CHAPTER 7

7 CCA Model with Training Approach to Improve Recognition Rate of SSVEP in Real Time

7.1 Introduction

Brain Computer Interface (BCI) is a direct communication channel or platform established between a human brain and an external machine, such as a computer [288]. It translates the electrical signals arising from different brain activities into the codes and commands, in a language that the machine can understand. BCIs are often designed to map, research, augment, assist or repair cognitive and sensory-based motor functions [289]. On the basis of Interface level, BCIs can be Invasive, partially invasive or non-invasive [290]. Various brain imaging techniques such as EEG, MEG, EcoG, Intracortical neuron recording, fMRI and NIRS can be used for BCIs [290].

Among them, Steady-State Visually Evoked Potentials (SSVEP) are highly used due to high signal to noise ratio and robustness [31]. SSVEP is a resonance phenomenon which is primarily observed in the occipital lobe of brain when the subject is focusing on a light source flickering at a constant frequency [17].

Methods discussed in section 2.6, have shown good accuracy in target identification when the subject is actually focusing on the target, but they do not identify idle state, i.e. when subject is not targeting any frequency, with the same accuracy. Hence increased number of False Positive outputs are often observed in these SSVEP-based BCIs. To tackle this important issue, this work proposes a method of using standard CCA for feature extraction and Linear Discriminant Analysis (LDA) for classification with label modification training algorithm at the preprocessing stage. This method is then compared with existing FFT and CCA methods for further discussion.

Following sections of this chapter are formalized as: section 7.2 describes the methods and materials used. Section 7.3 elucidates the experimental setup. Results and discussion are presented in section 7.4. Finally, the conclusion of this study is drawn in section 7.5.

7.2 Methods and Materials

7.2.1 Canonical Correlation Analysis (CCA)

Canonical Correlation Analysis (CCA) is a multivariable statistical method used to measure the underlying correlation between two sets of multidimensional data. First, CCA finds canonical variables, a pair of linear combinations, for 2 sets such that the correlation between them is maximized [291]. Starting with 2 multidimensional variables A, B and their respective linear combinations $a = A^T w_a$ and $b = B^T w_b$, CCA finds the weight vectors w_a and w_b, such that they maximize the correlation between a and b, by solving the following equations:

$$r(a,b) = max_{w_a,w_b} \frac{E[ab^T]}{\sqrt{E[aa^T]E[bb^T]}}$$

$$= max_{w_a,w_b} \frac{E[\mathrm{A}^T \mathrm{w}_a B w_b^T]}{\sqrt{E[\mathrm{A}^T \mathrm{w}_a A w_a^T]E[\mathrm{B}^T \mathrm{w}_b B w_b^T]}} \qquad (7.1)$$

Where $E[.]$ computes the expected value of a variable.

7.2.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a simple yet effective classifier and popularly used for a wide variety of problems. In this method, the different classes are identified based on a ratio parameter derived by the fisher method. An optimal between-class variance to within-class variance ratio is derived by maximizing the between-class variance while minimizing the within-class variance [292]. This optimal solution provides globally maximized separation between the classes. In our approach, we trained the LDA model for SSVEP target frequency detection.

7.2.3 Proposed Method

In this proposed method, CCA is used as a method of feature extraction. In Equation (7.1), A represents the set of multichannel EEG signals and B represents the set of reference signals, having same length as A. The r_i values for each stimulus frequency is computed and stored in a feature vector r defined as.

$$r = [\, r_1 \, r_2 \, r_3 \, r_4 \,] \tag{7.2}$$

In the training phase, the signal is processed every 2 seconds. We find the maximum $r_i$value from the feature vector r for each 2 second signal. Target frequency associated with this maximum r_i value is cross-checked with the original target frequency, on which the subject had to focus. If a mismatch is found between these two frequencies, the label is changed to 0 (idle class) so that classifier does not treat such signal as true data. All the feature vectors along with their class labels are then used to train the LDA model.

