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Title: A comprehensive comparison between steady-state visual evoked potentials frequency estimation methods in Brain-Computer Interface with the minimum number of EEG channels

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Abstract

Introduction: Brain-Computer Interface (BCI) systems build a communication pathway between users and systems. BCI systems based on SSVEP are widely used in recent decades. Different feature extraction methods have been introduced in the literature to estimate SSVEP responses for BCI applications.

Methods: In this study, the new algorithms including CCA, LASSO, L1MCCA, MsetCCA, CFA, and MLR are compared using proper statistical methods to determine which of these algorithms have better performance when using minimum number of electrodes.

Results: It was demonstrated that MLR, MsetCCA, and CFA algorithms provided the highest performances and significantly outperformed CCA, LASSO and L1MCCA algorithms when using 8 EEG channels. However, when only one or two EEG channel were used, CFA method provided the highest f-scores. This algorithm also outperformed MLR and MsetCCA when applied on different electrode montages, and also provided the fastest computation time on the test set.

Discussion: Although MLR method has already demonstrated to have higher performance in comparison with other frequency recognition algorithms, this study showed that in a practical SSVEP-based BCI system with one or two EEG channels and short time windows, CFA method outperforms other algorithms. Therefore, it is proposed that CFA algorithm is a promising choice for the expansion of practical SSVEP BCI systems.

Keywords— Brain-Computer Interface (BCI), Electroencephalogram (EEG), feature extraction, steady-state visual evoked potential (SSVEP)

List of Abbreviations:

Abbreviation	Explanation
BCI	Brain-Computer Interface
CCA	Canonical Correlation Analysis
CFA	Common Feature Analysis
EEG	Electroencephalogram
FMRI	Functional Magnetic Resonance Imaging
GEE	Generalized Estimating Equation
L1MCCA	L1-Regularized Multiway Canonical Correlation Analysis
LASSO	Least Absolute Shrinkage and Selection Operator
MCCA	Multiway Canonical Correlation Analysis
MEG	Magnetoencephalography
MLR	Multivariate Linear Regression
MsetCCA	Multiset Canonical Correlation Analysis
PCA	Principal Component Analysis
PSDA	Power Spectral Density Analysis
SD	Standard Deviation
SSVEP	Steady State Visual Evoked Potential

1. Introduction

Brain-Computer Interfaces (BCI) can give a new channel of communication and control between human brain and external devices. Although this communication method could be used by everyone, its applications have been emphasized till now for the patients with disabilities (Resalat & Saba, 2016) to improve their quality of life (Tello, Müller, Bastos-Filho, & Ferreira, 2014). Recently, many new BCI applications have been validated for disabled people, including spelling for communication, control of artificial hands and legs, neuroprostheses and to enjoy playing with games(Yangsong Zhang, Xu, Cheng, & Yao, 2014).

There are different techniques to detect brain activities for the realization of a BCI system, including electroencephalography (EEG), functional near-infrared spectroscopy, magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). Recording EEG signals from the scalp is one of the approaches used more than others in the neural data signal for BCI devices since it can be easily recorded in most of the circumstances by a comparatively ordinary, reasonable equipment. Also, it has a high temporal resolution (YU Zhang, Guoxu Zhou, Jing Jin, Xingyu Wang, & Andrzej Cichocki, 2014).

A variety of EEG-based BCI paradigms have been proposed based on different brain responses to transfer the user intent to the computer, such as sensorimotor rhythms (SMRs), slow cortical potentials (SCPs), P300 event-related potentials (ERPs), and steady-state visually evoked potentials (SSVEPs)(Yangsong Zhang et al., 2014). Recently research on SSVEP BCI systems has been extended because of their high information transfer rates (ITR) and few requirements for the training phase(Ge et al., 2017).

SSVEP is a neurophysiological reaction excited in the occipital and occipitoparietal region of the brain by a flickering visual stimulus at a specified frequency. Responses of SSVEP contain the basic frequency of the visual stimulus and some of its harmonics, are sometimes accompanied with a sub-harmonic. Therefore, SSVEP-based BCI systems understand the user commands when he/she looks at one stimulus by identifying the corresponding frequency components in the EEG(H. Wang et al., 2016).

Different approaches have been introduced in the literature to estimate SSVEP responses for BCI applications(Liu, Chen, Ai, & Xie, 2014). A conventional method is the power spectral density analysis (PSDA)(Wei, Xiao, & Lu, 2011). However, when using this algorithm, the length of processing time window has to be typically more than 3 s to have acceptable frequency resolution, resulting in low information transfer rate(Ming, Xiaorong, Shangkai, & Dingfeng, 2002).

Canonical correlation analysis (CCA)(Lin, Zhang, Wu, & Gao, 2007) is a method for exploring the relationships between two multivariate sets of vectors. One of these variables is the EEG signal from various channels and the other is the artificial sine-cosine signal. Researchers have demonstrated that CCA usually outperforms PSD analysis (R. Wang et al., 2014). Moreover, high accuracy BCI systems could be developed using CCA in which the required data frame is as short as 2 s (Yu Zhang, Jin, Qing, Wang, & Wang, 2012).

