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Investigation of multiple frequency recognition from single-channel steady-state visual evoked potential for efficient brain–computer interfaces application

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Abstract: In this study, the authors have examined a single-channel electroencephalogram from O_z for identification of seven visual stimuli frequencies with multivariate synchronisation index (MSI) and canonical correlation analysis (CCA). Authors investigated the feasibility in three case studies with varying overlapped as well as non-overlapped window lengths. The visual stimuli frequencies ≤10 Hz are considered in case study I and >10 Hz in case study II. Case study III contains frequencies of both case studies I and II. All the case studies revealed that CCA outperforms MSI for reference signals constituting fundamental, one subharmonics, and three super-harmonics. The results revealed that the accuracy of identification improves with 50% overlap in both the algorithms. Further, recognition accuracy is studied with varying combination sub- and super-harmonics for case study III with 50% overlap. The results revealed that CCA and MSI perform better with reference signals constituting fundamental and twice fundamental frequency compared with traditional power spectral density analysis (PSDA). In addition to recognition accuracy, the information bit transfer rate is also higher in CCA relative to MSI and PSDA.

1 Introduction

Steady-state visual evoked potential (SSVEP) is a continuous sequence of oscillatory potential changes in the visual cortex, when an observer is presented with a flickering or a repetitive visual stimulus [1, 2]. The frequency of evoked potential is the same as fundamental frequency (and its harmonics) of the flickering stimulus. These signals appear in the occipital and parietal lobes of the brain.

SSVEP-based brain–computer interfaces (BCI) have received significant attention recently [3, 4]. Some applications include SSVEP-based BCI for wheelchair control [5], spellers [6, 7], and neural engineering [8]. The factors that have contributed to SSVEP-based BCI interest is relatively less user training and its high information transfer rate compared with other types of electroencephalogram (EEG) signals. For acquiring SSVEP signals, a subject is required to gaze at a flickering stimulus for a prolonged period of time. The typical block diagram of BCI using SSVEP is shown in Fig. 1.

Recording SSVEP signal contains noise due to muscle activity, lack of consistency during concentration, inability to gaze at a screen for a prolonged period of time, unfamiliarity with the experiment, or improper placement of electrode as the position varies with the subject [9]. Further, when considering a large amount of data, a compromise with time is inevitable.

To overcome these drawbacks, some solutions have previously been proposed [10, 11]. These solutions deal with manipulating the window lengths by biasing and overlapping. In Atyabi *et al.* [12], the effect of subwindowing and overlapping has been studied, concluding that there is a relation between the length of subwindows and the impact of having extra samples for training the classifier.

Frequency classification of SSVEP signals is a popular field of research. There have been many algorithms proposed to perform this task [13–16]. In Tello *et al.* [17], a comparative analysis between different algorithms is performed using 12 channels and different stimuli. The authors found that the multivariate synchronisation index (MSI) performs best. In another study [18], MSI and canonical correlation analysis (CCA) were compared for the classification of three frequencies – 8, 9, and 10 Hz. The data was acquired using an Emotiv Epoc headset consisting of 14 channels. MSI was found to be the better performer of the two. In Tanaka *et al.* [19], a comparative study is performed using four channels with the frequencies 7, 11, 13, 17, and 19 Hz. The authors concluded that CCA was the better classifier for the frequencies and channels considered.

A multichannel approach of frequency recognition can achieve good classification accuracy, despite the fact that increases in the cost also limit the applicability of user with ease. One of the challenging tasks in SSVEP-based BCI is the accuracy in recognition of multiple stimulus frequency with single channel with better information transfer rate to improve the comfort of the user. In this paper, the authors attempted to study the frequency recognition with varying window length using two classifiers – MSI and CCA. The performance of the classifiers is analysed without overlap window to obtain optimal window size for good recognition rate and with overlapped window for the improvement of the information transfer rate. In previous implementations of these algorithms [20–22], multiple EEG channels with a few stimulus frequencies were used to assess accuracy. In this paper, analysis was done with respect to a single-channel input from ten subjects. Initially, window lengths of 1, 1.5, and 2 s are analysed with the two approaches. It has been observed that the accuracy of frequency identification improves with increase in window length.