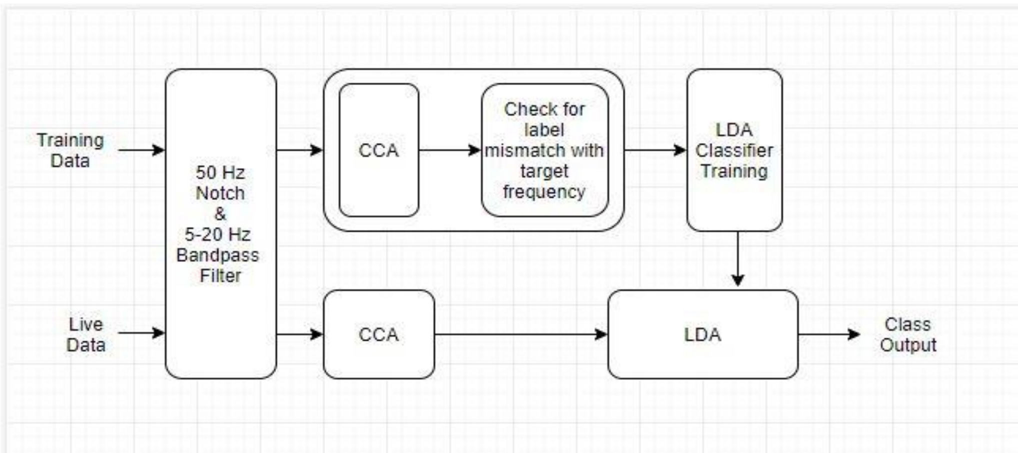


Figure 7.1 Workflow of the proposed method.

During live streaming, feature extraction is done by CCA in a similar manner. Feature vector r then acts as an input for the trained LDA classifier. Class output decided by the LDA classifier is then noted. The workflow of the proposed method is summarized in Figure 7.1.

7.3 Experimental Setup

7.3.1 Generation of visual stimulus

Design of a visual stimulator is an important experimental step to present flashing of lights. In this work, software modules used for the creation of stimulus are Matlab and Psychophysics Toolbox Version 3 available at http://psychtoolbox.org/. The users were instructed to follow the task paradigm presented on a 15.6-inch LCD monitor screen with a refresh rate of 60Hz. A 60 Hz refresh rate implies that the time duration of each frame is 1/60 sec. The colour of frames reverses from black to white or white to black per cycle. Hence, the stimulus frequency can be determined by controlling the number of frames per cycle as f=60/frame size. For instance, a 10 Hz stimulus is prepared when the frame colour is black for three frames and white for the next three frames during one complete cycle, thus there are in total six frames per cycle (f=60/6). Adopting the same method, four stimuli of frequencies 10 (60/6), 8.57 (60/7), 7.5 (60/8) Hz and 6 (60/10) Hz were obtained. In order to avoid the coincidence of harmonics, the chosen flicker frequencies are not the multiples of one another. The participants were sitting on an armchair at a distance of 60 cm from the monitor.

7.3.2 Data Acquisition

OpenBCI Cyton board and Mark IV headset were used to wirelessly record EEG of each subject. Sampling frequency of this equipment is 250 Hz. Recorded EEG was processed in MATLAB (Mathworks Inc.). Details of the subjects are shown in Table 7.1.

Table 7.1 Details of the subjects who performed the SSVEP task.

Subject No.	Age	Gender	Eyesight	Position	No. of Channels
1	22	M	Normal	Seated	3
2	27	M	Corrected	Seated	3
3	23	M	Corrected	Seated	3

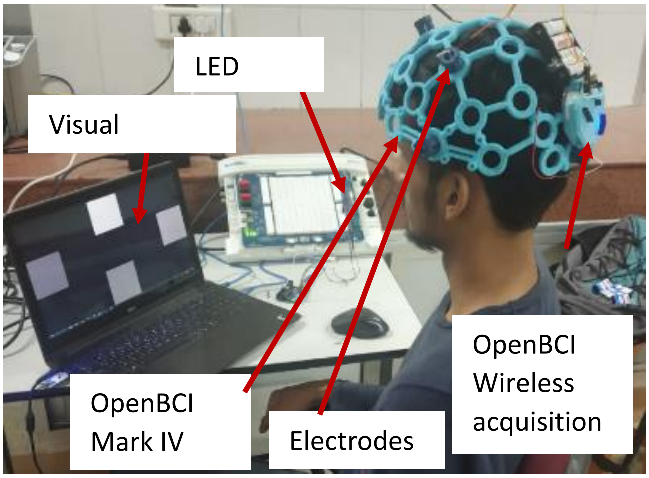


Figure 7.2 Framework of experiment performed.