Zhang *et al.*(Yu Zhang et al., 2011a) proposed a multi-way development of standard CCA (MCCA) by inspecting the correlation between various variables including space and trial modes of multidimensional EEG data and sine-cosine signals (H. Wang et al., 2016). MCCA and its L1-regularized development(L1MCCA)(Yu Zhang et al., 2013) have been introduced to supply refined SSVEP recognition fulfillment in comparison with standard CCA (H. Wang et al., 2016).

Least absolute shrinkage and selection operator (LASSO) algorithm (Yu Zhang et al., 2012) is another method proposed in the literature for computing the contribution of different stimulus frequencies and their harmonics in the recorded EEG signal. The frequency with maximum contribution degree was identified as the goal frequency. LASSO algorithm has been shown to improve frequency identification performance with a shorter time window compared with CCA algorithm (Liu et al., 2014).

Zhang *et al*. introduced a multi-set canonical correlation analysis method (MsetCCA) (Yangsong Zhang et al., 2014) for frequency identification in SSVEP. In this method, training information was used for reference signals (Yangsong Zhang et al., 2014). MsetCCA approach has better accuracy than CCA and MCCA methods when using time windows shorter than 2 s(Yangsong Zhang et al., 2014).

Zhang *et al*. considered that a set of EEG signals would share certain common components in response to a specified stimulus on different subjects. These EEG signals contain common components which may contain characteristics of SSVEP responses. Therefore, these components could be further efficient reference data for SSVEP identification in using correlation methods, so they proposed a common feature analyzes (CFA) method (Yu Zhang, Zhou, Jin, Wang, & Cichocki, 2015). It outperformed SSVEP identification accuracy compared with those of the CCA and the MCCA methods when a time window of 0.5 was (Yu Zhang et al., 2015).

Another approach that has been recently proposed for distinguishing features of SSVEP is multivariate linear regression (MLR) (H. Wang et al., 2016). This algorithm outperformed CCA, and MCCA algorithms, and especially provided higher classification accuracies when using a short time window of 1 s(H. Wang et al., 2016). The above-mentioned methods and their properties are listed in Table 1.

Table 1 about here

With the advancement in BCI research, BCI systems are coming out of the lab for practical applications. In addition to high accuracy and information transfer rate, user comfort in is critical. It must be met at least in a level that a potential user accepts and continues to work with the system(Qing, Zheng, Yue, Yuankui, & Ge, 2015).

One of the significant factors to ensure the user comfort is that the BCI system works with only a few EEG electrodes. A large number of electrodes increases the preparation time beyond the level acceptable for practical use and increases the size and final cost of the system. On the other hand, achieving high enough accuracy and information transfer rate with a minimum number of electrodes is challenging due to the reduction of information that is available from them. As shown in Table 1, most of the studies that proposed and compared algorithms for SSVEP detection are performed using a large number of EEG channels.

The goal of this study was to ascertain which of the newly proposed algorithms reviewed above is more appropriate for the development of a practical SSVEP-based BCI system with high accuracy and information transfer rate when using a minimum number of electrodes. Here CCA(Lin et al., 2007), LASSO(Yu Zhang et al., 2012), L1MCCA(Yu Zhang et al., 2013), MsetCCA(Yangsong Zhang et al., 2014), CFA(Yu Zhang et al., 2015) and MLR(H. Wang et al., 2016) methods are compared using proper statistical methods to determine their performance in real applications.

The rest of the paper is organized as follows: in the next section, information about the experimental protocol and the BCI methods used in this study as well as the statistical methods are presented. Section 3 supplies the results of the performance assessment. Ultimately, the discussion is provided in Section 4.

2. Materials and Methods

Numerous methods have been proposed for SSVEP frequency recognition in the literature. Among which, LASSO(Yu Zhang et al., 2012), L1MCCA(Yu Zhang et al., 2013), MsetCCA(YU Zhang et al., 2014), CFA(Yu Zhang et al., 2015), MLR(H. Wang et al., 2016), have been shown better performances and therefore were selected for this study. Also CCA method is a benchmark method and therefore were selected for this study. These algorithms are described as follows:

SSVEP detection based on CCA

CCA is a multivariate statistical method to explore the underlying correlation between two sets of data. The first set (X) is the EEG recorded from several channels while the second one (Y) is the sine-cosine reference signals reconstructed as below:

$$Y = \begin{bmatrix} \sin(2\pi(f_i)t) \\ \cos(2\pi(f_i)t) \\ \cdot \\ \cdot \\ \cdot \\ \sin(2\pi(Nf_i)t) \\ \cos(2\pi(Nf_i)t) \end{bmatrix}; t = \frac{1}{F_S}, \frac{2}{F_S}, \ldots, \frac{n}{F_S} \quad (1)$$

where N demonstrates the number of harmonics, f_i denotes the ith stimulus frequency (fundamental frequency), n represents the number of sampling points, and F_S is the sampling rate.

CCA tries to seek a pair of linear transforms, W_x and W_y that maximize the correlation between $x = X^T W_x$ and $y = Y^T W_y$. The following optimization problem is solved for each frequency (Yu Zhang et al., 2011a).

$$\rho_i = \max_{W_x, W_y} \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}} = \frac{{W_x}^T X Y^T W_y}{\sqrt{{W_x}^T X X^T W_x Y^T W_y Y^T W_y}} \tag{2}$$

where ρ_i is the association between the recorded signals and the synthetic waveform of the ith frequency. The frequency, with the maximum correlation coefficient, is selected as the target frequency(Lin et al., 2007).