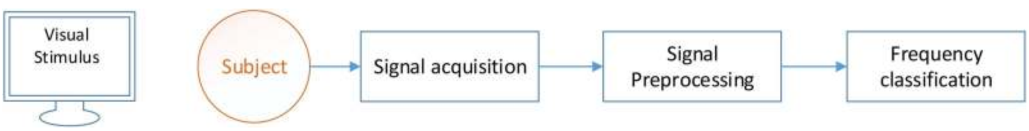

Fig. 1 *Classification accuracies for case study I for frequencies ≤10 Hz*

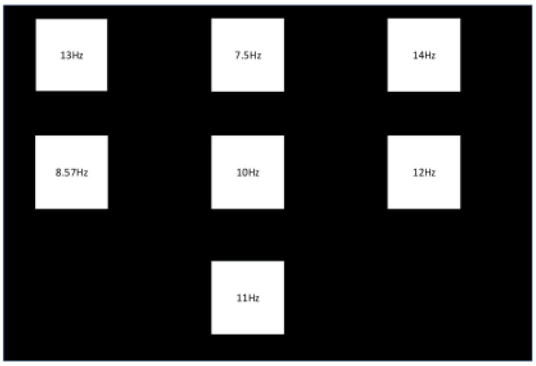

Fig. 2 *Seven visual stimuli pattern*

In order to obtain decision in lesser time with good accuracy, a constant window size of 2 s is analysed with overlap of 25, 50, and 75%.

It has been found, CCA shows good accuracy in three different case studies of data with reference signal constituting one subharmonics and three super-harmonics. The performance of CCA improves with increase in window length. MSI has shown a good performance with short length data for case studies I and II, however, less accurate than CCA. The results evinced that window length of 2 s with 50% overlap performs well, without significant difference for $P < 0.05$. In addition to the effect of window length, the influence of harmonics of reference is also studied with 2 s window length data with 50% overlap for one subharmonics with 0–3 super-harmonics as well as with 1–2 super-harmonics alone. The results shown that fundamental with one super-harmonics outperform various combinations of harmonics considered in CCA and MSI. It has been found the subharmonics has the effect of reducing the recognition accuracy. Also the recognition rate as well as information rate in CCA is superior than MSI and traditional power spectral density analysis (PSDA) using fast Fourier transform (FFT).

2 Methodology

The discrimination of frequencies is studied under three different case studies to identify an effective technique that discriminate multiple frequencies from single-channel EEG data. The stimulus frequencies have been divided into three case studies. In case study I, low-frequency visual stimuli of 7.5, 8.57, and 10 Hz is considered. In case study II, high-frequency visual stimulus of 11, 12, 13, and 14 Hz is considered. In case study III, both high-frequency and low-frequency visual stimuli data are considered for analysis.

2.1 Stimulator

The visual stimuli have been created using Psychophysics toolbox in MATLAB 2012. The seven visual stimuli targets, with frequencies 7.5, 8.57, 10, 11, 12, 13, and 14 Hz are coded based on framed-based approach [23] as shown in Fig. 2. Each target is a square of 3.5 cm × 3.5 cm and flickers in black and white colour pattern with a uniform gap on either side. The stimuli have been displayed on 18.5 inch HP V193 LCD monitor with a 60 Hz refresh rate.

2.2 Experimental set-up

In this study, the EEG signals are acquired in two protocols for the seven visual stimuli. The study has been conducted after getting approval from institutional human ethics committee. Ten healthy volunteers with normal or corrected-to-normal vision participated for this offline study in a room without electromagnetic shielding. Subjects were seated 70 cm from the LCD screen and data was acquired using Truscan EEG acquisition system manufactured by Deymed Diagnostics. Signals are acquired using silver–silver chloride electrodes placed at the O_z on the scalp with respect to the reference electrode at the mastoid bone behind the left ear. The ground electrode is placed at Nasion point on the forehead. The subjects were directed to gaze at the centre of square target during the signal acquisition.

