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Frequency Recognition of SSVEP with Adaptive Reference Signals Using CCA

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Abstract:
Background*: The brain signal obtained by electroencephalography (EEG) is widely used as low cost arrangement for BCI implementation. Steady-state visual evoked potential (SSVEP) is an EEG obtained by illustrating flickering type of visual stimuli. In the SSVEP based BCI, the main concern is to recognize the flickering (stimulus) frequency of test SSVEP signal. Canonical correlation analysis (CCA) has been widely used in the detection of one of the most SSVEP based BCI systems. The performance and usability in our daily life of SSVEP-based BCI system depends on the higher recognition accuracy with shorter processing time. MultisetCCA (MsetCCA) is one of the most popular SSVEP frequency recognition methods, whereas, it still has significant limitation due to the noise effects in the reference signals.*
Materials and Methods*: In this study, a novel method is introduced to eliminate the noise contamination of the reference set yielding the improvement of performance in stimulus frequency recognition. The required number of training trials and the average over all those trials are added in the training set. The joint spatial filter with MsetCCA is applied to the obtained set to optimize the artificially generated sin-cosine reference signals set by the set of training data and its average. The maximally correlated canonical variates and their corresponding weights are used to construct the reference set. Then the standard CCA is used to determine the multivariate correlation between test data and the obtained reference set. The frequency corresponding to the maximum canonical correlation is selected as the stimulus frequency of the test SSVEP signal.*
Results*: The experiments are conducted for twelve different stimulus frequencies for ten individual subjects. The performance of the proposed method is compared with standard CCA and MsetCCA in terms of recognition accuracy as well as information transfer rate (ITR). The results show that this method performs better than that of CCA and recently developed MsetCCA.*
Conclusion: *An effective method for frequency recognition of SSVEP signals is introduced here using adaptive reference signal. This is a training based approach to SSVEP based BCI implementation. To reduce the noise effects from the training signals the average over all the training trials is included in the training set. This study performs a quantitative comparison of the proposed method with standard CCA and MsetCCA. The proposed method outperforms the existing methods.*
Key Word*: Brain computer interface; canonical correlation analysis; frequency recognition.*

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I. Introduction

Over the past few decades BCI technology has been developed so widely that now it requires a very little training and provide stability, robustness, comfort and longevity for accurate long-term data collection. Technological improvements have also led to advanced algorithmic approach to analyzing and interpreting brain data collected under noisy and real-world environments, enabling an explosion of BCI research [1] and technology development even to the point of the commercialization of the first neutrally-based toys, such as Star Wars Force Trainer^{TM} by Uncle Milton or the Mindflex^{TM} by Mattel. But human brain can execute multiple tasks simultaneously. Signal of such task can affect the system target signal; it will consider as noise and decrease the performance of BCI. To decrease noise steady state visual evoked potential (SSVEP) technology is invented. In this technology, some visual flicker is show on the computer monitor and user has to gaze one of them to select a command. The reason of this technology is the frequency of brain signal generated by retina excitement is about same as the visual flicker, which made the retina excited and it helps a lot to classify the signal. This is the main reason of using steady state visual evoked potential (SSVEP) system.

The SSVEP is portable and safe for the user or participant. For the same task brain signal of different person will be different. But in the SSVEP for the same command brain will generate almost same frequency signal as user have to gaze at the same frequency flicker. So the retina will be elicited by the same frequency as brain will produce same frequency signal. Also SSVEP require low cost than other systems. Flickers are displayed on visual device using stimuli. A stimulus is a detectable change in the internal or external environment. In another words, stimuli are things that provoked a response or activity or that cause organs or tissues in the body to react in a certain way. Visual stimulus are used in SSVEP based BCI system.

