Review and Evaluation of Trending Canonical Correlation Analyses-Based Brain-Computer Interface Methods

Bayar Shahab

***Abstract*—**The fast development of technology that has advanced neuroscience and human interaction with computers has enabled solutions to various problems and issues of this new era. The Brain-Computer Interface (BCI) has opened the door to several new research areas and have been able to provide solutions to critical and vital issues such as supporting a paralyzed patient to interact with the outside world, controlling a robot arm, playing games in VR with the brain, driving a wheelchair. This review presents the state-of-the-art methods and improvements of canonical correlation analyses (CCA), an SSVEP-based BCI method. These are the methods used to extract EEG signal features or, to be said differently, the features of interest that we are looking for in the EEG analyses. Each of the methods from oldest to newest has been discussed while comparing their advantages and disadvantages. This would create a great context and help researchers understand the most state-of-the-art methods available in this field, their pros and cons, and their mathematical representations and usage. This work makes a vital contribution to the existing field of study. It differs from other similar recently published works by providing the following: (1) stating most of the main methods used in this field in a hierarchical way, (2) explaining the pros and cons of each method and their performance, (3) presenting the gaps that exist at the end of each method that can improve the understanding and open doors to new researches or improvements.

***Keywords*—**BCI, CCA, SSVEP, EEG.

I. Introduction

BRAIN computer interface (BCI) has been positioning itself as one of the significant fields in neuroscience and computational neuroscience for this current era as the technology evolves with time quicker than ever. One of the most interesting technological improvements that seem very promising is neurotechnology which studies the interaction between computers and human brains. Primarily, brain signals were recorded and printed on paper and analyzed by physicians or neurologists to assess the levels of brain activities for different purposes such as coma and tumors. Nowadays, current and potential applications of neurotechnology or BCI can support the rehabilitation of lost memory. Considering that various challenges face this field of study, from understanding the topics starting from the actual brain to the applications that might have safety and security concerns. Understanding the context of this research requires preliminary descriptions and explanations of the methods and techniques used to solve such problems and their evaluations, issues, advantages, and theories behind them. There are several methods for BCI feature extraction, as reviewed in the work of [1]. Despite the advancements of other methods, it is still one of the top used methods, and several improvements have been applied to the original CCA method to improve the recognition accuracy. In the next section, the CCA method and its improvements have been reviewed hierarchically, evaluating the methods and stating their advantages and disadvantages.

Bayar Shahab is with the Tor Vergata University of Rome, Italy (corresponding author, phone: +967504064125; e-mail: bayar.azeez@students.uniroma2.eu).

II. CCA-Based BCI Methods

Several improvements and extensions to the original CCA method have been applied to the original method to improve its accuracy. Most of the methods focus on improving or changing the reference signal of the CCA. In this review work, the major methods that have made a prominent contribution are explained and reviewed.

A. Canonical Correlation Analyses - CCA

CCA is a multivariate statistical method that recognizes the SSVEP-based signals between two sets of variables that are linear and correlated to each other. The first set of the variables are the EEG signal inputs or data with various electrodes/sensors and the second are reference signals generated which have the same length of the EEG data. The reference signals are generated sign-cosine waves. The concept of CCA is motivated in the work of [2] that introduced the concept of correlations between sets of linear variables. Later in 2007, it was introduced and used as the SSVEP feature extraction method [3]. The original/standard CCA method tried to find the linear combination between the coefficients of the two datasets that have the maximum correlation.

Let us consider that we have two data sets X=(X1,…, Xn) and Y=(Y1,…, Yn), with a linear correlation and the same length. X is the EEG signal, and Y is the sine-cosine reference signal with stimulus frequencies. CCA tries to find the linear correlations between X = $XT\ Wx$ and $Y = Y\ T\ Wy$ by maximizing the correlation between two data sets. The reference signal is represented as in (1).

$$Y = \begin{cases} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ \quad . \\ \quad . \\ \sin(2\pi N_h f_k t) \\ \cos(2\pi N_n f_k t) \end{cases}, t = \frac{1}{F_s}, \frac{2}{F_s}, \dots, \frac{T}{F_s} \qquad (1)$$

f_k: stimulus frequency, T: number of sampling points, F_s: is the sampling rate and N_h is the number of harmonics variables used.

