2018). In preprocessing segment the beginning time point of EEG signal with respect to the visual stimuli representation was calculated by the subtraction of optic sensor initial point from gtec.'s pulse onset. Therefore, each segment of EEG-SSVEP was separated. We checked the signals visually and removed trend of data with detrend command in the MATLAB software. Single trials and mean of 10 trials were calculated for each pattern in order to utilize them for further respective single and mean trials data analysis. The results showed that CCA could improve SSVEP-based BCI speed recognition than PSD because more robust discriminative features in shorter triphasic waves (TWs). The speed of recognition of SSVEP-based BCI depends to window length (WL) of the simple group or rhythmic group trials. Keihani et al. (2018) used 3 different methods to determine a good accuracy between PSD, LASSO, or CCA method. In simple group accuracy, CCA has higher percentage than others with 71.34% and 98.48% for single trial and mean of 10 trials, respectively. Meanwhile, 76.24% and 100% is successfully obtained in rhythmic group accuracy for single trial and mean of 10 trials during 2 s WL. Therefore, CCA becomes a multivariate statistical analysis approach for the SSVEP paradigm with an effective in recognizing multichannel EEG signals. In comparison to other SSVEP signal classification methods, the CCA classification algorithm is quick, efficient, simple, and user-friendly.

Table 1. Selected articles based on eligibility criteria which are

No	Year	Types of CCA Methods		eCCA Details	Ref.
		CCA	eCCA		
1	2018	✓			(Keihani et al., 2018)
2	2018	✓			(Dehzangi et al., 2018)
3	2018	✓			(Ibanez-Soria et al., 2018)
4	2018	✓			(Erkan & Akbaba, 2018)
5	2018		✓	FB-CCA	(Wittevrongel et al., 2018)
6	2018	✓	✓	IT-CCA	(Y. Zhang, Guo, et al., 2018)
7	2018	✓	✓	MsetCCA	(Jiao et al., 2018)
8	2018	✓	✓	Combine-CCA	(Waytowich et al., 2018)
9	2018	✓			(Xing et al., 2018)
10	2018	✓	✓	eCCA	(Youssef Ali Amer et al., 2018)
11	2018	✓			(Dehzangi et al., 2018)
12	2019	✓	✓	L1-MCCA, MsetCCA	(Neghabi et al., 2019)
13	2019	✓			(Niknamian, 2019)
14	2019	✓	✓	CP-CCA	(Gao et al., 2019)
15	2019	✓			(Fernandez-Fraga et al., 2019)

