Adaptive filters based efficient EEG classification for steady state visually evoked potential based BCI system

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ABSTRACT

Brain-computer interfaces (BCIs) system is a link to generate a communication between disable people and physical devices. Thus, steady state visually evoked potential (SSVEP) is analysed to improve performance efficiency of BCIs system using multi-class classification process. Thus, an adaptive filtering-based component analysis (AFCA) method is adopted to examine SSVEP from multiple-channel electroencephalography (EEG) signals for BCIs system efficiency enhancement. Further, flickering at varied frequencies is used in a visual stimulation process to examine user intentions and brain responses. A detailed solution for optimization problem and efficient feature extraction is also presented. Here, a large SSVEP dataset is utilized which contains 256 channel EEG data. Experimental results are evaluated in terms of classification accuracy and information transfer rate to measure efficiency of proposed SSVEP extraction method against varied traditional SSVEP-based BCIs. The average information transfer rate (ITR) results are 308.23 bits per minute and classification accuracy is 93.48% using proposed AFCA method. Thus, proposed AFCA method shows decent performance in comparison with state-of-art-SSVEP extraction methods.

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1. INTRODUCTION

Brain-computer interfaces (BCIs) system is a trending technological development, which provide immense power and strength to different medical applications such as neurophysiology, clinical neuroscience and computational neurology. Thus, BCIs system is a reliable and promising approach, which ensure widespread beneficial advancements in medical fields. Furthermore, BCIs system is utilized to generate a reliable and efficient link between computer device and user. This system is immensely beneficial for disable people, which works as an interface to communicate with the disabled person via some physical devices like electric wheelchairs, spellers and robot arms. This system utilizes electroencephalogram (EEG) signals to control activities and actions of brain in the disabled person [1]. Another application of this system is the nervous system break down in some patients. In case of patients with broken nervous system, the steering instructions are transmitted by the brain to the muscles or body organs. However, due to the failure of nervous systems in those patients, the transmitted instructions could not reach at their specified muscles or body organ. Therefore, BCIs is required to control the brain instructions and actions of those patients and set up a communication channel to link human brain with physical devices like electric wheelchairs.

The key focus of BCIs system utilization is to enhance self-care capacity of patients so that an exceptional communication medium is provided to these patients, especially in some conditions like patients with nervous system failure. The brain activities and actions can be evaluated using varied signal acquisition modalities. However, electroencephalography (EEG) is the most promising and commonly used signal acquisition technique, which can handle brain disorders efficiently. Further, EEG based approach has various qualities like non-invasiveness nature, high resolution, less expensive and easy signal acquisition process. Specifically, EEG is known as a common recording method with clinical experience. Furthermore, EEG is mainly used for controlling brain responses and quantifying user intentions. Moreover, different electrodes are present at the at scalp surface or inside the brain and EEG is utilized to acquire instructions from these brain electrodes. Brain cells provide electrical signal, which are present in different areas of brain or scalp surface [2]. These EEG signals help computer devices to recognize user instructions. Furthermore, varied multiple kind of EEG-based techniques are available with regards to brain-computer communication which are mainly focused on acquisition of brain signals and functioning of brain responses like sensorimotor rhythms [3]-[8], visual evoked potentials [9], motor imagery (MI) [10] and event-related potentials (ERPs) [11] and so on. Here, visual evoked potential (VEPs) are expressed as the brain response modulation, which take place due to visual stimuli in the cortex area. VEPs are mainly divided into two categories as transitional visual evoked potentials (TVEP) and steady state visually evoked potential (SSVEP). Further, SSVEP approach requires lesser training samples and provide higher information transfer rate (ITR) with higher communication speed. Further, SSVEPs are the brain activities, which enables user to select between different instructions. These brain activities are generated from occipital-parietal areas and brain occipital using visual stimulation process at a specified frequency. Furthermore, SSVEPs are an essential VEP stimulate using repetitive light stimulation. The essential and valuable patterns are generated using visual stimulus. Here, BCI system works on the principle that the frequency of evoked patterns or potentials remains similar to the flicker frequency of visual stimuli. As a result, every instruction has their own frequency so that operator can send the desired instruction by focusing at each visual stimuli. Thus, user instructions are recognised and analysed using SSVEP signals.