CCA will find the weight values Wx and Wy by maximizing the correlation between each of the data X and Y variables as in (2).

$$max_{WxWy}\ \rho(x,y) = \frac{E\,[x^T y]}{\sqrt{E\,[x^T x]\,E\,[y^T y]}} \qquad (2)$$

In that step, we will have several correlations ρ_i values, from 1 … K values and the highest correlation would be the maximum classified value, as shown in Fig. 1.

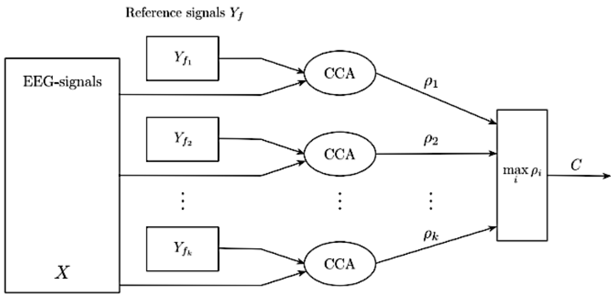

Fig. 1 CCA extraction block diagram

B. Individual Template-based CCA – ITCCA

This approach focuses on replacing the reference sine-cosine signal with a template of signal. The template signals are generated by averaging multiple training data of the SSVEP signal for each of the stimulus frequencies used. This method has been initially used for analyzing CCA for general EEG signals by [4]. After the individual template generation denoted by $\overline{x}$, then CCA can be computed by maximizing the coefficients of both the SSVEP signals and the templates as in (3).

$$max_{W_x W_{\overline{x}}}\ \rho(x,\overline{x}) = \frac{E\left[W_x^T X \overline{X}_n^T W_{\overline{X}}\right]}{\sqrt{E\,[W_x^T X X^T W_x]\,E\left[W_{\overline{x}}^T \overline{X}_n \overline{X}_n^T W_{\overline{X}}\right]}} \qquad (3)$$

C. Phase Constrained CCA – PCCA

The authors of [5] have proposed another method for improving the classification of the original CCA method by including the phase information in the CCA analyses. They have done that by including the phase information in the reference signal generated. The phase information has been extracted from the SSVEP response latency for multiple subjects and trails in the training phase and then assigned to the reference signal. In that way, CCA has been computed between the SSVEP signals and the reference signal that contains the phase information. Thus, it led to the accuracy improvement for the CCA method.

D. Multiway CCA – MwayCCA

Multiway CCA (MwayCCA), sometimes denoted by MCCA, was introduced by [6] in 2011 as an extension or improvement to the original CCA method. The core idea is again to improve the reference sine-cosine signal generated to an optimal level to have better accuracies later when used. MCCA works by maximizing the correlation between the EEG test data from a specific frequency for a certain number of trials and channels and the reference signal generated to find the optimal reference signal that will replace the originally generated reference signal. The optimal reference signal will be generated according to an alternating algorithm until the best signal is found. Once the optimal reference signal is found, a multi-linear regression (MLR) algorithm has been applied to find the features using the optimal reference signal and the test data. Fig 2. illustrates the MCCA concept and feature extraction.