Canonical correlation analysis (CCA) is the most widely used classical method for measuring similarity between two multivariate signals. These signals need not to have same number of variables. It is an extension of ordinary correlation between two random variables [2, 3, 4]. CCA finds a pair of linear combinations, called canonical variables, for two sets, in such a way that the correlation between the two canonical variables is maximized. In SSVEP those two sets are reference signal and multi-channel real EEG signals. The reference signal with maximal correlation is selected as the stimulus of SSVEP [3, 5]. CCA use artificial sine-cosine signal as reference signal which has less features than real EEG signal. A method was proposed to overcome this problem by optimizing reference signals through collaboratively maximizing correlation between real EEG and artificially generated sine-cosine signals [6]. This method is called Multi-way CCA. But the set of reference signals optimized completely based on real EEG might provide better result and improve the classification accuracy of SSVEPs. Based on this logic Multi-set CCA method was proposed which employs the joint spatial filtering of multiple real EEG training signals [5, 7].

But human brain can execute multiple tasks simultaneously so it is very common that our target signal will be affected by other task signals and it will be considered as noise. This is also a fundamental obstacle of SSVEP based BCI development. MsetCCA implements joint spatial filter but still it contains significant amount of noise which responsible for misclassification. We can eliminate those noises by using the most common averaging technique [8]. Averaging technique is used to calculate the oxygen saturation level and blood velocity, increase the signal-to-noise ratio. It also provides better result in frequency spectrum and can reduce the obscured noise which is very important in SSVEP classification. SSVEP system performance can be improved by increasing the classification accuracy. Motivated by this idea we have proposed a method using averaging technique.

II. Material And Methods

In SSVEP based BCI system, visual stimuli or flicker is shown in visual device like computer monitor. Each flicker represents a command. Each flicker or stimuli has different frequency. User or participant has to gaze at a particular flicker to select the command. Flickering approach is essential for SSVEP based BCI system. As a result, most of the SSVEP based BCI application is suitable for users or participants or subjects who have the capability to control their eye movement. When users gaze at a particular flicker, retina will be excited and brain will produce electrical potential at the same frequency or multiple of the flickering frequency. As brain may generate multiple of base frequency, the frequency of flicker should be selected carefully so that no flicker frequency becomes multiple of another flicker frequency. Most of the time, EEG is used to record the brain signals or activities. Later, an efficient classifier algorithm is used to recognize the command. Once the command is recognized, BCI system sends command to the external or output device to execute the specific task corresponding to the recognized command.

SSVEP frequency recognition by CCA

Canonical Correlation Analysis (CCA) is the most used method to recognize frequency in steady-state visual evoked potential (SSVEP) based brain-computer-interface (BCI) [7]. CCA is a statistical way to measure the underlying correlation between two sets of multidimensional variables. It has been widely used to detect the frequency of SSVEPs [9, 10]. Considering two multidimensional variables *X* and *Y* where *X* is the multi-channel EEG signals set. $x = X^T w_x$ and $y = Y^T w_y$ are their linear combination. CCA finds w_x and w_y which maximize the correlation between *x* and *y* by solving the following problem,

$$\rho(x, y) = \max_{w_x, w_y} \frac{E[xy^T]}{\sqrt{E[xx^T]E[yy^T]}} = \max_{w_x, w_y} \frac{E[w_x^T XY^T w_y]}{\sqrt{E[w_x^T XX^T w_x]E[w_y^T YY^T w_y]}} \tag{1}$$

The maximum ρ with respect to w_x and w_y is the maximum canonical correlation. Projections onto w_x and w_y are called canonical variants.

The set of reference signals $Y_n \in R^{2N_h \times N_s}$ of same length generated by

$$Y_n = \begin{bmatrix} \sin(2\pi f_n t) \\ \cos(2\pi f_n t) \\ \vdots \\ \sin(2\pi N_h f_n t) \\ \cos(2\pi N_h f_n t) \end{bmatrix}, t = \left[\frac{1}{f_s}, \frac{2}{f_s}, \cdots \frac{N_s}{f_s}\right] \tag{2}$$

Where f_n is the stimulation frequency, f_s is the sampling frequency and N_h is the number of harmonics. The canonical correlation ρ_n between the multi-channel EEG signals and the reference signals at each stimulus frequency Y_n is calculated by the CCA to recognize the frequency of the SSVEPs. The frequency of the reference signals with the maximal correlation was selected as the frequency of the SSVEPs by

$$\tau = \arg\max_n \rho_n, n = 1,2,..., N \tag{3}$$

As CCA use pre-constructed sin-cosine waves which has lack of features from real electro-encephalo-gram (EEG) data, the recognition accuracy result was not good enough [7]. To overcome this problem MwayCCA and MsetCCA use intelligent reference signal generated from the real EEG data.