No	Year	Types of CCA Methods		eCCA Details	Ref.
		CCA	eCCA		
16	2019	✓	✓	SC-CCA, IT-CCA, E-CCA	(Wei et al., 2019)
17	2019	✓			(Demir et al., 2019)
18	2019	✓			(X. Zhang et al., 2019)
19	2019	✓	✓	IT-CCA	(D. Kim et al., 2019)
20	2019		✓	FB-CCA	(Podmore et al., 2019)
21	2019		✓	FB-CCA	(X. Chen et al., 2019)
22	2019	✓	✓	FB-CCA	(S. Zhang et al., 2019)
23	2020	✓			(Yang et al., 2020)
24	2020	✓	✓	FB-CCA, TT-CCA	(Wong et al., 2020)
25	2020	✓	✓	IT-CCA, L1-MCCA, MsetCCA, ECCA	(J. Zhao et al., 2020)
26	2020	✓	✓	FB-CCA	(X. Chen et al., 2020)
27	2020	✓			(Shao et al., 2020)
28	2020		✓	FB-CCA	(Y. Peng et al., 2020)
29	2021		✓	FB-CCA	(Bassi et al., 2021)
30	2021	✓			(Do & Huynh, 2021)
31	2021	✓	✓	ECCA, FB-CCA	(H. Kim & Im, 2021)
32	2021	✓			(Zhou et al., 2021)
33	2021	✓			(Zhu et al., 2021)
34	2021	✓			(D. Zhao et al., 2021)
35	2021	✓			(A. Liu et al., 2021)
36	2021	✓	✓	FB-CCA	(Qin et al., 2021)
37	2021	✓	✓	FB-CCA	(Asanza et al., 2021)
38	2021	✓	✓	IT-CCA	(Lee & Choi, 2021)
39	2022	✓	✓	FB-CCA	(Tan et al., 2022)
40	2022	✓			(W. Chen et al., 2022)
41	2022	✓			(Sakkalis et al., 2022)
42	2022	✓	✓	IT-CCA	(F. Peng et al., 2022)
43	2022	✓	✓	TW-CCA	(Sun et al., 2022)
44	2022	✓	✓	FB-CCA	(X. Chen et al., 2022)
45	2022	✓	✓	FB-CCA	(B. Liu et al., 2022)
46	2022	✓	✓	MF-CCA	(Mu et al., 2022)
47	2022	✓			(C. Li et al., 2022)
48	2022	✓			(Arpaia et al., 2022)
49	2022	✓	✓	FB-CCA	(Wu et al., 2022)
50	2022	✓	✓	SS-CCA	(Norizadeh Cherloo et al., 2022)
51	2022	✓	✓	FB-CCA	(Yan et al., 2022)
52	2023	✓	✓	IISCCA	(Wei et al., 2023)
53	2023	✓			(Niu et al., 2023)
54	2023		✓	FB-CCA	(X. Wang et al., 2023)
55	2023	✓	✓	RLS-CCA	(S. Wang et al., 2023)
56	2023	✓			(de Paula et al., 2023)
57	2023	✓			(Kołodziej et al., 2023)
58	2023	✓	✓	FB-CCA, Tt-CCA	(Huang et al., 2023)
59	2023	✓	✓	FB-CCA	(Apicella et al., 2023)
60	2023	✓	✓	FB-CCA	(Yan et al., 2023)
61	2023		✓	MFCCA	(Mu et al., 2023)
62	2023	✓			(Mijani et al., 2023)
63	2023	✓	✓	FB-CCA	(Chailloux Peguero et al., 2023)
64	2023	✓			(Y. Zhang et al., 2023)
65	2023	✓			(Venkatesh et al., 2023)
66	2024		✓	FB-CCA	(Y. Liu et al., 2024)
67	2024	✓			(Zarei & Asl, 2024)
68	2024		✓	FB-CCA	(S. Zhang, Cui, et al., 2024)
69	2024	✓	✓	FB-CCA	(D. Li et al., 2024)
70	2024		✓	IT-CCA	(Pan et al., 2024)
71	2024		✓	TT-CCA	(S. Zhang, An, et al., 2024)

In another case, CCA methods also could solve signal detection time and accuracy to control robot system which is activated by subject's specific eye blink. The mean of accuracy enhanced from $\pm 77\%$ to 100% during the alteration of signal length from 0.7 s to 2 s, while the mean highest information transfer rate is at 103.62 bit/min with 1 s signal length.

Exactly, CCA still reliable to apply as a recognition method for SSVEP-based BCI in many case that we found from 2018-2024. Experimental flowchart of SSVEP-based BCI is performed by Figure 2.

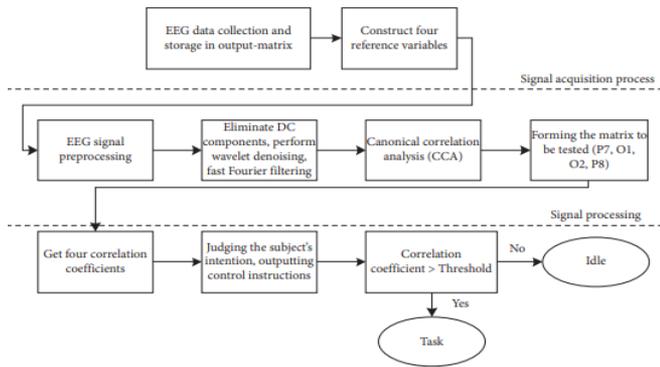


Figure 2. The example experimental flowchart of SSVEP-based BCI to utilize CCA as a recognition method (Shao et al., 2020).