In the first protocol, the subject was directed to gaze at one target for a minute and given rest till the subject was ready for the next target stimulus. In second protocol, the subject was directed to gaze at each target stimulus for 20 s and the EEG signals were recorded continuously for all the seven visual stimuli, starting from 13 Hz. The subjects were alerted to change between stimuli using an auditory stimulus beep at every 20 s.

2.3 Data segmentation

All signals were sampled at a rate of 256 samples/s and were filtered through a band-pass filter of 5–30 Hz. The performance of identification is studied with and without overlap of the window segment. The window segments of 1, 1.5, and 2 s without overlap are considered to identify the effect of window length on frequency discrimination. Further, window length of 2 s is studied with overlap of 0.5 s (25% overlap), 1 s (50% overlap), and 1.5 s (75% overlap) data to improve the information transfer rate.

2.4 Frequency classification

The CCA and MSI are used for the identification of visual stimulus frequencies of the three case studies. The results of classification are compared with PSDA using FFT. Further, the effect frequency recognition is studied considering, one subharmonics with 0–3 super-harmonics, 1–2 super-harmonics in reference signal for a window length of 2 s with 50% overlap.

2.4.1 Canonical correlation analysis: In CCA [24], the reference signals of frequency corresponding to visual stimuli frequencies are correlated with input EEG signal. The reference signal which constitutes signals of the visual stimuli frequencies, the sub- and super-harmonics of the same in the range of the pass band between 5 and 30 Hz, i.e. one subharmonics and three super-harmonics are obtained using the below equation

$$B(t) = \begin{bmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ . \\ . \\ \sin(2\pi N f t) \\ \cos(2\pi N f t \end{bmatrix} \tag{1}$$

where N is the number of harmonics

$$t = \frac{1}{F_s}, \frac{2}{F_s}, \frac{3}{F_s}, \ldots, \frac{M}{F_s}$$

where M is the number of sampling points and F_s the sampling frequency.

In CCA, a statistical correlation between multidimensional variables, i.e. the input EEG $\boldsymbol{A(t)}$ and the reference signal $\boldsymbol{B}(t)$ are calculated using the below equation

$$\begin{aligned} \rho(a, b) &= \max_{W_a, W_b} \frac{E(ab^{\mathrm{T}})}{\sqrt{E(aa^{\mathrm{T}})E(bb^{\mathrm{T}})}} \\ &= \max_{W_a, W_b} \frac{E(\boldsymbol{W}_a^{\mathrm{T}} AB^{\mathrm{T}} \boldsymbol{W}_b)}{\sqrt{E(\boldsymbol{W}_a^{\mathrm{T}} AA^{\mathrm{T}} \boldsymbol{W}_a)E(\boldsymbol{W}_b^{\mathrm{T}} BB^{\mathrm{T}} \boldsymbol{W}_b)}} \end{aligned} \tag{2}$$

where $a = \boldsymbol{A}^{\mathrm{T}}\boldsymbol{W}_a$ and $b = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{W}_b$; $\boldsymbol{W}_a$ and $\boldsymbol{W}_b$ are the weight vectors to be maximised.

This correlation is computed with the reference matrix $\boldsymbol{B}(t)$ for all the seven stimulus frequencies $f_1, f_2, \ldots, f_K$ with EEG data. The stimulus frequency should satisfy the below equation

