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Impact of adaptive filtering-based component analysis method on steady-state visual evoked potential based brain computer interface systems

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ABSTRACT

The significance of brain computer interface (BCI) systems is immensely high, especially for disabled people and patients with nervous system failure. Therefore, in this study, adaptive filtering-based component analysis (AFCA) model is presented to enhance target box identification efficiency at varied flickering frequencies in a visual stimulation process by efficient acquisition of electroencephalogram (EEG) signals for the application of steady-state visually evoked potential based BCI system. Furthermore, optimization of proposed AFCA model is performed based on the maximized reproducibility of correlated components. A multimedia authoring and management using your eyes and mind (MAMEM) steady-state visual evoked potential (SSVEP) dataset is utilized for efficient training of EEG signals and background entities are eliminated using adaptive filters in a pre-processing stage. Additionally, spatial filtering components are obtained to detect target flickering box based on the obtained quality features. Performance is measured by acquisition of SSVEP signals in terms of reconstruction efficiency, classification accuracy and information transfer rate (ITR) using proposed AFCA model. Mean classification accuracy for all 11 subject is 93.48% and ITR is 308.23 bpm. Further, classification accuracy is relatively higher than various SSVEP classification algorithms.

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1. INTRODUCTION

Recent technological advancements in electronic devices, gadgets, high-tech biomedical machines, medical instruments, wearable devices and signal acquisition techniques have changed the domination of medical and non-medical applications to a next level. Furthermore, due to these developments, neurology is one discipline of medical science, which has gained immense praise in recent years and becomes a hot topic for most of the scholars and research experts. As a result, these advancements in neurological science have unlocked the way for further assessment of the biological signals. Those biological signals are electroencephalogram (EEG) and brainwaves. Further, these signals are massively explored in last few years. The EEG signals are massively utilized in varied medical applications like emotion recognition [1], automatic diagnosis [2], brain computer interface (BCI) systems [3], [4] and biometric authentication [3]. Furthermore, BCI systems has gained immense popularity in previous few years, which works as a link between brain, and computer device to communicate with each other through brain signals [5]. BCI is the most advantageous application of neurological science for disabled people. The prime benefit of adopting BCIs is establishment of communication between physical device and disabled person without using peripheral nerves and muscle tissues. Thus, this system is heavily beneficial for the patients with damaged nervous system, which is mainly dependent on brain, signals to identify targets. Further, BCI systems are used to handle brain activities and actions of user and computer device is used to acknowledge the instructions from users.

Moreover, BCIs are mainly utilized for the disable patients, patients with damaged nervous system and paralyzed patients and brain signals directly communicate to the physical device in these patients rather than transmitting via muscles tissues and organs. Because of massive advantages in BCI systems, the scope of BCIs is extended to the applications such as vigilance estimation [6], emotion recognition [7], in gaming [8] and mental fatigue evaluation [9]. The communication between user and physical devices take place through EEG signals. In BCI systems, firstly, brain signals are extracted, then multiple features are carried out and further, those obtained features are classified to detect user instructions. Here, EEG signals are referred as the electrical events arises inside the brain and acquisition of EEG signals is performed at the brain electrodes of head scalp.