CCA Extension Method

Historically, the extension of CCA (eCCA) method was introduced due to a lack of a training procedure, the artificial reference signals seldom ever uncover the true SSVEP features that are hidden in EEG. Therefore, CCA could not provide the optimum accuracy for SSVEP detection, particularly when utilizing a little time window (TW) (Jiao et al., 2018). The eCCA uses the correlation coefficients between several projected signals as classification features, in contrast to the two CCA techniques that use the maximal values of canonical correlation ρ (1). The three spatial filters listed below are used by the combination technique to compute projection signals: (1) $w_x(X, \bar{\chi}_n)$ between a testing signal and the individual template $\bar{\chi}_n$; (2) $w_x(X, Y_n)$ between a testing signal X and the sine-cosine reference signals Y_n ; (3) $w_{\bar{\chi}_n}(\bar{\chi}_n, Y_n)$ between the individual template $\bar{\chi}_n$ and the sine-cosine reference signals Y_n . A correlation vector \hat{r}_n containing five correlation coefficients for a stimulus target/frequency $n, n = 1, 2, \dots, N_f$ is calculated between different projection vectors as follows:

$$\hat{r}_n = \begin{bmatrix} r_{n,1} \\ r_{n,2} \\ r_{n,3} \\ r_{n,4} \\ r_{n,5} \end{bmatrix} = \begin{bmatrix} \text{corr}(X^T w_x(X, Y_n), Y_n^T w_y(X, Y_n)) \\ \text{corr}(X^T w_x(X, \bar{\chi}_n), \bar{\chi}_n^T w_x(X, \bar{\chi}_n)) \\ \text{corr}(X^T w_x(X, Y_n), \bar{\chi}_n^T w_x(X, Y_n)) \\ \text{corr}(X^T w_x(\bar{\chi}_n, Y_n), \bar{\chi}_n^T w_{\bar{\chi}_n}(\bar{\chi}_n, Y_n)) \\ \text{corr}(\bar{\chi}_n^T w_x(X, \bar{\chi}_n), \bar{\chi}_n^T w_{\bar{\chi}_n}(X, \bar{\chi}_n)) \end{bmatrix} \quad (4)$$

Where $\text{corr}(a,b)$ denotes Pearson correlation coefficient between to vectors a and b . Finally, the weighted correlation coefficient r_n is used as feature for target recognition:

$$r_n = \sum_{l=1}^5 \text{sign}(r_{n,l}) \cdot r_{n,l}^2 \quad (5)$$

Where the function $\text{sign}(\cdot)$ is used in order to retain discriminative information from negative correlation coefficients. Finally, target recognition for the testing trial is completed as follows:

$$T = \arg \max_n r_n, \quad n = 1, 2, \dots, N_f \quad (6)$$

1. Multiset-CCA (MsetCCA)

Another extension of CCA method is Multiset Canonical Correlation Analysis (MsetCCA). It appears due to the lack of training process, thus the artificial reference signals on the real SSVEP features which are buried in EEG unrevealed (Jiao et al., 2018). For this case, CCA can hardly give the best accuracy for SSVEP recognition, especially in using a relatively short TW. MsetCCA is proposed by Zhang et al. (2014) for reference signal optimization by extracting the potential common features from multiple trials at a same stimulus frequency. The common features were then used as reference signals instead of artificial sine-cosine signals to improve recognition accuracy.

MsetCCA maximizes the overall correlation among canonical variables from multiple sets of random variables. In their study, Jiao et al. (2018) used MAXVAR approach that is adopted for MsetCCA optimization since it maximizes the largest eigen value of the correlation matrix, and hence provides a natural extension of CCA to multiple sets (Y. Zhang et al., 2014). Assume $X_i \in \mathbb{R}^{I \times J}$ ($i = 1, 2, \dots, N$) are multiple sets of random variables and have been normalized to have zero mean and unit variance. The objective function of MsetCCA is formulated as

$$\max_{u_1, \dots, u_N} \rho = \sum_{i \neq j} u_i^T X_i X_j^T u_j \quad (7)$$

$$s. t \quad \frac{1}{N} \sum_{i \neq j} u_i^T X_i X_j^T u_i = 1 \quad (8)$$

With the Lagrange multipliers, the aforementioned maximization can be achieved by solving the following generalized eigenproblem:

$$(R - G)u = \rho Gu, \quad (9)$$

where

$$R = \begin{bmatrix} X_1 X_1^T & \dots & X_1 X_N^T \\ \vdots & \ddots & \vdots \\ X_N X_1^T & \dots & X_N X_N^T \end{bmatrix} \quad (10)$$

$$G = \begin{bmatrix} X_1 X_1^T & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & X_N X_N^T \end{bmatrix} \quad (11)$$

$$u = \begin{bmatrix} u_1 \\ \vdots \\ u_N \end{bmatrix} \quad (12)$$

With the learned linear transforms u_1, u_2, \dots, u_N , multiple canonical variates are then obtained by $z_i = u_i^T X_i$ ($i = 1, 2, \dots, N$). The maximum overall correlation among the canonical variates can be achieved in using the linear transforms that are given as the eigenvectors corresponding to the largest generalized eigenvalue.

Assume $X_1, m, X_2, m, \dots, X_N, m \in \mathbb{R}^{C \times P}$ (C channels \times P time points) represent N EEG samples recorded at the m th stimulus frequency f_m . MsetCCA is applied to find multiple spatial filters $u_1, m, u_2, m, \dots, u_N, m \in \mathbb{R}^C$ that maximize the overall correlation among the samples. With the joint spatial filtering $z_{i,m} = u_{i,m}^T X_{i,m}$ ($i = 1, 2, \dots, N$), the N canonical variates $z_1, m, z_2, m, \dots, z_N, m$ capture the common features shared by the samples. Thus, the canonical variates are collected to form the more natural reference signal set at the stimulus frequency f_m as $Z_m = [z_1^T, m, z_2^T, m, \dots, z_N^T, m]^T$. For a new test sample $\hat{X} \in \mathbb{R}^{C \times P}$, the largest frequency is detected by using the standard CCA with the optimized reference signals. MsetCCA has shown its superior performance for SSVEP recognition in contrast to CCA and other competing methods (Y. Zhang et al., 2014).

2. Filterbank-CCA (FB-CCA)

Currently, FB-CCA is the gold-standard in the classification of frequency and phase encoded SSVEP and consistently achieves >90% cross-subject accuracy. This technique involves performing CCA across original EEG data and filter transformed data to expose fundamental and harmonic SSVEP frequency components (Podmore et al., 2019). When used in BCI, SSVEP-selectable targets are traditionally encoded with different flickering frequencies or phases, but in order to maximize the number selectable targets, a joint frequency-phase encoding has been suggested. Many SSVEP decoding algorithms have been described, but the more advanced ones are based on adapted versions of CCA, with the FB-CCA yielding the highest decoding accuracy, and on a spatiotemporal extension of the beam forming algorithm, successfully used for SSVEP as well as several other visual BCI paradigms (Wittevrongel et al., 2018). The FB-CCA method comprises three stages: filter bank analysis, CCA between SSVEP sub-band components and sinusoidal reference signals, and target identification (X. Chen et al., 2019). The first stage decomposes the original EEG signals X into sub-band components X_{SB_n} , $n = 1, 2, \dots, N$. The second stage applies the standard CCA process to each of the sub-band components separately, resulting in correlation values between the sub-band components and sine-cosine reference signals Y_{f_k} , $k = 1, 2, 3, 4$.

A correlation vector ρ_k was defined as follows:

$$\rho_k = \begin{bmatrix} \rho_k^1 \\ \rho_k^2 \\ \vdots \\ \rho_k^N \end{bmatrix} = \begin{bmatrix} \rho \left(X_{SB_1}^T W_X (W_{SB_1} Y_{f_k}), Y^T W_Y (X_{SB_1} Y_{f_k}) \right) \\ \rho \left(X_{SB_2}^T W_X (W_{SB_2} Y_{f_k}), Y^T W_Y (X_{SB_2} Y_{f_k}) \right) \\ \vdots \\ \rho \left(X_{SB_N}^T W_X (W_{SB_N} Y_{f_k}), Y^T W_Y (X_{SB_N} Y_{f_k}) \right) \end{bmatrix} \quad (13)$$