$$F_s = \max \rho(a, b) \tag{3}$$

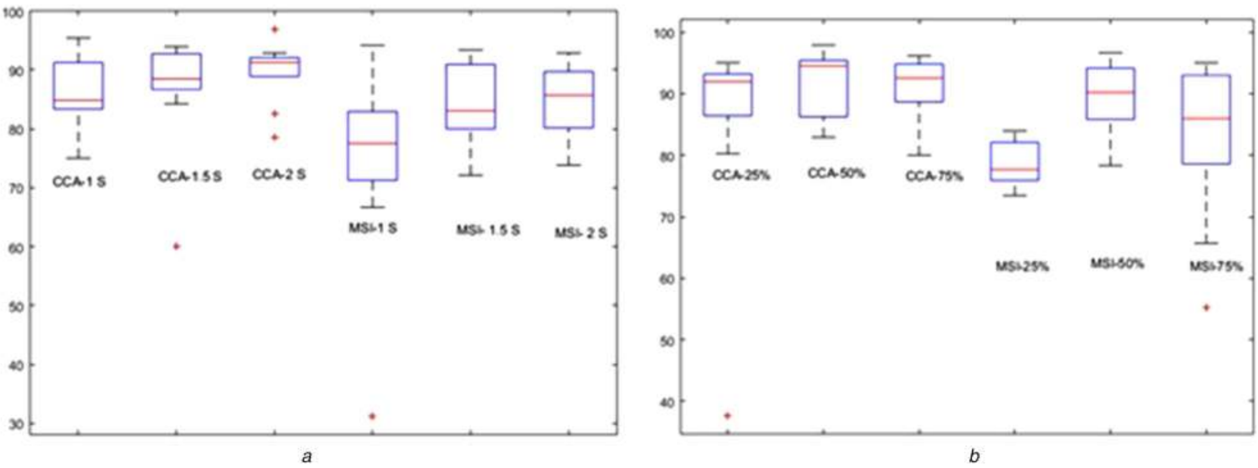

Fig. 3 *Classification accuracies for case study I for frequencies ≤10 Hz*
(a) Without overlap, ***(b)*** With overlap

where $\rho(a,b)$ represents the correlation coefficient between the two signals.

2.4.2 Multivariate synchronisation index: In this method, the synchronisation between the input SSVEP signal and a reference signal is computed [25]. According to the degree of synchronisation, an index with maximum synchronisation indicates the frequency. The reference signal is computed using (1).

The synchronisation is measured between single-channel input EEG signal (A) and the reference signal (B). Initially, a correlation matrix between the two signals is calculated using

$$D_{11} = \left(\frac{1}{M}\right)\boldsymbol{A}\boldsymbol{A}^{\mathrm{T}} \tag{4}$$

$$D_{22} = \left(\frac{1}{M}\right)\boldsymbol{B}\boldsymbol{B}^{\mathrm{T}} \tag{5}$$

$$D_{12} = D_{21} = \left(\frac{1}{M}\right)\boldsymbol{A}\boldsymbol{B}^{\mathrm{T}} \tag{6}$$

To remove the effect of autocorrelation on the synchronisation measure, a linear transformation is calculated (T)

$$\boldsymbol{T} = \begin{bmatrix} D_{11}^{(-1/2)} & 0 \\ 0 & D_{22}^{(-1/2)} \end{bmatrix} \tag{7}$$

Subsequently, the transformed correlation matrix is calculated using (7)

$$\boldsymbol{S} = \boldsymbol{T}\boldsymbol{D}\boldsymbol{T}^{\mathrm{T}} = \begin{bmatrix} I_{1\times 1} & D_{11}^{(-1/2)}D_{12}D_{22}^{(-1/2)} \\ D_{22}^{-(1/2)}D_{21}D_{11}^{-(1/2)} & I_{2N_h\times 2N_h} \end{bmatrix} \tag{8}$$

Let λ_1, λ_2,…, λ_z be the eigenvalues of $\boldsymbol{S}$. The normalised eigenvalues are calculated as

$$\lambda_i' = \frac{\lambda_i}{\sum\lambda} = \frac{\lambda_i}{\mathrm{tr}(\boldsymbol{S})} \tag{9}$$

The synchronisation index between the signals is calculated as

$$R_i = 1 + \frac{\sum(\lambda_i'\log(\lambda_i'))}{\log(P)} \tag{10}$$

where $P = N + N_h$ and N_h denotes the number of rows in the reference signal $\boldsymbol{B}(t)$.

The synchronisation index is computed with respect to reference signals of all stimulus frequencies, for every segment of EEG window data. The stimulus frequency that the user is gazing at will be determined as follows:

$$Q = \max(R_i), \quad \text{where } i = 1, 2, \ldots, K. \tag{11}$$

where K is the number of targeted stimuli frequencies.