Furthermore, varied kind of numerous brain disorders are handled using EEG. EEG signals are generally utilized for controlling of BCI systems due to their massive advantages like high temporal resolution, portability, inexpensive and ease of use [10]. Moreover, EEG performs far better for human brain signal recognition application in comparison to fingerprints and facial recognition due to liveliness detection capability [11]. Thus, EEG signal extraction is carried out using varied protocols like visual evoked potentials (VEPs), slow cortical potential (SCP), sensorimotor rhythms (SMR), event-related potential (ERP), motor imagery (MI) and using brainwaves [12], [13] and these protocols are actively and repeatedly utilizing due to their high-performance efficiency. However, from all the modalities of EEG signal extraction, VEPs are repeatedly utilize and gained massive attention in recent years by different research communities. Further, VEPs are referred as the brain events available at the brain cortex based on the visual stimulation at a fixed frequency and VEPs are sub-divided into two categories. Here, category one represents transient visual evoked potential (TVEP) and another category is referred to steady-state visual evoked potential (SSVEP). Between these two categories, SSVEP shows comparatively decent performance and higher stability than its counterpart does. The main reason behind the massive success of SSVEP based BCIs is their high signal-to-noise ratio (SNR) and quicker communication rate. Thus, SSVEP based BCIs are obvious choice for extensive research interests in recent time for effective implementation of BCIs system. Further, SSVEP based BCIs generally requires multiple visual stimuli like boxes or LEDs on a screen of a physical device or computer device to handle user instructions and the flickering in visual stimulation process is quite challenging. Thus, numerous research scholars have provided their efforts to control down this issue and analyse the importance of SSVEP-based BCIs system. However, implementation of SSVEP-based BCIs system in practice is quite challenging. There are two observations based on which the efficiency of SSVEP-based BCIs system can be enhanced. First observation is increment in number of classes (Visual stimuli) while feature classification process and refining the efficiency of target detection methods.

Therefore, adaptive filtering-based component analysis (AFCA) model is proposed in this article to improve target detection efficiency by extracting EEG signals efficiently for the application of steady-state visually evoked potential based BCI system. Here, EEG signals are obtained with higher efficiency using SSVEP based modality. Further, a communication channel is created between an operator and a physical or computer device to transmit and receive instructions and feedback in a visual stimulation process in which different boxes are flickered at multiple frequency, respectively. Adaptive filters are utilized to separate correlated visually evoked components and non-correlated visually evoked components. The proposed AFCA model enhances efficiency of BCI systems by removing background activities. The proposed AFCA model enhances classification accuracy of BCI system. Further, user instructions are identified with higher recognition efficiency and few frequencies utilization. Experimental results demonstrate performance efficiency results in terms of classification accuracy and information transfer rate (ITR).

This paper is arranged in the following style. In section 2, the related work with respect to BCI and SSVEP signal acquisition process is discussed with the help of proposed AFCA model. In section 3, mathematical methodology for the effective acquisition of SSVEP signals for the application of BCI system is discussed to transmit large number of instructions at minimum frequency. In section 4 experimental results are discussed and compared against classical SSVEP extraction methods and section 5 concludes the paper.

2. LITERATURE SURVEY

BCI systems has gained huge popularity in recent time due to their multiple advantages like cost effective nature and direct communication to physical device without using peripheral nerves and muscle tissues, which is massively beneficial for the people with nervous system broke down and organ failure. Additionally, BCI systems can be applied in varied medical applications such as for vigilance approximation, emotion detection, gaming and mental fatigue assessment. However, efficient EEG signal acquisition is the main task to get improved performance efficiency and stability of BCI systems. Thus, SSVEP is concluded as one of the most efficient and promising modalities for efficient acquisition of EEG signals. Thus, several researchers have shown their efforts to validate SSVEP based BCI system in terms of performance efficiency.

In [14], a data analytics based mechanism is presented to review steady-state visual evoked potential-based brain–computer interface. Here, visual stimuli process is adopted in which flickering is carried out at multiple frequencies. This technique provides high signal-to-noise ratio using SSVEP detection mechanism. Various challenges present in techniques like pre-processing, spectrum analysis, and signal decomposition are highlighted. In [15], a human recognition method is adopted for acquisition of steady-state auditory evoked potentials (AEPs) using EEG-based signals. Here, biometric potential of AEPs is investigated considering recordings of 40 subjects. Here, subject-unique features are generated with recognition rates up to 96.46% and error rate up to 2-4%. In [16], a feature fusion framework is presented for the application of SSVEP-Based BCIs based on spatio-spectral analysis. Here, short-time SSVEP signals are recognized using correlated component analysis. Here, two reference signals are generated based on spatial correlation coefficients. The weighted coefficients are acquired based on target stimulus frequency. In [17], a SSVEP Classification algorithm is presented based on convolutional neural network (CNN) architecture for the optimization of EEG signals. A filter bank is generated to extract and separate SSVEP signals to improve ITR and classification accuracy. Here, three parallel CNN channels are examined based on correlation among harmonics. In [18], a CNN framework is adopted for the classification of SSVEP based on Frequency-domain features. A time-domain signal is utilized to improve SSVEP performance using canonical correlation analysis model. The classification accuracy is obtained as 88.36%. In [19], a convolutional correlation analysis is introduced to improve performance efficiency of SSVEP-Based Brain-Computer Interface. A deep learning model is used to obtain multiple channel EEGs base on the correlation coefficients. Here, EEGs are joined in varied channels to ensure non-linear operations and improve performance efficiency. In [20], a spatial filter design is presented to improve performance efficiency of SSVEP-based BCIs and to eliminate background noise of brain signals. A linear model is presented maximum likelihood approximation of channel vectors. A dataset of 35 subjects is used to evaluate performance of SSVEP-based BCIs. In [21], a CNNs architecture is adopted for the classification of SSVEP. The performance of SSVEP-based BCIs is evaluated in terms of ITR and classification accuracy. Further, efficient SSVEP features are extracted based on stimulation frequency.