where $\rho(x, y)$ indicates the correlation coefficient between x and y . $W_X(X_{SB_i} Y_{f_k})$ and $W_Y(X_{SB_i} Y_{f_k})$, $i = 1, 2, \dots, N$, were linear combination coefficients obtained by standard CCA between X_{SB_i} and Y_{f_k} . An ensemble classifier was used to combine features derived from each sub-band component. In practice, the following weighted correlation $\tilde{\rho}_k$ was used as the feature for target identification:

$$\tilde{\rho}_k = \sum_{n=1}^N w(n) \cdot (\rho_k^n)^2 \quad (14)$$

where n is the index of the sub-band. The weights for the sub-band components were defined as follows:

$$w(n) = n^{-a} + b, n \in [1 N] \quad (15)$$

where a and b are constants that maximize the classification performance. Here we determined a and b using a grid search method using an offline analysis. Finally, $\tilde{\rho}_k$ corresponding to all stimulation frequencies (i.e. $\tilde{\rho}_1, \dots, \tilde{\rho}_4$) were used for determining the frequency of the SSVEPs. The frequency of the reference signals with the maximal $\tilde{\rho}_k$ is considered to be the frequency of the SSVEP (X. Chen et al., 2019).

3. Time-weighting CCA (TW-CCA)

The fusion weights are weighted to the pending SSVEP data. The standard CCA results are calculated to obtain the signal identification results with integrated time-domain features and frequency features. The computational details of TW-CCA method is shown in Fig. 3. In the calculation of the standard CCA, only the channel dimension of the data is calculated and the time-dimension is ignored. The difference between TW-CCA and CCA is adding the weight information in the time-domain. Thus, the TW-CCA method makes fuller use of the temporal feature information (Sun et al., 2022).

$$\rho = \arg \max_{W_x, W_y} \frac{u^T (XW_f) Y^T v}{\sqrt{u^T XW_f W_f X^T u} \sqrt{v^T Y Y^T v}} \quad (16)$$

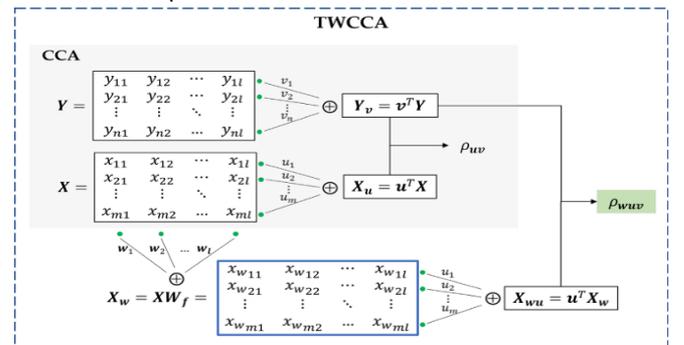


Figure 3. the calculation framework of TW-CCA method (Sun et al., 2022).

4. Channel Projection-based Target Recognition Method with CCA (CP-CCA).

Although the powerful performance of the CCA-based method in detecting SSVEP has been proved by researchers (kutipan). However, the detectability of SSVEP with different frequencies can be influenced by the power-law distribution of the power spectra spontaneous EEG signals. Thus, CCA may not give best accuracy for SSVEP classification, especially in using a relatively short time window. Several studies have tried to alleviate this problem. An unsupervised method is reported to derive normalized canonical correlation coefficients for CCA to enhance the frequency detection of SSVEP. This method optimize sine-cosine reference signals by correlating the multiple dimensions of EEG signals. Then, the common features were used as reference signals instead of sine-cosine signals to improve recognition accuracy. The core idea of those methods is using multiple trials that the subject focuses attention on the same visual stimuli to get a reference signal through the training procedure, which can reduce the inherent differences of the subject.