Training based SSVEP recognition by MwayCCA

Multi-way canonical correlation analysis was introduced by Y. Zhang [42]. The MwayCCA method use reference signal generated and optimized by collaboratively maximizing correlation between the multiple dimensions of EEG tensor data and pre-constructed sine-cosine waves [7]. Let use consider a three-way tensor $X_m = (X)_{i_1,i_2,i_3} \in R^{C\times P\times N}$ where C is the number of channel, *P* is the number of time points and *N* is the number of trials. Also the tensor is constructed by EEG data from *N* experimental trials at m^{th} stimulus frequency (*m* = 1, 2, 3… *M*). Also consider an original reference signal set

$$Y_m = \begin{pmatrix} \sin(2\pi f_m t) \\ \cos(2\pi f_m t) \\ \bullet \\ \bullet \\ \bullet \\ \sin(2\pi H f_m t) \\ \cos(2\pi H f_m t) \end{pmatrix}, t = \frac{1}{F}, \frac{2}{F}, ..., \frac{P}{F} \tag{4}$$

The MwayCCA method quest three linear transforms. Those transforms are $w_{1,m} \in R^C$, $w_{3,m} \in R^N$, $v_m \in R^{2H}$. Those transforms are used to maximize the correlation between linear combinations $\tilde{z}_m = X_m \times_1 w_{1,m}^T \times_3 w_{3,m}^T$ and $\tilde{y}_m = v_m^T Y_m$ as

$$\max_{w_{1,m} w_{3,m} v_m} p_m = \frac{E[\tilde{z}_m \tilde{y}_m^T]}{\sqrt{E[\tilde{z}_m \tilde{z}_m^T] E[\tilde{y}_m \tilde{y}_m^T]}} \tag{5}$$

Where $X \times_k w^T$ denotes the k^{th} way projection of a tensor with a vector. The projection definitions found in literature [6]. Now we compute the canonical variate $\tilde{z}_m$ as the optimized reference signal at stimulus frequency f_m. The maximal correlation coefficient p_m between a new test data set $\hat{X} \in R^{C\times P}$ and each of the optimized reference signals $\tilde{z}_m$ (*m* = 1, 2, 3… *M*) is computed by canonical correlation analysis (CCA). The SSVEP frequency of a test set is then recognized by

$$\hat{f} = \arg\max_{f_m} p_m, \text{ m} = 1, 2, …, M \tag{6}$$

Training based SSVEP recognition by MwayCCA

According to many studies on SSVEP-based BCI [11, 12] multi-set canonical correlation analysis (MsetCCA) gives better recognition accuracy. In CCA method we use pre-constructed sine-cosine reference signal. But it does not provide enough good result as it has less feature than real SSVEP data. A set of trials recorded for a certain stimulus frequency on the same subject should have some common features [7]. Those features can be used in constricting sine-cosine reference signal and it will provide better recognition accuracy result.

MsetCCA use joint spatial filter to generate the optimized reference signals from the multiple sets of EEG training data for each stimulus frequency using the common or shared features. Instead of sine-cosine waves, those optimized reference signals are used in the CCA method to recognize SSVEP frequency [7].