3 Results and discussion

An efficient classification algorithm is an important factor that contributes to the performance of a BCI system. We focused initial study using reference signal of one subharmonics and three super-harmonics with a single-channel data for identification of suitable window based on length of EEG data as well as amount of overlap in three case studies using CCA and MSI algorithms from ten subjects. Figs. 3*a* to 5*a* show the classification accuracies for case studies I–III under condition of with and without overlap window segment. The CCA classifier significantly outperforms MSI with case study III for $P < 0.05$ in overlapped as well as non-overlapped window segments. A common phenomenon that is observed in all the three case studies is that the classification accuracy increases as the window size increases for both the algorithms. This can be attributed to the fact that with the increase in window size, the amount of data/information considered for classification increases. Therefore, the average accuracy increases with increase in more data/information.

An important aspect to consider with window sizes is the amount of time for the identification of frequency. There is a significant compromise with time and information transfer rate. Keeping these constraints, window size of 2 s is considered for applying overlapped window analysis.

Figs. 3*b* to 5*b* show the classifier accuracies for different lengths of overlap for case studies I–III. The analysis was performed for three degrees of overlap, i.e. 25, 50, and 75%. The overlap represents the percentage of older data that will be considered for every epoch of classification. It has been observed that the classifier accuracy is best with a 50% overlap in CCA as well as MSI. In the case of CCA, the accuracy increases slightly with 75% and decreases with MSI. Similar to non-overlapped window, the CCA significantly outperforms MSI with case study III for $P < 0.05$. In addition to window length, the harmonics of reference signals also found to influence the frequency recognition rate. Therefore, reference signal constituting 1 subharmonics, 0–3 super-harmonics, and 1–2 super-harmonics composition are analysed with case study III. Fig. 6 shows the performance of CCA and MSI with varying harmonics of reference signals. It is clear from Fig. 6 that the presence of subharmonics deteriorates frequency recognition in MSI as well with CCA. In MSI, the performance with one super-harmonics is significantly outperform other combination frequencies for $P < 0.05$. Further, there is no significant difference in performance of CCA and MSI with one super-harmonics of reference signals. However, the classification accuracy of CCA is more than MSI.

Further, the classification accuracy of CCA, MSI with one super-harmonics is compared with PSDA in Fig. 7. The

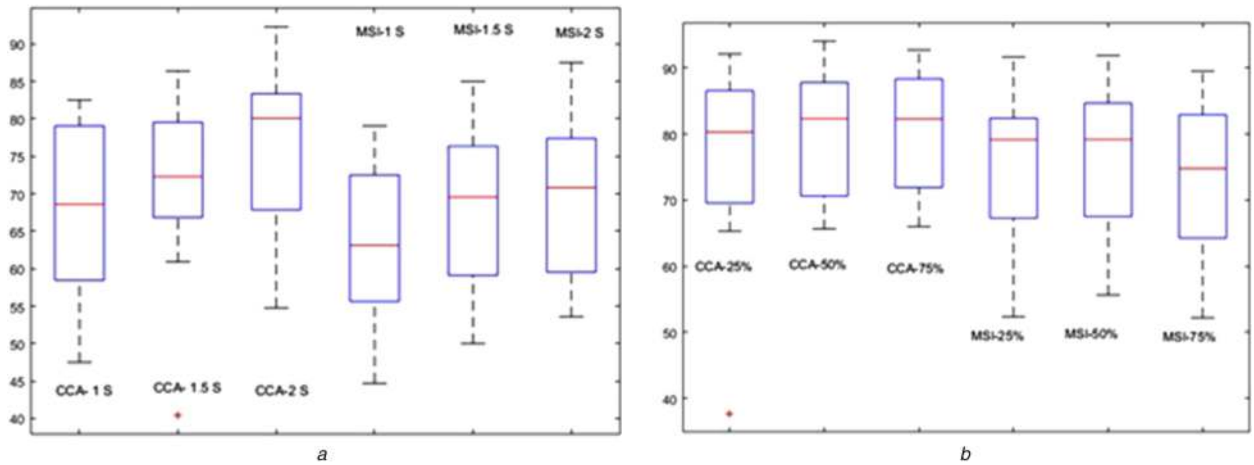

Fig. 4 *Classification accuracies for case study II for frequencies >10 Hz*
(a) Without overlap, ***(b)*** With overlap