A spatio-spectral feature fusion architecture is introduced for the application of BCIs to acquire SSVEP signals [12]. Here, EEG classification is performed based on the correlated component analysis (CORRCA) and two type of reference signals are acquired from the training trails. Thus, weighted coefficients are obtained to fuse target stimulus frequency. Zhao *et al.* [13], convolutional neural network (CNN) architecture is presented to classify SSVEP signals for controlling of BCI applications. Further, filter-based CNN is adopted to optimize SSVEP classification. Here, filters are utilized to acquire and separate signal components and acquired data is converted into frequency domain. Here, obtained harmonic features are used to generate accurate response. Ding *et al.* [14], convolutional neural network is presented for the classification of state visually evoked potentials (SSVEP) base on the time-domain signals [15], [16]. Here, a filter bank tCNN is utilized to enhance performance efficiency. The filter bank tCNN is compared against varied SSVEP acquisition techniques like canonical correlation analysis (CCA). A spatial filter design is introduced to handle application of SSVEP-based BCIs. Here, linear generative signal model is also adopted to maximize likelihood estimation of SSVEP signals [17]-[19]. A considerable improvement is obtained in terms of signal-to-noise ratio. An event-related potentials are detected based on spatio-temporal equalization and performance of ERP signals are enhanced based on EEG multichannel information [20]-[22], [24]. Multivariate autoregressive (MVAR) model is introduced to evaluate spatio-temporal correlation [24].

However, acquisition of accurate SSVEP signals to enhance efficiency of BCI system is quite challenging. Therefore, in this article, precise acquisition of SSVEP signals are performed based on the visual stimulation process for the application of BCI system. Here, proposed SSVEP based BCI system is utilized to setup a link between operator and a physical device. Here, brain responses are acquired to analyse user intentions and ERPs evoked with the help of visual stimuli. Furthermore, an adaptive filtering-based component analysis (AFCA) method is utilized to improve SSVEP acquisition efficiency. The proposed adaptive filtering method is used to improve signal-to-noise ratio (SNR) of SSVEP signals by removing EEG background activities. Here, adaptive filters are adopted to acquire correlated visually evoked components for each flicker at a specified frequency. Large number of training data is present and computational complexity is reduced by efficient training. Experimental results are evaluated in terms of normalized mean square error (MSE), SNR and ITR. This article is arranged in the following style. Section 2 discusses about the mathematical representation of proposed SSVEP based BCI system for the acquisition of SSVEP signals. Section 3 discusses regarding simulation results and their comparison with classical BCI based approaches and section 4 concludes the article.

2. MODELLING OF PROPOSED SSVEP BASE BRAIN-COMPUTER INTERFACES

This section discusses about the mathematical representation of visual stimulation process to acquire SSVEP signals for controlling BCIs system. Furthermore, this study is focused on the identification of SSVEP signals to improve the efficiency of BCIs system based on flickering in visual stimulation process. The proposed AFCA method is utilized to enhance signal-to-noise ratio and improves reproducibility of SSVEP signals. Here, performance is improved by eliminating background EEG events. However, acquisition of SSVEP signals is a quite challenging task. Here, proposed adaptive filters are used to extract high quality features based on the discrete information standardization with multiple frequency stimulation. Therefore, a detailed mathematical modelling of SSVEP signal acquisition and performance improvement is presented based on the flickering at a specific frequency in a visual stimulus process.

Here, target detection for visual stimulation is done based on the the discrete information standardization using proposed AFCA method. The discrete information standardization for $\mathrm{l}-\mathrm{th}$ visual stimulus trial is expressed in form of a tensor with four power coefficients and test data for a singular trial is given in form of a tensor with two power coefficients. Thus, four power coefficients considering $\mathrm{l}-\mathrm{th}$ visual stimulus trial is given by (1) and (2).

$$\aleph = (\aleph)_{\mathrm{lmik}} \in \mathbb{G}^{\mathrm{L_t \times L_d \times L_j \times L_u}} \tag{1}$$

Then, test data with two power coefficients are given by,

$$\partial \in \mathbb{G}^{\mathrm{L_d \times L_j}} \tag{2}$$

where visual stimuli index are denoted as l and channel index are given by m. Further, the number of visual stimuli used are indicated by $\mathrm{L_t}$ and total available channels are indicated by $\mathrm{L_d}$ and index of sample values are expressed by i. Here, total number of sample values in every trial are given by $\mathrm{L_j}$ whereas total number of training events are indicated by $\mathrm{L_u}$ and training trial index is given by k. Here, an input Y is considered for efficient target detection using visual stimuli and this input is given to one of the classes $\mathrm{B_l}$ of visual stimuli $\mathrm{L_t}$ and the assigned frequency with respect to the class $\mathrm{B_l}$ is given by (3).