SSVEP detection based on LASSO

In the Least absolute shrinkage and selection operator (LASSO) algorithm, each EEG trial assumes that SSVEPs are standard linear regression models (Eq. 1) for the response $y \in R^n$.

$$y = X\beta + \varepsilon \tag{3}$$

Where $X = (x_1, x_2, \ldots, x_p)$ denote the predictor variables, y is the response and ε represents a noise vector. LASSO approximation is given by:

$$\hat{\beta} = \arg\min_{\beta}(\|y - X\beta\|_2^2 + \lambda\|\beta\|_1) \tag{4}$$

Where $||\cdot||_1$, $||\cdot||_2$ demonstrate the l_1-norm and l_2-norm respectively(Tibshirani, 2011) and λ is a penalty parameter. The optimization problem demonstrated by Eq. (2) was resolved by quadratic programming(Schittkowski, 1986).

To create the model of SSVEP identification, a symmetric square-wave signal X, corresponding to the stimulus frequencies, is considered as reference signal shown in Eq. (3).

$$X = \begin{bmatrix} \sin(2\pi(f_i)t) \\ \cos(2\pi(f_i)t) \\ \cdot \\ \cdot \\ \cdot \\ \sin(2\pi(Nf_i)t) \\ \cos(2\pi(Nf_i)t) \end{bmatrix}; t = \frac{1}{F_S}, \frac{2}{F_S}, \dots, \frac{n}{F_S} \tag{5}$$

Where N demonstrates the number of harmonics, f_i denotes the i^th^ stimulus frequency (fundamental frequency), n represents the number of sampling points, and F_S is the sampling rate.

The LASSO estimator $\hat{\beta}$ among the EEG signals y and the artificial reference set X were calculated from Eq. (2).

Then the contribution degree of each stimulus frequency is calculated for all the recorded channel of EEG as:

$$CD_i = \frac{\sum_{k=1}^{M} \sum_{j=1}^{2K} \left| \beta_{i,j}^{k} \right|}{M} \tag{6}$$

where M is the number of channels, K denotes the number of harmonics and CD_i denotes the contribution degree of the i^{th} square-wave in the signal. The maximum contribution implies the target frequency which subject has been gazing at (Yu Zhang et al., 2012).

SSVEP detection based on L1MCCA

L1-regularization (L1-MCCA) was proposed in the literature to give a function which can select features automatically for optimizing reference data in SSVEP-BCI detection(Yu Zhang et al., 2017).

To construct the SSVEP recognition model, consider a three-way tensor $X \in R^{I\times n\times K}$(channel × time ×experiment) formed by EEG signals recorded from some channels from numerous experiments with a particular stimulus frequency and a signal collection $Y \in R^{2N\times n}$ shown in Eq. (3).

The optimization problem in L1-MCCA is formulated as:

$$w_1, w_3, v = \arg\min_{w_1,w_3,v} \frac{1}{2}\left\|X \times_1 w_1^T \times_3 w_3^T - v^T Y\right\|_2^2 + \lambda_1\|w_1\|_1 + \lambda_2\|v\|_1 + \lambda_3\|w_3\|_1 \quad (7)$$

$$s.t.\ \|w_1\|_2 = \|w_3\|_2 = \|v\|_2 = 1$$

where $w_1 \in R^I, w_3 \in R^K, v \in R^{2N}$ are projection vectors and $\lambda_1, \lambda_2. \lambda_3$ are adjustment parameters. The LASSO estimation is equivalent to (5) (Tibshirani, 2011; Yu Zhang et al., 2012) when any two of w_1, w_3 , and v are constant. This problem would be resolved by an alternating LASSO method (Yu Zhang et al., 2013).

SSVEP detection based on MsetCCA

The multi-set CCA (MsetCCA) method was recently proposed for reference data optimization from a common component in numerous calibration experiments(Nakanishi, Wang, Wang, & Jung, 2015). MsetCCA was extended for correlation maximization among canonical variables from numerous collections of random variates with distinguishing multiple linear transforms (Y. Zhang, G. Zhou, J. Jin, X.

Wang, & A. Cichocki, 2014). Assume numerous groups of random variables $X_i \in R^{I_i \times J}$ $(i = 1,2, \ldots, N)$, in order to maximize of the throughout correlation across canonical variables; the MAXVAR objective function is characterized as:

$$\max_{w_1,\ldots,w_N} \rho = \sum_{i \neq j}^{N} w_i^T C_{ij} w_j \quad (8)$$

$$s.t. \ \frac{1}{N} \sum_{i=1}^{N} w_i^T C_{ii} w_i = 1,$$

where $C_{ij} = X_i X_j^T$ is the between-set covariance matrix, and ρ is the correlation coefficient. The objective function in (6), may be transformed into the eigenvalue problem with the approach of Lagrange multipliers as:

$$(R - S)w = \rho S w \quad (9)$$

where

$$R = \begin{bmatrix} C_{11} & \cdots & C_{1N} \\ \vdots & \ddots & \vdots \\ C_{N1} & \cdots & C_{NN} \end{bmatrix},$$

$$S = \begin{bmatrix} C_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & C_{NN} \end{bmatrix}, \quad w = \begin{bmatrix} w_1 \\ \vdots \\ w_N \end{bmatrix}.$$