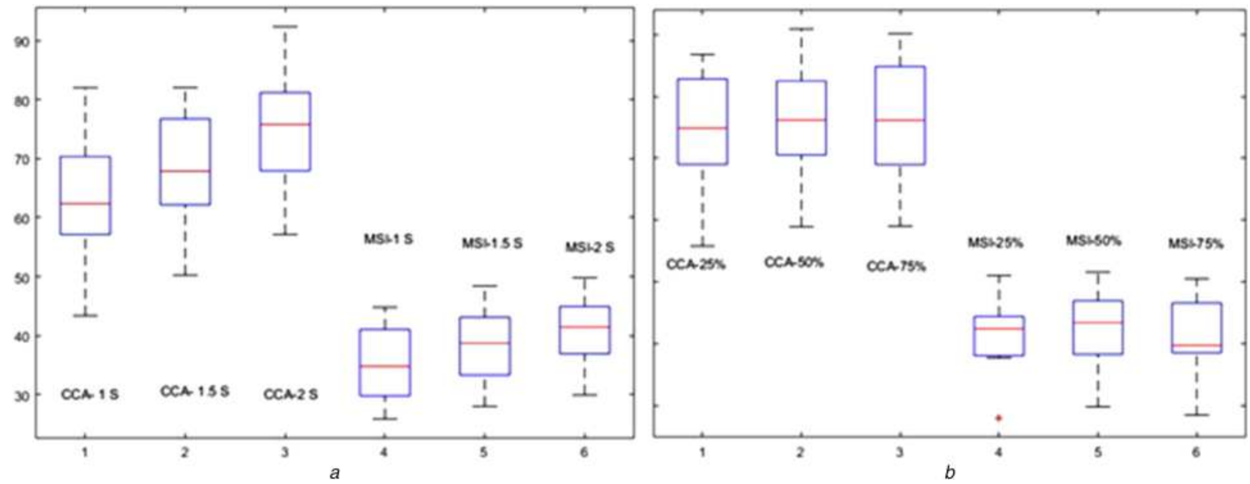

Fig. 5 *Classification accuracies for case study III with all frequencies*
(a) Without overlap, ***(b)*** With overlap