EEG signals were recorded from 3 channels: Oz, O1 and O2 according to the international 10-20 system, with reference electrode at Fz and ground at Fpz position. EEG signals were then passed through 50 Hz notch filter and 5-20 Hz bandpass filter to remove major artifacts. Figure 7.2 presents the key components used during the experiment.

7.3.3 Experiment paradigm

In the training period, subjects were asked to focus on a single flickering box for total of 5 minutes in 5 repetitions of 1 minute each. During the test period, subjects were instructed to focus on one box at a time in a specific sequence for 15 seconds each. A beep sound was generated to guide the subject to change the focus to next box. In the last 15 seconds, subjects were instructed not to focus on any of the stimuli boxes.

7.4 Result and Discussion

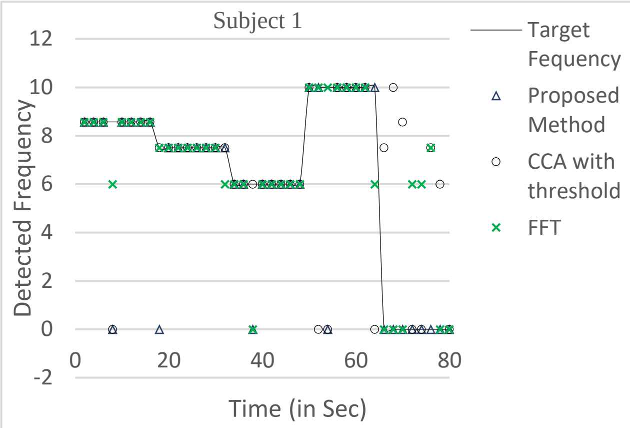
In this section results of the proposed method are presented and discussed in comparison with the standard algorithms used for SSVEP detection such as CCA, and FFT. Analysis of the proposed algorithm is done in both off line and real-time scenario.

Classification accuracy, Information transfer rate (ITR) and confusion matrices are evaluated to present the superiority of the proposed scheme in off line mode. Results of which are listed in Table 7.2.

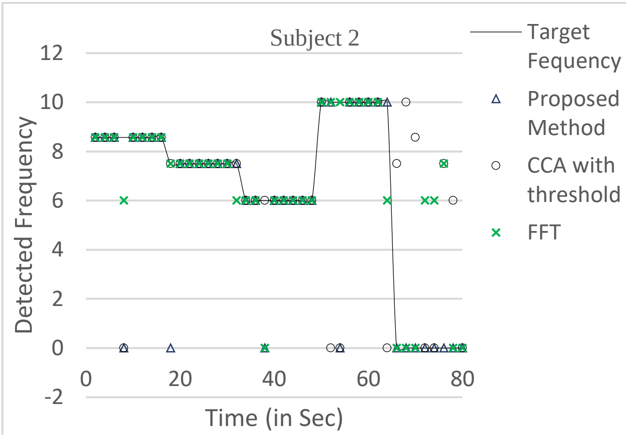
As seen in table 7.2, the average accuracy of the proposed method (92.50) is increased when compared to FFT (84.17) and CCA (85.83). The Information Transfer Rate (ITR) is also increased to 90.68 bits/min. The most significant change in the results is in specificity of classifier output. Specificity of the proposed method (0.96) is significantly superior to that of FFT (0.54) and CCA (0.67). This is due to the reduced percentage of False Positive outputs in this method. It can also be noted that this amelioration in specificity is achieved without any significant drop in sensitivity and with even increased precision. Further analysis of the results is presented in Figure 7.3 by plotting the detected frequency achieved using CCA, FFT and proposed method of all the subjects. It is notable that the proposed method performed better in comparison to CCA and FFT for detection of idle-state, i.e., when the subject is not focusing on any target frequency.