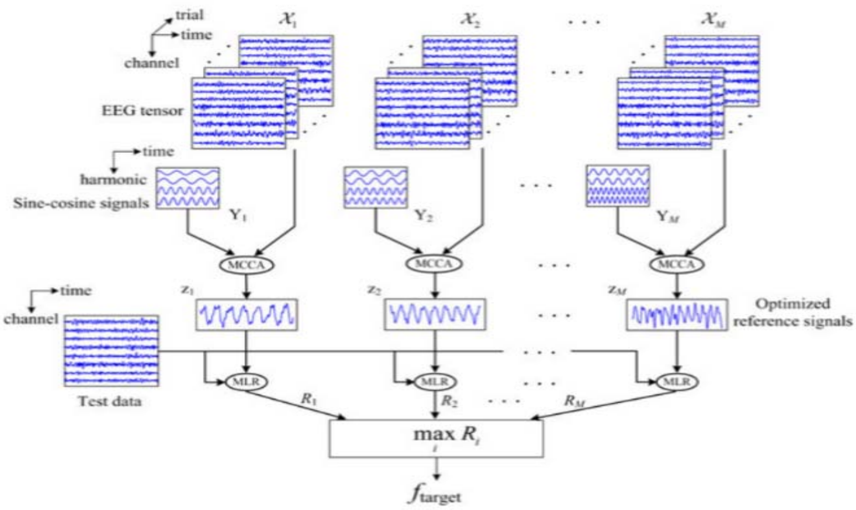

Fig. 2 SSVEP and feature extraction using MCCA [6]

To explain the above concept mathematically, let us assume $x_n \in \mathbb{R}^{N_c*N_s*N_t}$ be the EEG training data with (channel*sample points*trial) and $y_n \in \mathbb{R}^{2N_h*N_s}$ the reference signal with (harmonics* sample points). The CCA here will find the liner combination between them to find the optimal reference signal denoted as $z_n = X_n * 1^{W_1^T} * 3^{W_3^T}$. Finally, the MLR between the new optimal reference signal and EEG test data will be done as $z_n = b_n^T x_{test\ data} e^n$ where $b_n^T \in \mathbb{R}^{I*1}$ a coefficient vector and $e^n \in \mathbb{R}^{1*J}$ a noise vector with zero mean and constant variance.

E. L1-Regularized Multiway CCA - L1-MCCA

L1-MCCA is an extension of the MCCA method with some minor improvements done on the reference signal generation. In 2013 [7], the authors proposed a more advanced version of the MCCA that deals with a trial selection from the EEG training data. As stated before, for generating the optimal reference signal, some trials of the EEG data for a specific duration of time would be used in the training period. However, sometimes some of these trials contain noise and artifacts. This method selects the best trials and removes the artifacts while generating the optimal reference signal.

F. Multi-Set CCA – MsetCCA

MsetCCA is also another extension of CCA proposed by [8] in 2014. The authors have stated that for generating the artificial sine-cosine reference signal, the better way is to use the original EEG dataset from multiple trials of a single subject using a certain stimulus frequency. Furthermore, they have stated that those multiple sets share some common features that can be used to generate a better reference signal. Those common features have been extracted using joint spatial filtering. They have compared their results with MCCA and CCA and tend to have better accuracies. To further explain that, let us assume $x_{n,h} \in \mathbb{R}^{N_c*N_s}$ with multiple EEG trials, the function that maximizes the correlation between the multiple sets of the training data of EEG can be defined as in (4).

$$max_{W_1,\dots,W_N}\ \rho = \sum_{h\neq h2}^{N_t} W_{h1}^T x_{n,h1} x_{n,h2}^T W_{h2} \tag{4}$$

Using the Lagrange multipliers technique, the above definition can be transformed into an eigenvalue (5).

$$(R_n - S_n)w = \rho S_n w \tag{5}$$

where,

$$R_n = \begin{bmatrix} x_{n,1}x_{n,1}^T & \dots & x_{n,1}x_{n,1}^T \\ . & \dots & . \\ x_{n,N_t}x_{n,1}^T & \dots & x_{n,N_t}x_{n,1}^T \end{bmatrix},$$

$$S_n = \begin{bmatrix} x_{n,1}x_{n,1}^T & \dots & 0 \\ . & \dots & . \\ 0 & \dots & x_{n,N_t}x_{n,1}^T \end{bmatrix},$$

$$w = \begin{bmatrix} W_1 \\ . \\ W_{N_t} \end{bmatrix}$$

MsetCCA is solving or finding multiple linear transformations among the weight values $w_{1,\dots,}w_N$ that maximizes the correlation among the multiple canonicals denoted as Z with spatial filtering $\overline{z} = \overline{w}_{n,h}^T x_{n,h1}$. Hence the newly generated reference signal from the EEG multiple sets would be as in (6).

$$Z_n = \left[\overline{z}_{n,1}^T, \overline{z}_{n,2}^T, \dots \overline{z}_{n,N_t}^T{}^T\right] \tag{6}$$

Finally, CCA is computed between the newly generated reference signal Z_n and the Test EEG data X.