Assume $X_{1,m}, X_{2,m}, \ldots, X_{N,m} \in R^{C \times P}$ (C channels × P points) demonstrate EEG signals groups including N experiments at the m-th stimulus frequency f_m. The MsetCCA is performed to distinguish numerous spatial filters $w_{1,m}, w_{2,m},, \ldots, w_{N,m}$ to maximize throughout correlation between the canonical variables $\tilde{z}_{1,m}, \tilde{z}_{2,m}, \ldots, \tilde{z}_{N,m}$ with the linked spatial filtering $\tilde{z}_{i,m} = w_{i,m}^T X_{i,m}$ $(i = 1,2, \ldots, N)$. These canonical variables show the common components between numerous training signals considered to have better accuracy of the real SSVEP specifications in comparison with sine-cosine reference signals. Canonical variables were combined to construct the reference signal optimization at frequency f_m. These optimized reference signal are defined as:

$$Y_m = \left[\tilde{z}_{1,m}{}^T, \tilde{z}_{2,m}{}^T, \dots, \tilde{z}_{N,m}{}^T\right]^T. \tag{10}$$

For each stimulus frequency f_m, the corresponding reference signal Y_m is consumed for computing the maximum correlation coefficients with the EEG signals(Yangsong Zhang et al., 2014).

SSVEP detection based on CFA

Another approach is to explicitly model the common and distinct components. This approach has a similar concept with the multi-set approach (H. Wang et al., 2016) to exploit the common features which multiple EEG signals share at the same stimulus frequency.

In this method, a set of matrices $X = \{ X_k \in X^{I_k \times T}: k = 1,2, \dots, K \}$, share at least one common dimension T. They can be, e.g., a set of multichannel EEG signals (channel × time × point) recorded for the same visual stimulus but from different subjects. These data matrices can be factorized in a linked way shown in Eq. (9):

$$X_k = A_k B_k^T = [\bar{A}_k \ \check{A}_k] \begin{bmatrix} \bar{B}^T \\ \check{B}_k^T \end{bmatrix} = \bar{A}_k \bar{B}^T + \check{A}_k \check{B}_k^T = \bar{X}_k + \check{X}_k \tag{11}$$

$$\forall \ k = 1,2, \dots, K$$

where $\bar{B} \in R^{T \times C}$, $\check{B}_k \in R^{T \times \tilde{R}_k}$, $R_k = \tilde{R}_k +$ C is the number of latent components with $R_k < I_k$ and C is the number of common components, $\bar{A}_k$ and $\check{A}_k$ are the partitions of the mixing coefficients A_k corresponding to $\bar{B}$ and $\check{B}_k$. For M stimulus frequencies, the common features $\bar{B}_k(k =$

$1,2,\ldots,K)$ at each frequency would be exploited for a new test signal $\hat{x} \in X^{R^T}$, the target frequency is identified as(Yu Zhang et al., 2015):

$$f_t = \arg\max_{f_k} \|\hat{x}^T B_k\|_2, \; (k = 1,2,\ldots,K) \tag{12}$$

SSVEP detection based on MLR

MLR is a technique for modeling the relationship between a scalar dependent vector and one or more independent vectors. Consider EEG training data X = $[x_1, x_2, \ldots x_N] \in R^{D\times N}$ where D demonstrates the dimension of feature (D = C channels × P temporal points) and N is the number of signal points. Corresponding to the training points, a matrix of the label is created, using one-of M class coding. The goal of MLR is to find distinguished subspaces by minimizing the objective function as follows:

$$\min_{\mathrm{W},b} \frac{1}{2} \left\| y^{(i)} - \left(\mathrm{W}^T \tilde{x}^{(i)}\right) + b \right\|_2^2 \tag{13}$$

where W = $[w_1, w_2, \ldots w_C] \in R^{S\times C}$ demonstrate the projection matrix and b is the model separation.

The model of MLR is then considered as:

$$W = \arg\min_{W} \frac{1}{2} \sum_{i=1}^{N} \left\| y^{(i)} - \left(W^T \tilde{x}^{(i)}\right) \right\|_2^2 \tag{14}$$

or in the Vectorized form:

$$W = \arg\min_{W} \frac{1}{2} \left\| Y - W^T \tilde{X} \right\|_F^2 \tag{15}$$

where $\|.\|_F$ demonstrate the Frobenius norm. Then, optimal solution is provided by:

$$\mathrm{W} = \left(\tilde{X}\tilde{X}^T\right)^{\dagger} \tilde{X} Y^T \tag{16}$$

Where $(.)^{\dagger}$ demonstrates the Moore Penrose pseudoinverse. The columns of W represent the features of training data. Ultimately, the k-NN (5-NN) classifier is used to classify the sub-space features which exploited via the MLR(H. Wang et al., 2016).