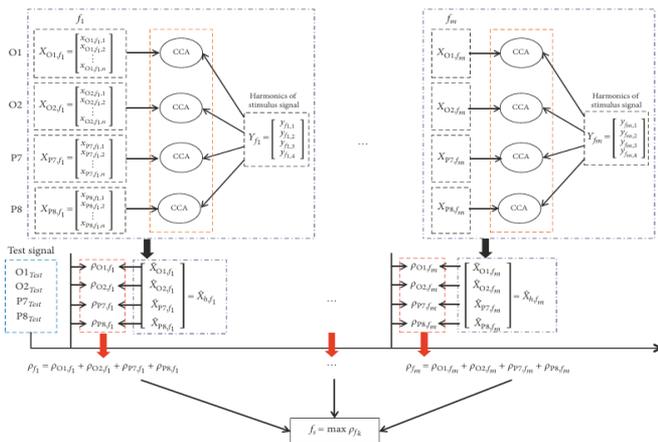


Figure 4. The process of the proposed CP-CCA for SSVEP target recognition. For the same target frequency f_m , the different trials of recorded EEG data are dispersed and then reorganized according to the different channels, \mathbf{X}_{O1,f_k} , \mathbf{X}_{O2,f_k} , \mathbf{X}_{P7,f_k} , and \mathbf{X}_{P8,f_k} . The optimal reference signals of different channels (\mathbf{X}_{O1,f_k} , \mathbf{X}_{O2,f_k} , \mathbf{X}_{P7,f_k} , and \mathbf{X}_{P8,f_k}) under certain stimulus frequency f_k are obtained by the CCA between the channel-based EEG data and the sine-cosine signals \mathbf{Y}_{f_k} . The SSVEP target frequency f_s of a new test data of single trial is recognized according to the maximum value of the sum of ρ_{h,f_k} (Gao et al., 2019).

In the Gao et al. (2019) study, they utilized the CCA method to find optimal data to represent the multiple trials of EEG data that were recorded by the single channel when the subject gazed at the same frequency of visual stimuli. The flowchart of the proposed CP-CCA is shown in Figure 4.

5. Multi-Frequency CCA (MF-CCA)

This method support plug and play that improves practically of the BMI with its advantage in multi-frequency SSVEP decoding by introducing the linear interactions in decoding without the need of training. In Mu et al. (2023), MF-CCA was shown to be a feasible training-free option to use in decoding multifrequency SSVEPs. However, the time complexity of MF-CCA is shown to be $O(n^3)$ which will lead to long computation time as n grows, where n represents the input size in decoding. Therefore, they proposed novel decoding algorithm with the aim to reduce the time complexity. The algorithm is based on linear Diophantine equation (LDE) solvers and has a reduced computation cost $O(n \log n)$ while remaining training-free. They simulation results demonstrated that LDE decoder run time is only one fifth of MF-CCA run time under respective optimal settings on 5-s single-channel data. This reduced computation cost makes it easier to implement MF-CCA in real-time systems. The effectiveness of this new decoding algorithm is validated with nine healthy participants when using dry electrode scalp EEG (Mu et al., 2023).

6. Intra- and Inter-Subject CCA (IIS-CCA)

IIS-CCA aims to extract task-related knowledge with EEG data from a target subject, a set of source subjects and both a target subject and a set of source subjects, and thus can be used for estimating three spatial filters. Thereby, IISCCA includes two types of CCA algorithms, i.e., intra-subject CCA and inter subject CCA. Schematically, IIS-CCA is described in Figure 5. in all variables, the index i denotes i th stimulus target/frequency. $x_t^{(i)}$ and $x_{s,m}^{(i)}$, $m = 1, 2, \dots, N_s$ are the EEG data from the target subject and m th source subject respectively. $\tilde{\mathbf{X}}$ and $\tilde{\mathbf{X}}_t^{(i)}$ denote the testing data and the template data from the target subject respectively.

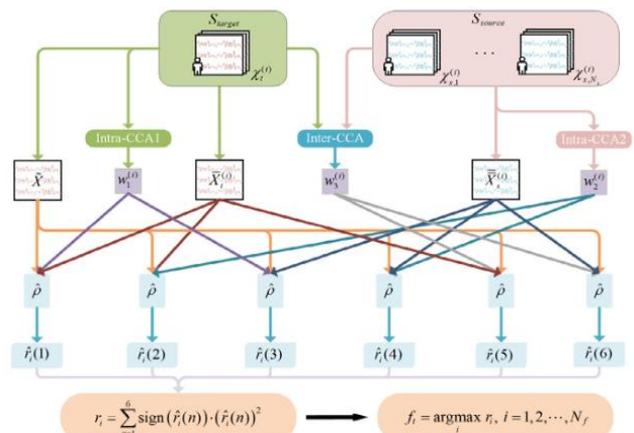


Figure 5. The flowchart of the proposed IIS-CCA algorithm for target recognition (Wei et al., 2023).