$$\mathrm{t_l} = \{\mathrm{t_1, t_2, \dots \dots, t_{L_t}}\} \tag{3}$$

The proposed AFCA method is utilized to break down SSVEP components into varied sub-bands components. The decomposition of SSVEP components into sub-band components take place to acquire proficient valuable information available in the harmonic components. The efficiency of target detection is enhanced using optimized features in a SSVEP based BCIs system. Furthermore, target detection is achieved using proposed AFCA method by generating features related to correlation in a $\mathrm{n}-\mathrm{th}$ sub-band for a $\mathrm{l}-\mathrm{th}$ visual stimuli and represented by (4).

$$\mathrm{A_l^{(n)}} = \mathrm{t}(\aleph^{\mathrm{n}}, \mathrm{Y^n}) \tag{4}$$

Then, feature weights are evaluated by joining the correlation coefficients obtained from all the components of different sub-bands. Then, square of combined correlation coefficients are computed and finally weighted sum of obtained correlation coefficients after squaring are expressed by (5).

$$\Omega_{\mathrm{l}} = \sum_{\mathrm{n=1}}^{\mathrm{L_n}} \mathrm{e(n)}.\left(\mathrm{A_l}^{(\mathrm{n})}\right)^2 \tag{5}$$

Where $\mathrm{L_n}$ shows quantity of total sub-bands and target class $\mathrm{B_\varphi}$ is evaluated using (6).

$$\varphi = \arg\max_{\mathrm{l}} \Omega_{\mathrm{l}} \ , \mathrm{l} = 1,2, \dots \dots, \mathrm{L_t} \tag{6}$$

Here, the accuracy of proposed AFCA method is improved by using an efficient feature extraction function $\mathrm{t}(\cdot)$ to identify target from visual stimuli. Here, event components are acquired efficiently using proposed AFCA method by exploiting the reproducibility for a certain time period. Further, two type of base signals are considered in which one is named as correlated visually evoked components and uncorrelated visually evoked components. Here, correlated visually evoked components are denoted as $(\mathrm{j(u)} \in \mathbb{G})$ whereas uncorrelated visually evoked components are indicated as $(\mathrm{l(u)} \in \mathbb{G})$. Furthermore, a linear productive representation of available EEG signals $\mathrm{y(u)} \in \mathbb{G}^{\mathrm{L_d}}$ in a multi-channel dimension is expressed by (7).

$$y_m(u) = e_{1,m}j(u) + e_{2,m}l(u), m = 1,2, \dots \dots, L_d \tag{7}$$

Where channel index is indicated by m and the base signals are projected to the multi-channel EEG signals using channel coefficients $e_{1,m}$ and $e_{2,m}$. Here, reconstruction of correlated visually evoked components from a linear summation of detected multi-channel EEG signals is quite challenging and problem while recovering of correlated visually evoked components $j(u)$ are given by (8) and (9).

$$C(u) = \sum_{m=1}^{L_d} v_m\, y_m(u) \tag{8}$$

$$C(u) = \sum_{m=1}^{L_d} \left(v_m e_{1,m} j(u) + v_m e_{2,m} l(u)\right) \tag{9}$$

This problem can be sorted by assigning $\sum_{m=1}^{L_d}(v_m e_{1,m}) = 1$ and $\sum_{m=1}^{L_d}(v_m e_{2,m}) = 0$ so that we get a linear solution as $C(u) = j(u)$ and this solution is obtained using maximization of inter-event correlation. Here, the multi-channel EEG signal and predicted correlated visually evoked components $j(u)$ are expressed as $y^{(k)}(u)$ and $C^{(k)}(u)$ considering $k - th$ event where parameter k is given by $k = 1,2, \dots \dots, L_u$. Further, the fixed interval of predicted correlated visually evoked components are given by $u \in [u_k, u_k + U]$. The time period of every event is given by U and correlation between two events such as $k_1 - th$ and $k_2 - th$ of predicted correlated visually evoked components $C(u)$ are given by (10) and (11).

$$D_{l_1 l_2} = \mathrm{Corr}\left(C^{(l_1)}(u), C^{(l_2)}(u)\right) \tag{10}$$

$$D_{l_1 l_2} = \sum_{m_1,m_2=1}^{L_d} v_{m_1} v_{m_2}\, \mathrm{Corr}\left({y_{m_1}}^{(l_1)}(u), {y_{m_2}}^{(l_2)}(u)\right) \tag{11}$$