2.1 Data Description

EEG data from an online available dataset (H. Wang et al., 2016) was used in our study. The dataset contained data from ten subjects (all males, aged from 21 to 27 years) and recorded from 8 channels (P7, P3, Pz, P4, P8, O1, Oz and O2). The sampling rate was fixed at 250 Hz. During the experiment, the participants were seated in a comfortable armchair 60 cm away from the center of the monitor. The experiment was performed in a shielded room. The EEG data was then band-pass filtered from 4 to 45 Hz. Four frequencies (6, 8, 9 and 10 Hz) were adopted in a recording session. The subjects were asked to gaze at each stimulus frequency for 4 s. Overall, there are 80 trials in this dataset. This dataset has been widely used in the literature as benchmark (H. Wang et al., 2016; Yu Zhang et al., 2012; Yangsong Zhang et al., 2014; Yu Zhang et al., 2013; Yu Zhang et al., 2015).

2.2 Experimental Evaluation

In this study, the new algorithms including MLR and CFA algorithm are compared with MsetCCA, L1MCCA, LASSO and CCA algorithms to assess their efficacy for target frequency detection in a practical BCI system.

The number of harmonics that are needed to define reference signals was set to 2 for CCA, LASSO and L1MCCA algorithms.

In LASSO and L1MCCA methods, the lambda parameter was set to 0.5 and 0.02(Yu Zhang et al., 2012; Yu Zhang et al., 2013), respectively. The leave one- run-out cross-validation was used to assess the average detection accuracy in the entire analyzed methods. The signals from 19 runs were used as training signals whereas the signals from the left-out run were used for validation (Yangsong Zhang et al., 2014).

2.3 Validation

The performance of the methods was assessed using the F-score (F1 score). It was shown in the literature that this criterion is more suitable than the overall accuracy of multi-class problems (Sokolova & Lapalme, 2009). It is because the later index, overestimate the performance of the analyzed methods. Moreover, by using F-score, it is possible to analyze the performance of the system for each class better than the traditional accuracy measure. For the calculation of F-score, first, the multi-class confusion matrix of four frequency is created. Then, precision, sensitivity, and F-score are calculated for each frequency class as below:

$$\mathrm{Pr} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{15}$$

where Pr is precision and TP and FP are the number of true and false positive predictions for each class.

$$\mathrm{Se} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{16}$$

where Se is sensitivity and FN is the number of false negative predictions for each class.

$$\text{F-score}= \frac{2\times\mathrm{Pr}\times\mathrm{Se}}{\mathrm{Pr+Se}} \tag{17}$$

where F-score is the harmonic mean of the precision and sensitivity (=recall) of the corresponding class. This parameter is not dependent on TN (True negative), and thus the performance of the analyzed system is not overestimated (Marateb, Mansourian, Adibi, & Farina, 2014).

2.4 Statistical methods

It is important to use proper statistical tests for rigorous comparison between different approaches, otherwise random or insignificant differences are considered as substantial (Bossuyt et al., 2015; Karimimehr et al., 2017). The McNemar's test(Webb & Copsey, 2011) was used to identify SSVEP frequency estimation algorithms outperforming the other methods. Pairwise comparisons were performed using the McNemar's test. Then, methods with more significant outperformance were shown as significantly outperforming methods. For further analysis, GEE (Generalized Estimating Equation)(Hardin & Hilbe, 2007) was applied to determine any significant differences between the selected algorithms when different electrode montages (monopolar or bipolar) and the number of channels (one or two channels) were used with repeated measurements in the time windows of one second. The level of statistical significance was considered 0.1 to be more certain not to miss significant differences in this small sample size data(Lavrakas, 2008).

3. Results

The performance of different SSVEP frequency estimation algorithms was compared. Fig. 1 demonstrates the resulted F-scores for time windows of 0.5-4 seconds when all eight channels of recorded EEG were used. MLR method outperformed the other six methods in terms of mean F-score performance for the time windows of 0.5 to 1.5 sec. MsetCCA and CFA methods were ranked second , while the performance of the CFA method was significantly higher than that of MsetCCA method for the time window of 0.5 s (p-value <0.05). Overall, LASSO had the lowest performance compared with the others.

Figure 1 about here

Overall, pairwise McNemar's test on these results demonstrated that MLR, MsetCCA and CFA algorithms significantly outperformed the other analyzed methods in the detection of gazed frequencies using 8 EEG channels (p-value <0.05). In fact, in the entire analysis windows, MLR, MsetCCA and CFA, L1MCCA, CCA and LASSO significantly outperformed 5,3,3,2,1,0 times in pairwise comparisons. Thus, only those three methods were studied in the rest of the paper.

In a practical SSVEP BCI system, when only one channel of EEG is used, the performance of the algorithms might change compared with using more channels. Therefore, the F-score measures of MLR, MsetCCA and CFA algorithms were compared when only one channel of EEG (Oz-Pz channel)(Diez, Mut, Laciar, & Avila, 2010) is used (Figure 2).

Figure 2 about here

For one channel EEG, McNemar's test was implemented to determine significant differences between CFA, MLR and MsetCCA methods in different time windows (see Table 2). In time windows smaller than 2 s, CFA method had better F-score in target frequency recognition than MLR and MsetCCA methods.