G. Cluster Analysis of Canonical Correlation Coefficient – CACC

This technique introduced by [9] is improving the CCA coefficients used in the analyses. It tries to find the weight and values of each channel (sensors) for all the stimulus frequencies used to identify the detection and idle state of the electrodes. Thus, it will improve the extraction accuracy by having predefined and calculated EEG signals. In this method, the three highest CCA coefficients (ρ) would be used for each stimulation frequency. The coefficients are the results of the CCA between the EEG signals and the patterns of inputs. Feature space for each of the coefficients will be created to identify the detection and idle states of the analyses. The authors have split the method into two stages: calibration and working mode. Fig. 3. shows the space created for each of the coefficients with blue color as detected and red as idle, while green is the mean distance between them.

In calibration mode, CCA is computed between the EEG test data and the generated stimulus responses. As a result, the three coefficients per stimulus frequency would be calculated, i.e., $\rho 1, \rho 2\ and\ \rho 3$. Later, using the k-means cluster, the detection and idle states would be identified. Then, the center (centroid) or distance between the idle and detection classes would be done using the standard Euclidean distance function. The calibration for each of the stimulus frequencies ends only if idle and detection distance β= 0.25. In working mode, there is information about the locations of the idle and detection states for each of the stimulus frequencies, which will improve the extraction accuracy. The CCA would be computed between the EEG test data and stimulus responses in the calibration mode. After that, the nearest neighbor method would be used to extract the features to identify the simulation into idle or detection firstly, and secondly, to analyze the output of the classification as follows:

- No detection for the frequencies (idle state).
- Detection for a single ρ feature that refers to a user looking into a certain frequency.
- Detection for multiple ρ features, which is the ambiguous state, user intention is not clear.

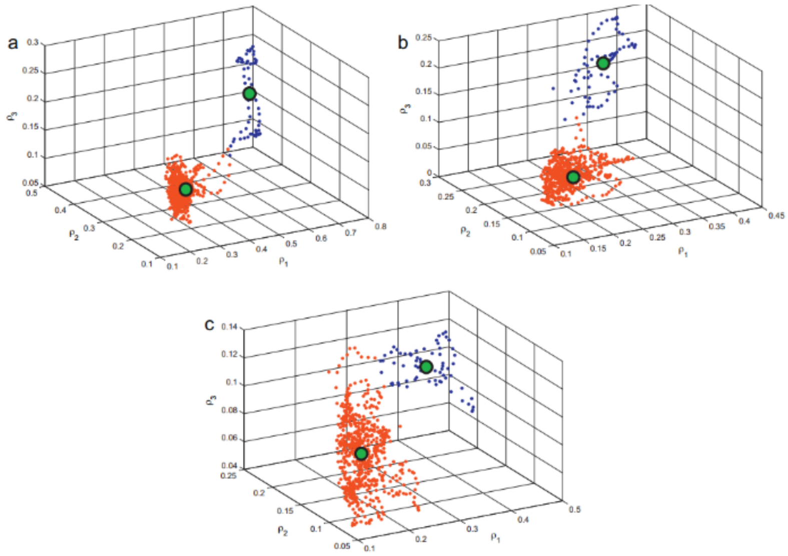

Fig. 3 Feature space for the coefficients in CACC method. Idle class is marked red, detection class is marked blue. Centroids of both classes are marked green [9]