However, differentiation and extraction of correlated visually evoked components and non-correlated visually evoked components is complex process. Moreover, most of the classical SSVEP acquisition methods shows limited classification results, which affects overall performance of BCI system. Therefore, in this article, an AFCA model is presented to improve classification results and avoid performance and frequency related issues of SSVEP based BCI system.

3. MODELLING FOR EFFICIENT SSVEP ACQUISITION FOR BCI IMPLEMENTATION

In this section, a mathematical modeling of proposed AFCA model is presented for efficient acquisition of multi-channel EEG signals for implementation of SSVEP based BCI systems. Here, correlated visually evoked events and uncorrelated visually evoked events are differentiated using adaptive filters to improve performance efficiency of classification process. Here, a box is flickered at multiple frequencies in a visual stimulation process and background noise is eliminated using adaptive filters. Extraction of correlated visually evoked events is a complex and challenging process. Further, minimum bandwidth is utilized to handle multiple user intentions.

A block diagram of SSVEP based BCI system using proposed AFCA model is presented in Figure 1. Moreover, SSVEP based signals are obtained and noise attached to SSVEP signals are reduced in pre-processing stage using adaptive filters. Then, multiple features are generated and efficient classification is carried out on generated feature weights using proposed AFCA model and those classified components are transformed into the instructions, which are input to the physical device. Finally, the output of physical device is fed back to the brain. Further, a BCI system is an essential interface to exchange information between user and a physical device. Here, EEG signals are transformed into desired output. The proposed BCI system contains four main blocks which are signal extraction, signal processing, controlling block, and feedback medium. Further, signal processing consists of pre-processing, feature weight generation and feature weight classification. BCIs system can control brain signals of specific patterns. Further, a detailed mathematical modeling is presented to acquire SSVEP using proposed AFCA model in the following paragraph.

Here, targets flickering box is detected using proposed AFCA model based on the distinct standardization information in a visual stimulation process. Then, for $m-th$ visual stimuli, the distinct standardization information is expressed by a four–power-tensor value. Further, the distinct standardization information for test samples considering a distinct trial is given by a two-power-tensor value by a (1) and (2),

$$\beta = (\beta)_{mnjq} \in \mathbb{E}^{M_l \times M_g \times M_k \times M_z} \tag{1}$$

$$\mathbb{T} \in \mathbb{E}^{M_g \times M_k} \tag{2}$$

where, M_l represents the total number of visual stimuli and index for visual stimuli is indicated by m and total quantity of channels are given by M_g and channel index is expressed by n. Further, sampling point index and total number of sampling points for each trail is indicated by j and M_k, respectively. Total number of training events and index of training events are denoted by M_z and q, repectively. Moreover, to detect target flickering box an input is given as V and this input is given to one of the classes C_m for visual stimuli M_l. The frequency stimulated with respect to the class C_m is given by (3).