Table 2 about here

For a more extensive analysis, the F-score values for MLR, CFA and MsetCCA methods was calculated for a time window of 1 s, when different electrode montages (monopolar or bipolar) and the number of channels (one or two channels) were used (Table 2). The results are based on leave one out cross validation test on all 20 trials of the data. CFA and MLR methods outperformed MsetCCA in the entire scenarios. Moreover, on average, CFA outperformed MLR method.

GEE test was applied to determine any significant differences between these algorithms when different scenarios (Table 3) were used. The result showed that CFA method significantly outperformed the other two algorithms (p-value <0.07). Also, MLR significantly outperformed MsetCCA method (p-value=0.001).

Table 3 about here

The other important factor in the development of an online BCI system is the computational cost of the algorithms. The average running time for 19 runs of algorithms was obtained on a laptop with Windows 8.1 Operating System and 2.6 GHz Intel Core i5 CPU with 2 GB RAM and all of the algorithms were implemented in MATLAB 2014a (Table 4). It should also be stated that the MLR and CFA methods were implemented in the Vectorized form.

Table 4 about here

In the training phase, MLR is the fastest and L1MCCA is the most time-consuming algorithms. However, in applying the tuned algorithm to frequency detection in the test set, CFA provided the fastest computations, while LASSO needed the most computational time.

4. Discussion

In a practical SSVEP-based BCI system, it is important to use accurate frequency detection algorithms when a short time window of only a few EEG channels are used for analysis. In this study, the state-of-the-art algorithms for SSVEP detection, including CCA, LASSO, L1MCCA, MsetCCA, CFA, and MLR were compared on a benchmark database. The results demonstrated higher f-scores for MsetCCA, CFA and MLR methods in comparison with CCA, LASOO and L1MCCA methods for entire time windows when eight channels of EEG are used. These results are in accordance with the results reported by (H. Wang et al., 2016) demonstrating a higher performance for MLR method in comparison with CFA, MCCA and CCA methods. Zhang *et al*. (2014) suggested that MsetCCA provides a higher accuracy in comparison with MCCA and CCA methods. Here it is demonstrated that MsetCCA also outperformed L1MCCA. In another study, Zhang et al. (2015) showed that the CFA method provides higher accuracies than MCCA and CCA methods. Here it is demonstrated that CFA method also provides higher F-scores in comparison with L1MCCA.

Further analysis demonstrated that while MLR method outperforms the other two algorithms when several EEG channels are used for analysis, it is the CFA method that provides the highest f-scores when only one or two EEG channels are used. We also compared the performance of CCA with a set of monopolar signals Oz, and Pz or bipobar (Oz-Pz) with that of the other methods in Fig.2 (namely as CFA, MLR, MsetCCA). The results did not change and CFA and MLR methods still outperformed the other two algorithms for time windows shorter than 1 s.

The results presented in Table 3 can also be examined from another aspect. The 8th row in table 3 represent the f-scores for Oz-Pz EEG channel, while in rows 1-7, the f-scores are provided when an additional bipolar channel was used. In most cases, the MLR method could effectively use additional information provided by the extra channel to improve the f-score of the system. For CFA method, although the f-scores are higher, using an extra EEG channel does not have a consistently positive effect on the f-scores and the same can be observed for MsetCCA method. This capability of the MLR technique can also be observed when comparing the f-scores for Oz montage with Oz, O1 and Oz, O2 montages. Therefore, the MLR method could use information in multi-channel EEG towards providing higher f-scores.

In practical applications of an SSVEP-based BCI system without the help of experts, the proper positioning of the electrodes is also challenging. Therefore, another question is how much the algorithms are robust to correct position of electrodes. The results provided in Table 3 demonstrated that performance of frequency detection algorithms is quite sensitive to the placement of electrode Oz. In fact, changing the position of this electrode to O1 or O2 considerably degrades the f-score of the system. This result can be observed when Oz or Oz-Pz montages were used. Despite this, the results show that CFA method was less sensitive to the placement of Oz electrode compared with other methods. The Comparison of F-score values between monopolar and bipolar montages in Table 3 indicates that Oz-Pz montage has better f-score value than other monopolar montages. This result is in accordance with the result reported by (Diez et al., 2010).

The CFA algorithm also has the lowest computational time which is important for online implementation of a BCI system. Therefore, it is proposed that CFA algorithm may be a proper choice in the development of practical SSVEP-Based BCI systems. In the literature, different methods were only compared with CCA and MCCA methods (Yu Zhang et al., 2012; Yangsong Zhang et al., 2014; Yu Zhang et al., 2013; Yu Zhang et al., 2015). Our study suggests that newly developed algorithms could also be compared with CFA due to its higher performance for short time windows when few number of EEG channels are used.

The limitations of the study are the small dataset, a small number of participants and the limited number of frequencies and therefore it is suggested to test these methods on a large dataset. Moreover, more detailed analysis of sensitivity on the electrode placement can be performed when a large number of electrodes are used.

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Tables/Figure Legends

Table 1: Different methods used for SSVEP recognition in BCI

Table 2: Statistical analysis of the F-score differences between CFA, MLR and MsetCCA methods by using the McNemar test for SSVEP recognition in BCI.