H.Filter Bank CCA – FBCCA

Filter Bank CCA is another interesting method and extension to the original CCA method introduced by [10]. The authors are trying to solve an SSVEP-based BCI speller problem that identifies letters based on certain frequencies. FBCCA consists of three stages; filter bank analyses which involve decomposing the SSVEP data into different sub-bands, CCA computation between SSVEP sub-bands and the reference signals, and finally, target identification, as in Fig. 4. Filter bank analyses have been applied on the original SSVEP signals using multiple filters with different bands to decompose the signal into different sub-bands. The band-pass filters that are used to extract the sub-bands have zero-phase IIR filters. The second step is then to apply CCA analyses between each of the sub-bands along with the reference signals generated per each of the stimulus frequencies that form a correlation vector $\overline{\rho}_f = \left[\rho_f^1, \dots, \rho_f^N\right]^T$ with N being the number of correlation values. A sum square weighted correlation between the sub-bands has been calculated and computed as the target feature (7).

$$\overline{\rho}_f = \sum_{n=1}^{N} W(n) * (\rho_f^n)^2 \qquad (7)$$

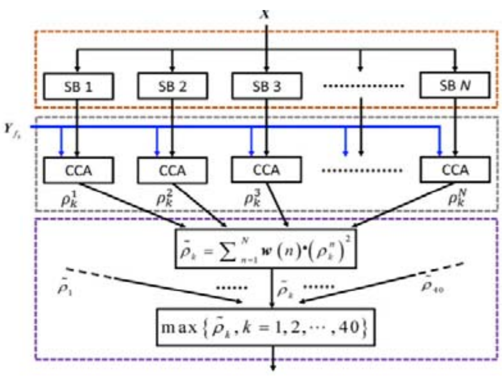

Fig. 4 FBCCA analyses stages and diagram [10]

III. Performance Measures of CCA-Based Methods

The original CCA method has the advantage of speed, which is suitable for online computation and has a high accuracy of classifications. However, on the other side, as stated by [9], CCA sometimes fails to identify the idle and detection stages due to a lack of information while doing the analyses. To further improve the issues of CCA, IT-CCA has been developed that eliminates the usage of reference signals by averaging multiple sets of training data from EEG signals and hence improves the accuracy. On the other side, PCCA further improves the accuracy by including the phase information into the reference signal generated. MwayCCA and L1-regularized MwayCCA has been introduced to improve the optimal reference signals from the training EEG data. They have further enhanced the accuracy of the classification compared to previous methods. Finally, MsetCCA has been introduced the eliminate the use of artificial reference signal generation. One advantage of MsetCCA compared to MwayCCA and PCCA is that there is no need to define the number of harmonics since the reference signal does not depend on an artificial reference sin-cosine signal. The reference signals are generated from the SSVEP training data, and hence it has better accuracy than CCA, MwayCCA, and PCCA. Cluster analyses and filter bank also improve the overall classification of the SSVEP data and are doing much better compared to the original CCA method. Table I shows the taxonomy of CCA-based methods along with their description, advantages, and disadvantages.

IV. Conclusion and Discussion

Neurotechnology is a prominent method that has improved so much in the past decades due to technological developments. This has opened the door to several interesting and life-saving applications such as supporting paralyzed patients to interact again with the world, brain rehabilitation, and recovering memory loss. In this work, CCA methods and their improved versions and methods that play a significant role in solving EEG-BCI issues have been reviewed, analyzed, and evaluated. As one of the most famous methods used to extract the useful EEG signal features of the brain, CCA is a multivariate statistical method that recognizes the SSVEP-based signals between two sets of variables that are linear and correlated to each other. The first set of the variables are the EEG signal inputs or data with various electrodes/sensors and the second are reference signals generated which have the same length of the EEG data. Additionally, the paper gives a comprehensive analysis and states the advantages and disadvantages of the methods available. Hence, any researcher could use this review as a benchmark for making decisions about each method. This work services future researchers to have a strong knowledge of previous related works. It shows, analyses, and evaluates existing and state-of-the-art methods in the related area of the research to avoid duplication and repetition.