Assume $X_{1,m}, X_{2,m}, \ldots, X_{N,m} \in R^{C\times P}$ (*C* and *P* denote number of channels and sampling points respectively) denotes SSVEP data sets recorded from *N* training trails at m^{th} stimulus frequency f_m. Then MsetCCA method implement joint spatial filter and find linear transforms $w_{1,m}, w_{2,m}, \ldots, w_{N,m}$ which result in the maximization of overall correlation among the canonical variates $\widetilde{z}_{1,m}, \widetilde{z}_{2,m}, \ldots, \widetilde{z}_{N,m}$ with joint filter targeting $\widetilde{z}_{i,m} = w_{i,m}^T X_{i,m} \quad (i = 1,2,\ldots,N)$. The optimized reference signal set at stimulus frequency f_m is then constructed by the combination of canonical variates as,

$$Y_m = \left[\widetilde{z}_{1,m}^T, \widetilde{z}_{2,m}^T, \ldots, \widetilde{z}_{N,m}^T\right]^T \tag{7}$$

When a new test data set $\hat{X} \in R^{C \times R}$ arrive, the maximal correlation coefficient p_m between new test data set and optimized reference signal sets $Y_m \in R^{N \times P}$ (m = 1, 2, …, M) is computed by CCA. The SSVEP frequency is then recognized by,

$$\hat{f} = \underset{f_m}{\arg\max}\ p_m \quad \text{where, } m = 1, 2, \ldots, M \tag{8}$$

Proposed method for SSVEP recognition

Although MsetCCA implements joint spatial filter it still contains a large amount of noise. Figure 4.3 shows the original EEG signal, MsetCCA reference signal and average signal of all EEG signals of training set. All signals of Fig. 1 are taken for subject 1, channel 1 and trial 1 at frequency 9.25 Hz. It is noted that the average signal contains less noise than others and hence it is more efficient to use as the reference signal.

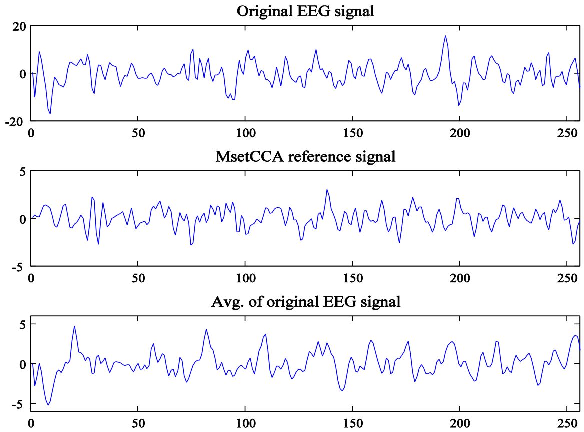

Fig. 1: Noise comparison of original EEG, MsetCCA reference and average of all training trials

Using the statistical technique of signal averaging, it is possible to reduce the noise and enhance the signal [8]. It will also increase signal-to-noise (S/N) ratio. Motivated by this idea, we proposed a method based on MsetCCA to increase the SSVEP frequency recognition accuracy. We have added the average training trail in the data set which is used by the MsetCCA to generate reference signals for the test data sets. Therefore, we will get one extra reference signal than normal MsetCCA. This extra reference signal will lead us to the better recognition accuracy than normal MsetCCA. The algorithm of adding average trail signal at the end of training trail data set which is used by MsetCCA to generate reference signal.

Then this EEG data will be used by the MsetCCA method to generate the reference signal sets. Therefore, we will get one extra reference signal and those reference signal set will use to recognize frequency of new test data set.

Consider that $X_1^{(m)}, X_2^{(m)}, \ldots, X_N^{(m)}, \overline{X}_{N+1}^{(m)} \in R^{C \times S}$ (C and S denote number of channels and samples respectively) denotes N training trails of SSVEP data at m^{th} stimulus frequency f_m; where $\overline{X}_{N+1}^{(m)} = \frac{1}{N}\sum_{n=1}^{N} X_n^{(m)}$. Then MsetCCA method implement joint spatial filter and find weights of linear transform as $w_1^{(m)}, w_2^{(m)}, \ldots, w_N^{(m)}, w_{N+1}^{(m)}$ which result in the maximization of overall correlation among the canonical variates $\hat{z}_1^{(m)}, \hat{z}_2^{(m)}, \ldots, \hat{z}_N^{(m)}, \hat{z}_{N+1}^{(m)}$ with joint filter targeting $\hat{z}_i^{(m)} = (w_i^{(m)})^T X_i^{(m)}$ $(i = 1,2,\ldots,N,N+1)$. The optimized reference set at stimulus frequency f_m is then constructed as,

$$\widetilde{Y}_m = \left[(\hat{z}_1^{(m)})^T, (\hat{z}_2^{(m)})^T, (\hat{z}_3^{(m)})^T, \ldots, (\hat{z}_N^{(m)})^T, (\hat{z}_{N+1}^{(m)})^T\right]^T \tag{9}$$