7. Recursive Least Square CCA (RLS-CCA)

For improving the classification accuracy, CCA constantly evolving its extension to extract differences between spontaneous EEG signals and SSVEP, thus the SSVEP features can be strengthened by extracting this differences. RLS is an iterative algorithm that can achieve the best result in each step of the adaptive iterative process. The basic steps of RLS algorithm are as follows.

(1) For data initialization:

$$w(0) = 0, R(0) = \sigma I \quad (17)$$

(2) For data $n = 1, 2, 3$, update the calculation.

Filtering:

$$y(n) = w^H(n-1)u(n) \quad (18)$$

Estimation error:

$$e(n) = d(n) - y(n) \quad (19)$$

Update $k(n)$:

$$k(n) = \frac{P(n-1)u(n)}{\lambda + u^H(n)P(n-1)u(n)} \quad (20)$$

Update weight vector:

$$w(n) = w(n-1) + k(n)e'(n) \quad (21)$$

$$P(n) = \frac{1}{\lambda} [P(n-1) - k(n)u^H(n)P(n-1)] \quad (22)$$

Wang et al. (2023) use the algorithm above to calculate the actual output of the filter obtained from $u(n)$ at $n - 1$ time using exponential weighting, where $d(n)$ represents the SSVEP signal with noise in the occipital region, $u(n)$ as the obtained nonoccipital mean signal, $y(n)$ is the output noise signal, and $e(n)$ is the pure SSVEP feature signal that is desired. Clearly, the flow hart is shown in Figure 5.

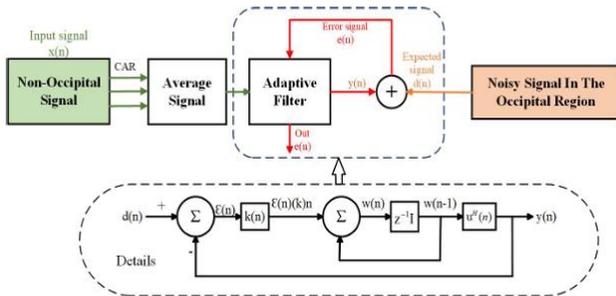


Figure 6. Adaptive filtering for EEG signal (X. Wang et al., 2023).

Thereafter, the CCA step is applied to enhanced SSVEP features with the equation (1).

8. Transfer Template CCA (TT-CCA)

TT-CCA computed the multi-channel transferred EEG template by averaging data across source subjects. The linear projection weight vector for transfer was learned by implementing CCA with the averaged source template and reference sine-cosine template. The linear projection weight vector for maximizing the SNR of the target subject was obtained by implementing CCA with

the target data and reference sine-cosine template. The first and second Pearson correlation coefficients can be calculated from the two mentioned projection directions, and the third Pearson correlation can be obtained through standard CCA with the target data and reference sine-cosine template. Then, the sum of three coefficients was used as the final measurement of the similarity between the source subjects and the target subject. However, the transfer performance of this method depends on the sine-cosine template, and its robustness and transferability are relatively poorer due to the low SNR property of EEG data (S. Zhang, An, et al., 2024).

Synthesis of Result

One of the appropriate algorithms that is frequently used to measure the connection between two sets of data is CCA. However, a number of extensions developed different methods for SSVEP decoding in several case studies. Our findings about this approach begin with the lack of training process in CCA.

First of all, MsetCCA arises because there is no training procedure, which leaves the false reference signals on the actual SSVEP characteristics hidden in the EEG (Jiao et al., 2018). In this instance, CCA is barely able to provide the highest accuracy for SSVEP detection, particularly when utilizing a comparatively short TW. Zhang et al. (2014) suggest using MsetCCA to optimize reference signals by identifying possible shared characteristics across several trials with the same stimulus frequency. To increase recognition accuracy, the common characteristics were then utilized as reference signals rather than synthetic sine-cosine signals. The total correlation between canonical variables from several sets of random variables is maximized by MsetCCA.