Table 7.2 Comparison of classification accuracy, confusion matrices and ITR between three methods: CCA with threshold, FFT, and proposed CCA+LDA training method.

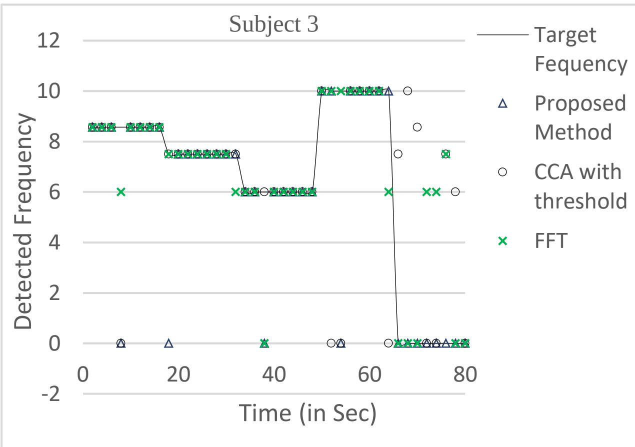
Method	**FFT**				**CCA**				**CCA+LDA**			
Subject #	**Sub 1**	**Sub 2**	**Sub 3**	**Avg**	**Sub 1**	**Sub 2**	**Sub 3**	**Avg**	**Sub 1**	**Sub 2**	**Sub 3**	**Avg**
Accuracy	82.50	87.50	82.50	**84.17**	90.00	90.00	77.50	**85.83**	100.0	90.00	87.50	**92.50**
ITR	63.22	75.50	63.22	**67.31**	82.35	82.35	52.45	**72.38**	114.2	82.35	75.50	**90.68**
Sensitivity	0.97	0.97	0.97	**0.97**	0.91	0.94	0.88	**0.91**	1.00	0.91	0.84	**0.92**
Specificity	0.50	0.50	0.63	**0.54**	0.88	0.75	0.38	**0.67**	1.00	0.88	1.00	**0.96**
Precision	0.88	0.89	0.90	**0.89**	0.97	0.94	0.85	**0.92**	1.00	0.97	1.00	**0.99**



(a)



(b)



(c)

Figure 7.3 Comparison of SSVEP detection between three methods: CCA with threshold, FFT, and proposed training method for (a) subject 1 (b) subject 2, and (c) Subject 3. Zero detected frequency corresponds to idle-state.

During real-time implementation of the proposed setup, we control a LED panel as shown in Figure 7.4. As seen in the Figure 7.4, each LED was labelled corresponding to the four target frequencies (6, 7.5, 8.57, and 10 Hz) and it glows according to the detected frequency by our proposed method whereas other LEDs are off. Idle state represents while the subject is not indulged in SSVEP task, hence no LED glows at that time. Result in Figure 7.4 shows successful implementation of the method in real-time.

Detected Frequency corresponding to the LED
6 Hz
7.5 Hz
8.57 Hz
10 Hz

Target frequency	6 Hz	7.5 Hz	8.57 Hz	10 Hz	Idle state

Figure 7.4 Real-time control of a LED panel using the proposed method.

7.5 Conclusion

In an SSVEP BCI, identifying the correct frequency in non-idle state has never been a problem, as seen by values of sensitivity in all the methods. Many existing methods can detect the increased presence of any target frequency in EEG, even when the subject is in idle state i.e. not focusing on any target. These False Positive outputs must be reduced in order to use SSVEP BCI for real life applications such as home appliance control or wheelchair control. The combined use of CCA and LDA in this method addresses this issue with great effect. It is very good at differentiating between idle state and intended target. Hence this method can be successfully implemented in SSVEP BCI and the same BCI system can be extended to many more real-life applications.