Table 3. F-score values based on MLR, CFA and MsetCCA methods, with a time window of 1 s when different electrode montages (monopolar or bipolar) and the number of channels (one or two channels) was used, the best result is displayed in bold characters.

Table 4.The average computational time (in a sec) of the CCA, LASSO, L1MCCA, MsetCCA, CFA and MLR methods for training and testing phases at time windows of 1 s and 4 s. The best result for the testing phase is displayed in bold.

Figure 1. The F-scores of the frequency recognition based on MLR, CFA, MsetCCA, L1MCCA, CCA and LASSO approaches, with various time windows from 0.5 to 4 s when all eight channels of recorded EEG were used.

Figure 2. F-scores for frequency recognition based on MLR, CFA, MsetCCA, approaches, with various time windows from 0.5 to 4 s when only one channel of EEG (Oz-Pz channel) was used.

Tables and Figures

Table 1

Method	Concept	Training requirement	Reference	number of EEG channels used in the study
PSDA	Significant peaks at the frequencies of the stimuli are detected from Power Spectral Density of the user's EEG signal within a time window	_	(Ming et al., 2002)	2
CCA	A method for exploring the relationship between two multivariate sets of vectors	_	(Lin et al., 2007)	8

MCCA	It uses the optimal reference signals after adjustment, with increased computational time.	yes	(Yu Zhang et al., 2011b)	8
L1MCCA	This method is extension of the CCA for reference signal optimization	yes	(Yu Zhang et al., 2013)	8
LASSO	It assumes that SSVEPs are standard linear regression models of stimulation signals.	_	(Yu Zhang et al., 2012)	3
MsetCCA	An extension of CCA to recognize multiple linear transforms to optimize signal references with EEG signals	yes	(Yangsong Zhang et al., 2014)	8
CFA	A method to exploit the latent common features shared by a set of EEG signals experiments as the improvement reference.	yes	(Yu Zhang et al., 2015)	8
MLR	Multivariate Linear Regression is implemented to exploit the distinguished SSVEP components	yes	(H. Wang et al., 2016)	8

Table 2

time methods	0.5	1	1.5	2	2.5	3	3.5	4	0.5-4
CFA vs. MLR	NS	NS	NS	NS	NS	NS	NS	NS	NS
CFA vs. MsetCCA	CFA	NS	NS	NS	NS	NS	NS	NS	CFA
CFA vs. CCA	CFA	CFA	CFA	CFA	CFA	NS	NS	NS	CFA
MLR vs MsetCCA	NS	NS	NS	NS	NS	NS	NS	NS	MLR
MLR vs. CCA	NS	NS	NS	MLR	MLR	MLR	MLR	MLR	MLR
MsetCCA vs. CCA	NS	NS	NS	NS	NS	NS	NS	MsetCCA	MsetCCA

NS: There is not a significant difference.

Table 3

Number	Channel	MsetCCA	CFA	MLR
1	Oz-Pz,O1-P7	0.82	**0.97**	0.82
2	Oz-Pz,O1-P8	0.73	0.88	**0.9**
3	Oz-Pz,O2-P8	0.88	**0.97**	0.93
4	Oz-Pz,O2-P7	0.76	**0.98**	0.88
5	Oz-Pz,O1-Pz	0.84	0.85	**0.92**
6	Oz-Pz,O2-Pz	0.79	0.85	**0.89**
7	Oz-Pz,O1-Oz	0.84	**0.97**	0.92
8	Oz-Pz	0.81	**0.92**	0.84
9	O1-Pz	0.35	0.65	**0.69**
10	O2-Pz	0.45	**0.67**	0.58
11	O1,Oz	0.77	0.84	**0.86**
12	O2,Oz	0.82	0.85	**0.88**
13	O1,O2	0.4	**0.81**	0.78
14	Oz	0.78	**0.88**	0.86
15	O1	0.55	**0.76**	0.66
16	O2	0.56	**0.76**	0.66
Maximum		0.88	**0.98**	0.93

SD		0.173847	0.102337	0.109953
Mean		0.696875	0.850625	0.816875

Table 4

				1Channel		Methods		
TW	Method		LASSO	L1MCCA	CCA	MsetCCA	CFA	MLR
1 s	Train	Mean	--	1.1881	--	0.0296	0.0338	0.0063
		SD	--	0.46853	--	0.00232	0.00036	0.00071
	Test	Mean	0.0082	0.0024	0.0045	0.0037	**0.0018**	0.0026
		SD	0.00115	0.00068	0.00136	0.00073	0.00064	0.00049
4 s	Train	Mean	--	1.5056	--	0.0315	0.0363	0.0097
		SD	--	0.44638	--	0.00256	0.00036	0.00114
	Test	Mean	0.0104	0.0028	0.0048	0.0055	**0.0019**	0.0027
		SD	0.00096	0.00041	0.00131	0.00050	0.00041	0.00040