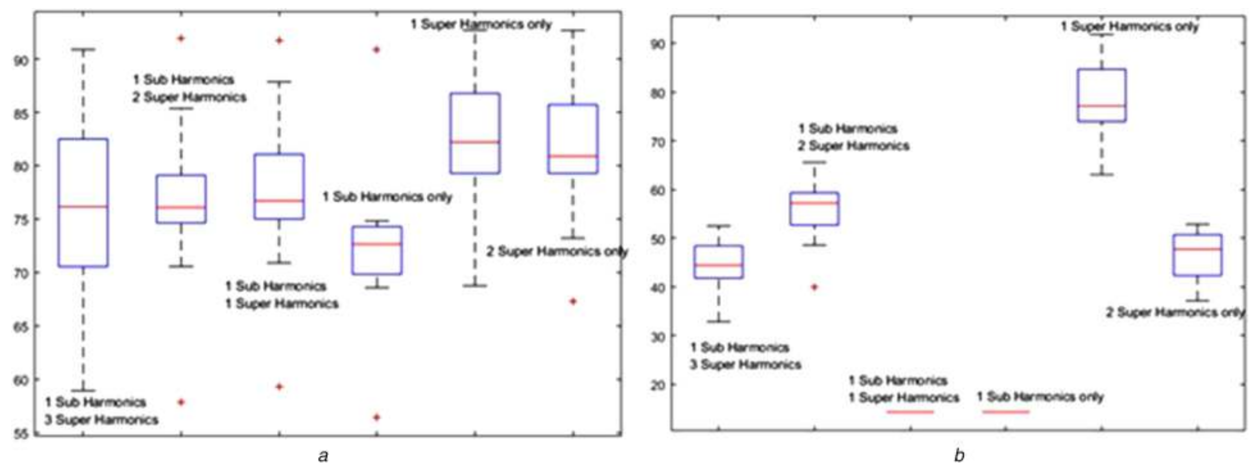

Fig. 6 *Classification accuracies for case study III with varying harmonics of reference signal*
(a) CCA Technique, ***(b)*** MSI Technique

information transfer rate has been calculated for the same condition is shown in Fig. 8. With respect to the performance of the algorithms, we observe that CCA performs better than MSI and PSDA. MSI has previously been proven to outperform CCA [17], when dealing with a small number of channels. However, with single channel, it has been found that CCA outperforms MSI as well as PSDA in accuracy as well as information transfer rate. The average information transfer rate of CCA >100 bits/min. However, the information transfer rate is <100 bits/min in MSI as well as with PSDA. However, there is no significant difference in recognition accuracy as well as information transfer rate of CCA with MSI using one super-harmonics. An important observation that was observed was the performance of MSI varied significantly depending on the combination of stimuli frequencies as well as reference signal frequencies considered. We observed that MSI performed better when the stimuli were divided into different case studies depending on their frequencies as opposed to when we considered a single group for all the stimuli when subharmonics is considered. CCA, on the other hand, showed a consistent

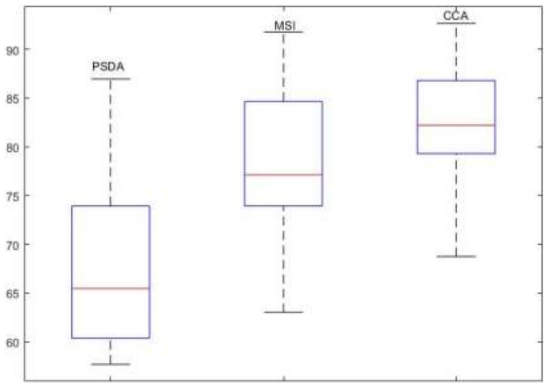

Fig. 7 *Comparative performance of PSDA, MSI, and CCA*

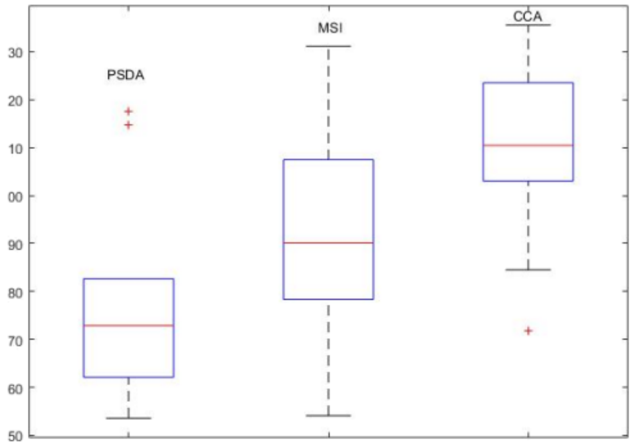

Fig. 8 *Information transfer rate of PSDA, MSI, and CCA*

performance irrespective of the cases and reference signal frequencies considered.

4 Conclusion

For single-channel EEG data, CCA has proven to be the better classifier when compared with MSI and PSDA. The classifier accuracy has been consistently greater for CCA for all the cases that were analysed. From this study, we can conclude that the CCA is a better frequency classification method than MSI, when dealing with single-channel EEG data. We further propose that a 2 s window size with an overlap of 50% is ideal for better classification accuracy, without compromising computation time and also minimising errors due to the subject's temperament during the course of the experiment. Also, it is observed that the classifier accuracy is significantly affected with the number of super-harmonics and subharmonics. The recognition rate is good only considering one superharmonic with 50% overlap for 2 s window length.

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