When any test data $\widetilde{X} \in R^{C \times S}$ arrive, the maximal correlation coefficient p_m between the test data $\widetilde{X} \in R^{C \times S}$ and each of the optimized reference signal sets $\widetilde{Y}_m \in R^{(N+1) \times S}$ (m = 1, 2, …, M) is computed by standard CCA. The SSVEP frequency is then recognized by using Eq. (8).

III. Experimental Results and Discussion

We have showed the recognition accuracy of SSVEP frequency for all the ten subjects obtained with 0.5s to 4s time windows (TWs) by the CCA, MsetCCA and the proposed method. We have also observed the recognition accuracy for individual frequency of all subjects. Information Transfer Rate (ITR) is one of the most commonly used techniques to measure the performance of BCI system. We have measured the performance of BCI system using CCA, MsetCCA and our proposed method and found that our proposed method had better performance than CCA and MsetCCA.

Data description

The data used in this experiment are collected from publicly available source [7]. There were 12-target visual stimuli (6×6 cm each). They were presented on a 27-inch LCD monitor (ASUS VG278) with refresh rate 60Hz and resolution 1280×800 pixels. The stimuli were arranged in 4×3 matrix as shown in Fig. 2 as a virtual keypad of phone [13] and tagged with different frequencies $(f_0 = 9.25Hz, \Delta f = 0.5Hz)$. Stimulus program was developed under MATLAB using Toolbox extensions.

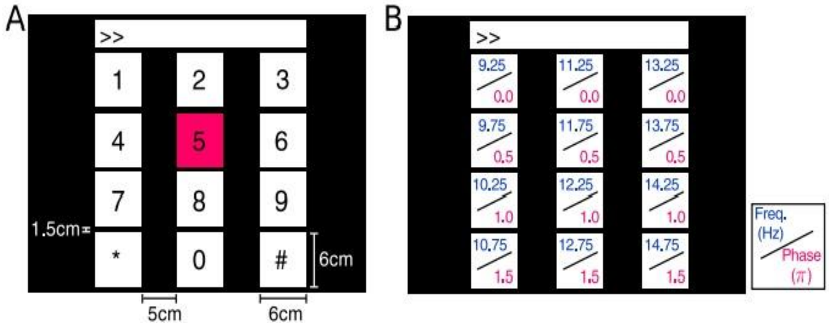

Fig. 2: stimulus design of the 12-target BCI system. (A) User interface of a virtual keypad for a phone-dialing program. (B) Frequency and phase values specified for each target. The red square in (A) is the virtual cue indicating a target symbol '5' in the experiment [14].

Ten healthy subjects with normal or corrected-to-normal vision participate in this study. Nine of them were male and one female with mean age 28. EEG data were recorded with eight Ag/AgCl electrodes covering the occipital area using a BioSemi ActiveTwo EEG system (Biosemi, Inc). Signals on the scalp are too low, therefore it has to amplify. EEG signal is amplified and digitized at 2048Hz sampling rate. The onsets of visual stimuli were sent from the parallel port of the computer to the EEG system. This indicates an event trigger. Synchronized event channels record the EEG data.