TABLE I
CCA-BASED EXTRACTION METHODS WITH THEIR ADVANTAGE(S) AND DISADVANTAGE(S)

METHOD	DESCRIPTION	ADVANTAGE(S)	DISADVANTAGE(S)
CCA	Statistical method that recognizes the SSVEP based signals between two sets of variables that are linear	Has high speed for online computation and has high accuracy calculation	Sometimes fails to identify the idle and detection stages due to lack of information
ITCCA	Replacing the reference sine-cosine signal by a template of signal	Averaging multiple sets of training data from EEG signals	Display resolution and refresh rate affect the accuracy
PCCA	Including the phase information to the reference signal generated	Including the phase information into the reference signal	A fixed latency should be adopted to stabilize the phase estimation
MWAYCCA	Improve the reference sine-cosine signal generated to an optimal level	Improve the optimal reference signals from the training EEG data	Have high calculation time
L1-MCCA	Some trails of the EEG data for a specific duration used in the training period to general optimal reference signal		
MSETCCA	Uses the original EEG dataset from multiple trails of a single subject using a certain stimulus frequency	Eliminates the use of artificial reference signal generation	Conspiring the noise as features sometimes
CACC	Find the weight and values of each of the channels (sensors) for all the stimulus frequencies used to identify the detection and idle state of the electrodes	Identifying idle and detection stages for each of the stimulus frequencies	With the increase of noise, classifications of user intentions tend to be incorrect
FBCCA	Filter bank analyses which involve decomposing the SSVEP data into different sub-bands	Have basic and frequency harmonics elements for recognition	Basic sine-cosine waves are used for generating reference signals

REFERENCES

[1] Zerafa, R., Camilleri, T., Falzon, O., & Camilleri, K. (2018). To train or not to train?A survey on training of feature extraction method for SSVEP-based BCIs. Journal of Neural Engineering, 29.

[2] Hotelling, H., (1936). relations between two sets of variates, biometrika, volume 28, issue 3-4, december 1936, Pages 321–377, https://doi.org/10.1093/biomet/28.3-4.321

[3] Lin, Z., Zhang, C., Wu, W., & Gao, X. (2007). Frequency Recognition Based on Canonical. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, 1172 - 1176.

[4] Bin, G., Gao, X., Wang, Y., Li, Y., Hong, B., & Gao, S. (2011). A high-speed BCI based on code modulation VEP. Journal Of Neural Engineering, 8(2), 025015. doi: 10.1088/1741-2560/8/2/025015

[5] Pan, J., Gao, X., Duan, F., Yan, Z., & Gao, S. (2011). Enhancing the classification accuracy of steady-state visual evoked potential-based brain–computer interfaces using phase constrained canonical correlation analysis. Journal Of Neural Engineering, 8(3), 036027. doi: 10.1088/1741-2560/8/3/036027

[6] Yu, Z., Guoxu, Z., Qibin, Z., Akinari, O., Jing, J., Xingyu, W., & Andrzej, C. (2021). Multiway Canonical Correlation Analysis for Frequency Components Recognition in SSVEP-Based BCIs. In Neural Information Processing - 18th International Conference, ICONIP 2011. Shanghai. Retrieved from http://10.1007/978-3-642-24955-6_35

[7] Zhang, Y., Zhou, G., Jin, J., Wang, M., Wang, X., & Cichocki, A. (2013). L1-Regularized Multiway Canonical Correlation Analysis for SSVEP-Based BCI. *IEEE Transactions On Neural Systems And Rehabilitation Engineering*, *21*(6), 887-896. doi: 10.1109/tnsre.2013.2279680

[8] Zhang, Y., Zhou, G., Jin, J., Wang, X., & Cichocki, A. (2014). frequency recognition in ssvep-based bci using multiset canonical correlation analysis. *international journal of neural systems*, *24*(04), 1450013. doi: 10.1142/s0129065714500130

[9] Poryzala, P., & Materka, A. (2014). Cluster analysis of CCA coefficients for robust detection of the asynchronous SSVEPs in brain–computer interfaces. Biomedical Signal Processing and Control, 201-208.

[10] Chen, X., Wang, Y., Gao, S., Jung, T., & Gao, X. (2015). Filter bank canonical correlation analysis for implementing a high-speed SSVEP-based brain–computer interface. Journal Of Neural Engineering, 12(4), 046008. doi: 10.1088/1741-2560/12/4/0460