Moreover, all likely event combinations are represented by (12) and (13).

$$\sum_{\substack{k_1,k_2=1 \\ k_1 \neq k_2}}^{L_u} D_{h_1 h_2} = \sum_{\substack{k_1,k_2=1 \\ k_1 \neq k_2}}^{L_u} \sum_{m_1,m_2=1}^{L_d} v_{m_1} v_{m_2} \mathrm{Corr}\left({y_{m_1}}^{(l_1)}(u), {y_{m_2}}^{(l_2)}(u)\right) \tag{12}$$

$$\sum_{\substack{k_1,k_2=1 \\ k_1 \neq k_2}}^{L_u} D_{h_1 h_2} = V^U J V \tag{13}$$

Where J is indicated as the matrix and represented by (14)-(17).

$$J = \left(\mathbb{Z}_{m_1 m_2}\right)_{1 \le m_1, m_2 \le L_D} \tag{14}$$

$$\mathbb{Z}_{m_1 m_2} = \sum_{\substack{k_1,k_2=1 \\ k_1 \neq k_2}}^{L_u} \mathrm{Corr}\left({y_{m_1}}^{(l_1)}(u), {y_{m_2}}^{(l_2)}(u)\right) \tag{15}$$

$$\mathbb{E}\left(C(u)\right) = \sum_{m_1,m_2=1}^{L_d} v_{m_1} v_{m_2}\, \mathrm{Corr}\left(y_{m_1}(u), y_{m_2}(u)\right) \tag{16}$$

$$\mathbb{E}\left(C(u)\right) = V^U H U \tag{17}$$

Then, the optimization problem is sorted by (18).

$$\hat{V} = \arg\max_{V} (V^U J V).\,(V^U H U)^{-1} \tag{18}$$

Then, the optimization coefficients are acquired in the form of matrix $H^{-1}J$, which consists of Eigen values. Further, Eigen values ψ are acquired in descending order and these Eigen values are represented as the cost function for the respective Eigen vector $\hat{V}$. Thus, these obtained Eigen values shows reproducibility and consistency of correlated visually evoked components among multiple events. In this way, correlated visually evoked components are reconstructed in a SSVEP based BCIs system using proposed AFCA method. Furthermore, the proposed AFCA method improves SSVEP acquisition efficiency by efficiently recovering correlated visually evoked components.

3. RESULT AND DISCUSSION

This section discusses about the simulation results to evaluate reconstruction efficiency of SSVEP signals and performance of SSVEP based BCIs system using proposed adaptive filtering-based component analysis method. Here, performance of proposed AFCA method is carried out in terms of classification accuracy and information transfer rate based on the efficient feature extraction process. Furthermore, adaptive filters are adopted to obtain correlated visually evoked components for each flicker at a specific frequency. The simulation results are obtained using a SSVEP dataset. This dataset is formed by capturing multi-channel EEG signals from 11 different subjects [17]. Total number of 256 channels are present in the EEG signals. Furthermore, EEG signals are acquired at a sampling frequency of 250 Hz. All the 11 subjects participated in this experiment, works for centre for research and technology Hellas (CERTH). Out of those 11 volunteers, number of female participants are 3 and rest of the participants are male. The age group of all the subjects ranges in between 25 to 39 years.

The visual stimuli process is carried out considering five varied frequencies such as 6.66 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz and 12.00 Hz. All the captured EEG signals of the SSVEP dataset are publically available in [17]. The performance of proposed AFCA method is compare against convolutional neural network based SSVEP signal acquisition technique and with their varied models [18] in terms of classification accuracy and information transfer rate [25]. Here, Table 1 demonstrates mean classification accuracy results obtained using proposed AFCA method against CNN based SSVEP acquisition method. Here, the classification accuracy is obtained by conducting 23 trails for every subject from S1 to S11. Further, mean classification accuracy is evaluated for all 11 subjects individually. It is evident from Table 1 results that the classification accuracy is quite higher for all 11 subjects. Here, classification accuracy is improved by 7.81% considering subject S-1 and improvement in classification accuracy is observed as 41.98% for subject S-6 whereas for last subject S-10, the performance improvement is computed as 25.55%. Finally, the overall improvement in classification accuracy is observed as 66.40%. Thus, performance efficiency is massively enhanced using proposed AFCA method. Here, Figures 1 and 2 demonstrates a graphical representation of SSVEP reconstruction performance in terms of ITR in bits per minute. The ITR results are carried out for all 11 subjects. Specifically, mean ITR results are calculated for each subject by averaging ITR for 23 trials. The ITR results are quite higher for most of the subjects, especially in case of S-1, S-3, S-6, S-9, S-10 and S-11. The mean ITR results are observed as 308.23 bpm considering all these subjects. Thus, the proposed AFCA method shows decent results in terms of ITR and classification accuracy.