The subjects were seated in a comfort chair at a distance of 60cm in front of the monitor in a dim room. For each subject, the experiment consists of 15 blocks. In each block, subjects were asked to gaze at one of the visual stimuli indicated by the stimulus program in a random order for 4s and complete 12 trials corresponding to all 12 targets. A red square will appear for 1s at the position of the target stimulus before each trail (Fig. 2). Subjects were asked to shift their gaze to the target within the same 1s duration. After that, all stimuli started to flicker simultaneously for 4s on the monitor. Subjects were asked to avoid eye blinks during the stimulation period to reduce eye movement artifacts. Data epochs comprising eight-channel SSVEPs were extracted according to event triggers generated by the stimulus program. All data epochs were down-sampled to 256Hz and then band-pass filtered from 6-80Hz with an infinite impulse response (IIR) filter. Zero-phase forward and reverse IIR filtering was implemented using the filtfilt() function in MATLAB. Considering a latency delay in the visual system, the data epochs were extracted in [0.135 s 0.135+d s], where the time 0 indicated stimulus onset and d indicated data length used in the offline analysis. The 135-ms delay was selected towards the highest classification accuracy.

Result analysis

In this study, the proposed method is compared with CCA and MsetCCA [7] method to validate its effectiveness for SSVEP frequency recognition. For CCA and MsetCCA methods, leave-one-run-out cross-validation is implemented to evaluate the recognition accuracy. More specifically, the data 14 runs are used as training data to generate reference signal set while the data from the left-out run for validation. This procedure is repeated for 15 times such that each run serves once for validation.

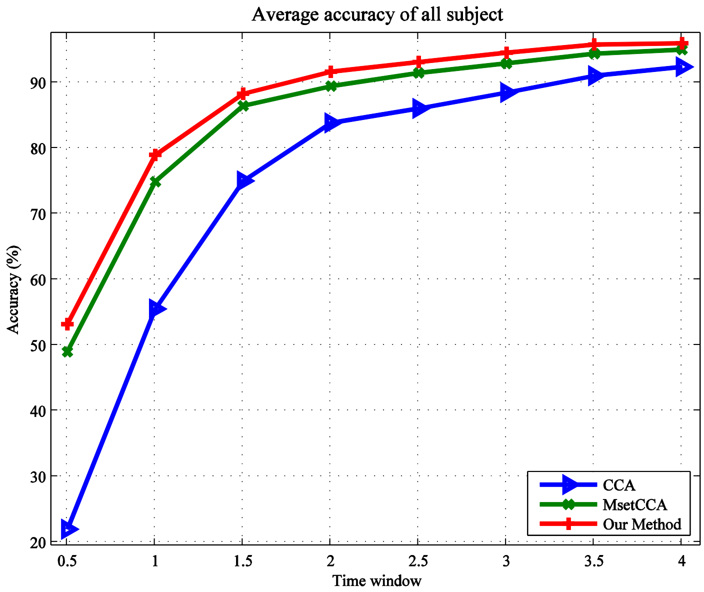

Fig. 3: Average recognition accuracy for all subjects

Fig. 3 shows the averaged recognition accuracy across all subjects with different data lengths 0.5 s to 4 s. The number of harmonics in the reference signals, the number of training trial and the number of channels were set to 2, 14 and 8 respectively. The comparison between CCA, MsetCCA and proposed method indicates that the performance of proposed method is better than standard CCA and MsetCCA. MsetCCA achieved higher performance than CCA but out proposed method achieved the highest performance.

The classification accuracy of CCA based method was estimated using leave-one-out cross-validation. The classification cross-validation was run 15 times for each frequency. In each of 15 rounds, cross-validation was performed using 14 run data for training and 1 run data for testing. In addition, BCI classification accuracy was also evaluated by ITR

$$ITR = \left(\log_2 N_f + P \log_2 P + (1-P) \log_2 \left[\frac{1-P}{N_f - 1} \right] \right) \times \left(\frac{60}{T} \right) \tag{10}$$

Where P is the classification accuracy, N_f is the number of class and T is the average time for a selection (seconds/selection). Here target gazing time is 0.5 s to 4 s and gaze shifting time is 1 s. In this session, classification performances using different T are illustrated.