Then, the gold-standard in the classification of frequency and phase encoded SSVEP was found. That is FB-CCA with its consistently achieves >90% cross-subject accuracy. This method exposes basic and harmonic SSVEP frequency components by applying CCA over the original EEG data and filter-transformed data (Podmore et al., 2019). SSVEP-selectable targets are typically encoded with distinct flickering frequencies or phases when employed in BCI; however, a combined frequency-phase encoding has been proposed to increase the number of selectable targets.

Afterwards, the addition of weight data in the time domain distinguishes TW-CCA from CCA. Consequently, the TW-CCA approach utilizes the temporal feature information more fully. In another case, an unsupervised method is reported as CP-CCA to derive normalized canonical correlation coefficients for CCA to enhance the frequency detection of SSVEP. This method optimize sine-cosine reference signals by

correlating the multiple dimensions of EEG signals. Then, the common features were used as reference signals instead of sine-cosine signals to improve recognition accuracy. The core idea of those methods is using multiple trials that the subject focuses attention on the same visual stimuli to get a reference signal through the training procedure, which can reduce the inherent differences of the subject.

A similar method with MsetCCA also found as MF-CCA. This plug-and-play technique enhances the BMI practically by incorporating linear interactions in multi-frequency SSVEP decoding, which eliminates the requirement for training. In Mu et al. (2023), It was demonstrated that MF-CCA is a workable training-free method for decoding multifrequency SSVEPs. MF-CCA's temporal complexity, however, is $O(n^3)$, meaning that as n increases—where n is the amount of the input used for decoding—it will take longer to compute. Therefore, in an effort to lower the temporal complexity, they suggested a unique decoding technique. The algorithm's computation is minimized and it is based on linear Diophantine equation (LDE) solvers.

We examine the IIS-CCA, which may be used to estimate three spatial filters because of its exceptional performance in extracting task-related information from EEG data from a target subject, a set of source subjects, and both a target subject and a set of source subjects. As a result, IISCCA encompasses both intra-subject and inter-subject CCA methods.

In order to increase the classification accuracy, CCA is continuously expanding its capability to extract differences between spontaneous EEG signals and SSVEP. By doing so, the SSVEP characteristics may be reinforced. RLS is an iterative method that may optimize the adaptive iterative process at every stage.

Conclusion

CCA analysis is powerful for SSVEP recognition and signal classification, but a few disadvantages triggered various modifications, such as the lack of training process in CCA, which gave rise to MsetCCA to overcome this. Then to improve the classification standard and phase-encoded SSVEP, FB-CCA emerged with high consistency. Temporal feature information more fully is also needed in classifying SSVEP, so TW-CCA is present to facilitate the addition of weight data in the time domain. Other needs, such as increasing frequency detection, are also needed; therefore, CP-CCA emerged to overcome these obstacles, which can normalize the standard CCA. Another necessary method is the plug-and-play technique. It is called MF-CCA, which enhances the BMI practically by incorporating linear interactions in multi-frequency SSVEP decoding, which eliminates the requirement for

training. All of the specified CCA extensions are completed by IIS-CCA and RLS-CCA, which may be used as three spatial filters for task-related information and increase the classification accuracy, respectively.

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Author Contributions

Conceptualization, Muhamad Agung Suhendra. and Ahmad Sofyan Sulaeman.; methodology, Ahmad Sofyan Sulaeman.; software, Anderias Eko Wijaya.; validation, Iqbal Robiyana., M. Faizal Amri and Arief Budiman.; formal analysis, Tedi Sumardi and Permono Adi Putro.; investigation, Sunanto Ajidarmo and Usep Tatang Suryadi.; resources, Nurizati.; data curation, Nurizati.; writing—original draft preparation, Muhamad Agun Suhendra and Ahmad Sofyan Sulaeman.; writing—review and editing, Ahmad Sofyan Sulaeman.; visualization, Iqbal Robiyana.; Permono Adi Putro, Muhamad Agung Suhendra.; project administration, Muhamad Agung Suhendra and Sunanto Ajidarmo.; funding acquisition, Muhamad Agun Suhendra. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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