Moreover, Figure 1 demonstrates a graphical representation of average classification accuracy of all 11 subjects using proposed AFCA method against varied SSVEP acquisition techniques. Those classical SSVEP extraction methods are support vector machines (SVM), K-nearest neighbors (KNN), linear discriminant analysis (LDA), CNN and CNN with leave one subject out (LOSO) [18]. The least performance accuracy is observed using KNN among all models and highest performance accuracy is computed by proposed AFCA method. Table 1 shows the mean classification accuracy from each subject. Figure 2 shows the average classification accuracy comparison against traditional SSVEP extraction techniques. Thus, the proposed AFCA method outperforms all these models in terms of classification accuracy of EEG signals and high reconstruction efficiency of SSVEP signals is achieved than compare to traditional SSVEP extraction techniques.

Table 1. Mean classification accuracy from each subject

Subject ID	CNN (%)	AFCA (%)
S-1	92.75	100
S-2	80.43	83.48
S-3	44.93	97.11
S-4	57.61	90.22
S-5	27.39	92.18
S-6	70.43	100
S-7	61.30	90.44
S-8	28.26	82.61
S-9	96.09	98.27
S-10	78.26	98.27
S-11	95.65	95.66

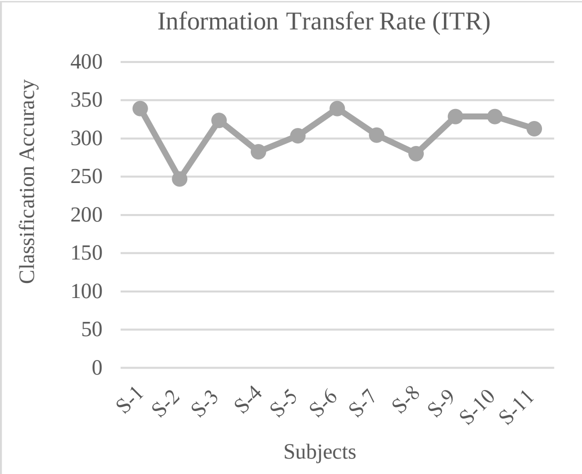

Figure 1. Information transfer rate in bits/min (bpm) for all 11 subjects

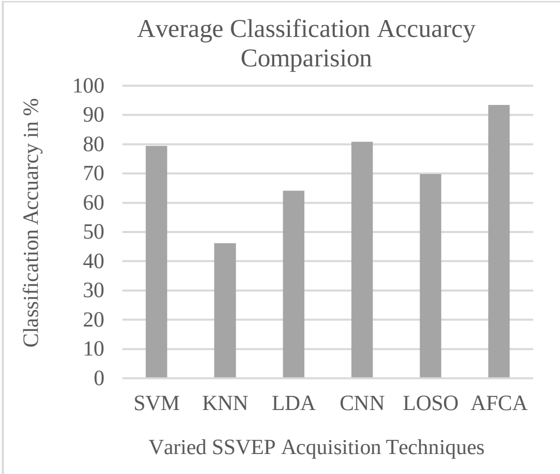

Figure 2. Average classification accuracy comparison against traditional SSVEP extraction techniques

4. CONCLUSION

The significance of efficient SSVEP signal extraction is quite massive in BCIs. Therefore, in this work, AFCA method is introduced for an accurate SSVEP signal extraction based on flickering of visual stimuli at varied frequencies to control BCI system. Further, a detailed mathematical representation for the reconstruction of correlated visually evoked components is presented. Here, proficient and valuable information is acquired from multichannel EEG signals and then efficient feature weights are generated using proposed AFCA method. Finally, solution for optimization problem is presented in form of Eigen vector. In this way, reproducibility and consistency of correlated visually evoked components among multiple events are enhanced. Furthermore, a SSVEP dataset is utilized to evaluate performance of proposed AFCA method in terms of classification accuracy and ITR. The overall improvement in classification accuracy is observed as 66.40% against CNN based SSVEP signal extraction technique. The average ITR results are measured as 308.23 bpm considering all 11 subjects. Thus, the proposed AFCA method outperforms all the traditional SSVEP extraction models in terms of classification accuracy and ITR results.

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