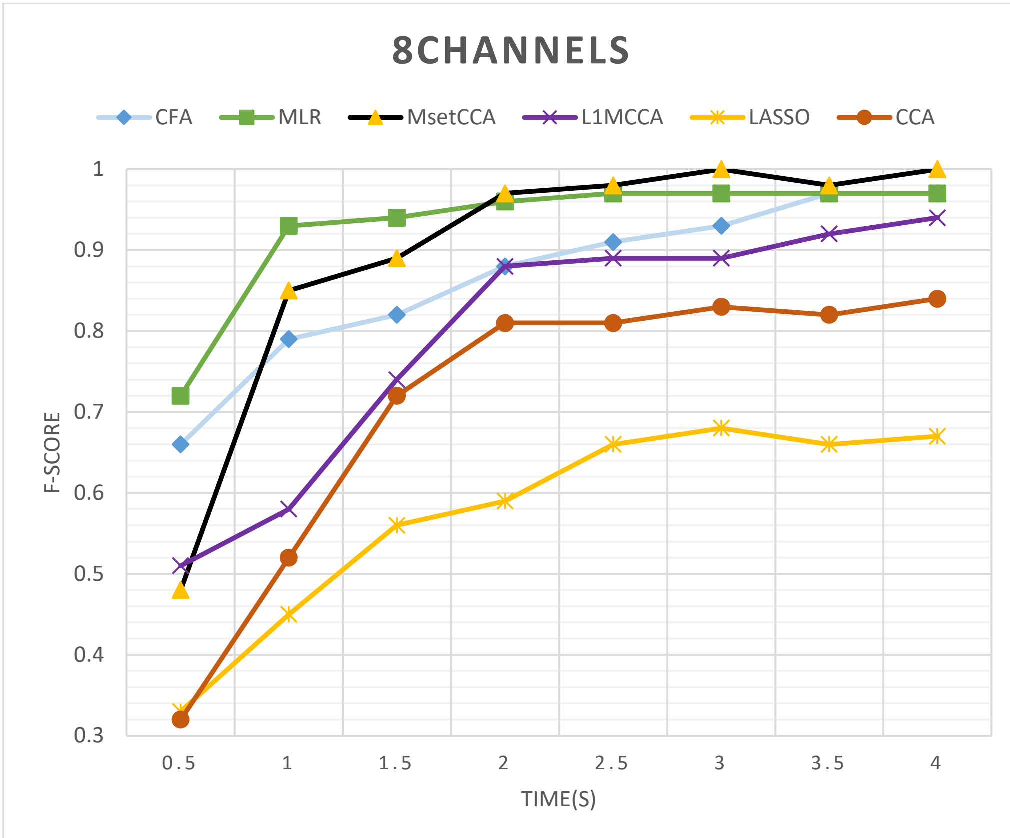
8CHANNELS
CFA
MLR
MsetCCA
L1MCCA
LASSO
CCA
F-SCORE
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.5
1
1.5
2
2.5
3
3.5
4
TIME(S)

Figure 1

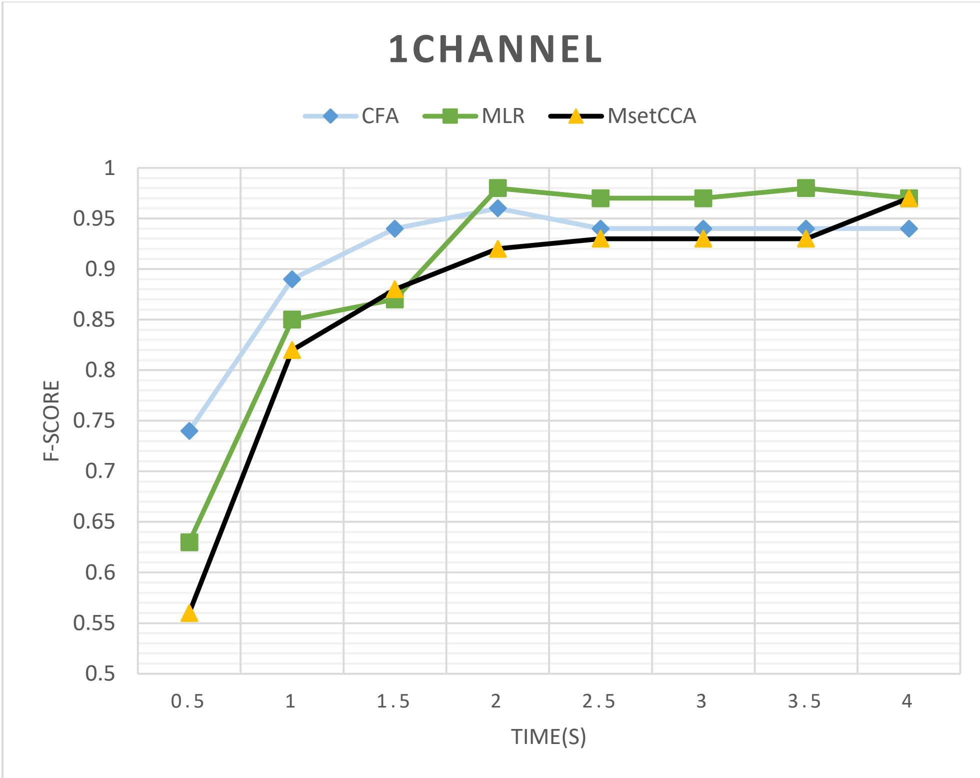
1CHANNEL
CFA
MLR
MsetCCA
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
0.5
F-SCORE
0.5
1
1.5
2
2.5
3
3.5
4
TIME(S)

Figure 2