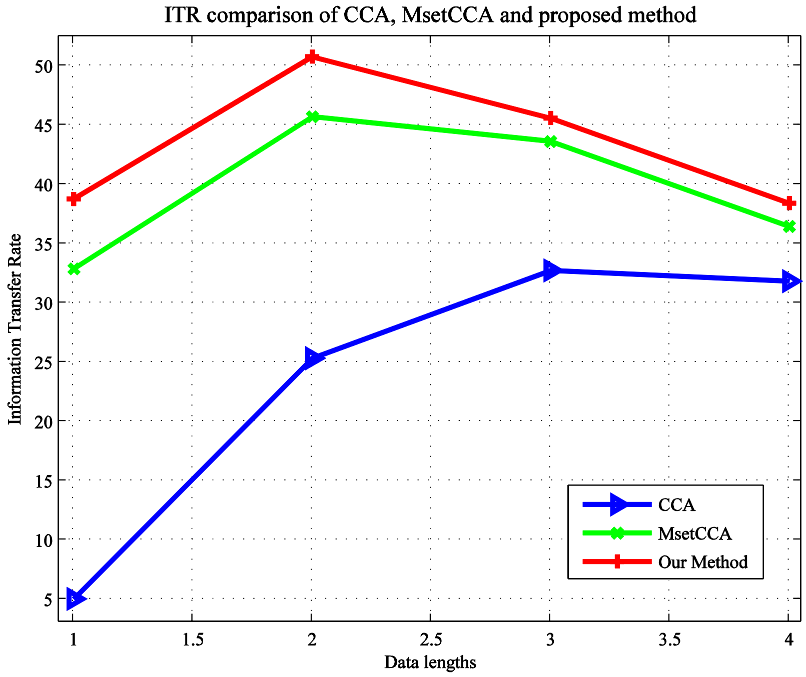

Fig. 4: ITRs across subjects using different data lengths.

Fig. 4 shows the ITR of CCA, MsetCCA and proposed method for all subject average with different data lengths from 0.5 s to 4 s. MsetCCA higher ITR than CCA but our proposed method achieved highest ITR for all data lengths. Therefore, proposed method can improve the BCI performance. The BCI performance can be further improved by optimizing parameters such as the number of visual stimuli and the time duration for gaze shifting.

IV. Discussion

Many researches have confirmed that a sophisticated calibration with appropriate analysis method could significantly improve the accuracy of EEG classification or frequency detection [13, 14].

The research in this thesis paper aimed to improve the classification accuracy of SSVEP frequency selection. Fig. 3 shows average classification accuracy for all subject and our method provide better result than standard CCA and MsetCCA.

The information transfer rate is used as an evaluation measurement in a brain-computer-interface (BCI). It is the most popular method. Fig. 4 shows the ITR comparison of those methods. Our proposed method achieved higher ITR than standard CCA and MsetCCA.

As human brain can think about multiple tasks synchronously, it is very common to have effect of other task in the EEG signal. Those effects will be considered as noise. Same method will provide better result with less noisy signal. So, we reduce the noise of EEG signal before classification. We used average noise reducing technique to reduce noise and used it as a trial to generate corresponding reference signal. So, if any frequency failed to recognize with the artificial reference signal then it may recognize by the average reference signal as it has less noise but more feature than artificial reference signal.

V. Conclusion

An efficient method for frequency recognition of SSVEP signals is introduced here. This is a training based approach to SSVEP based BCI implementation. The reference signals are generated from the training set using spatial filtering similar as implemented in MsetCCA. To reduce the noise effects from the training signals the average over all the training trials is included in the training set. The spatial filter is applied to the updated set of training signals. Then the standard CCA is used to recognize the SSVEP frequency of test trial using the reference set obtained by spatial filtering. The average of all training trials are included in the reference signals. Hence, the test trials with reduced noise are more accurately recognized with the modified training set.

This study performs a quantitative comparison of the proposed method with standard CCA and MsetCCA. The MsetCCA performs better over recently developed training based approach to frequency recognition in SSVEP based BCI, whereas, the proposed method outperforms the MsetCCA in terms of recognition accuracy as well as information transfer rate (ITR). Twelve different commands (stimulus frequencies) are used in this experiment for ten individual subjects. The recognition accuracy is observed for individual subjects, each command and average over all subjects. In all cases, the performance of the proposed method is better than that of the mentioned methods. Thus, the proposed method is more effective for SSVEP-based BCI system.

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