$$l_m = \{l_1, l_2, \dots \dots, l_{M_l}\} \tag{3}$$

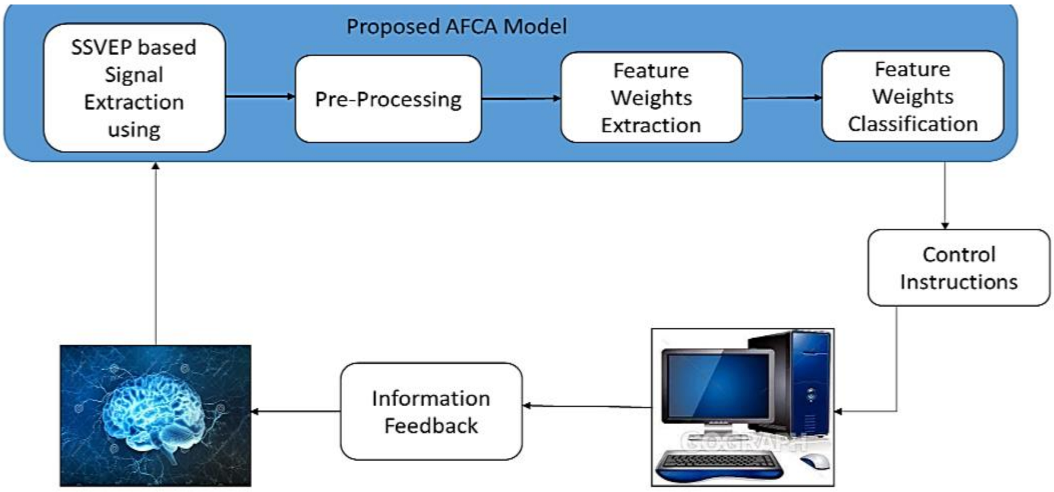

Figure 1. A block diagram of SSVEP based BCIs using proposed AFCA model

Then, the adaptive filters are utilized to split SSVEP signals into sub-bands components and this is to estimate distinct information available in harmonic components. Then, the training and testing data after applying proposed Adaptive Filtering based Component Analysis model to the visual stimulation process is given by $\beta^{(b)} = \mathbb{E}^{M_l \times M_g \times M_k \times M_z}$ and $\mathbb{T}^{(b)} = \mathbb{E}^{M_g \times M_k}$, respectively. Further, correlated features are generated using proposed Adaptive Filtering based Component Analysis model considering $m - th$ visual stimuli and $b - th$ sub-band component by (4).

$$P_m^b = \mathbb{f}(\beta^{(b)}, \mathbb{T}^{(b)}) \tag{4}$$

Then, the optimum feature weights to detect target flickering box are estimated by combining all the values of correlation coefficients which is obtained with respect to all the sub-bands components and then, weighted sum of acquired correlation coefficient's square are computed using (5),

$$\varphi_m = \sum_{b=1}^{M_b} d(b).\left({P_m}^{(b)}\right)^2 \tag{5}$$

where, total quantity of sub-bands components is indicated by M_b and selected class for detection of target is indicated as C_ρ and can be selected using (6),

$$\rho = \arg\max_m \varphi_m \tag{6}$$

where, m belongs to $m = 1,2, \dots \dots, M_{\mathbb{f}}$ and multiple features are evaluated using proposed AFCA model to improve classification accuracy of target detection in visual stimulation process for SSVEP based BCIs.

3.1. Optimization of proposed AFCA model

Here, proposed AFCA model is utilized to estimate SSVEP components in a certain time based on the reproducibility maximization. Then, SSVEP components are decomposed into correlated visually evoked components and uncorrelated visually evoked components. Here, correlated components are indicated as $k(z) \in \mathbb{E}$ and uncorrelated components are denoted as $m(z) \in \mathbb{E}$. Furthermore, multichannel EEG signals are assessed using a linear productive model and EEG signals are indicated as $v(z) = \mathbb{E}^{M_g}$. Further, linear productive model is given by (7),

$$v_n(z) = d_{1,n}k(z) + d_{2,n}m(z) \tag{7}$$

where, channel index is given by $n = 1,2, \dots\dots, M_g$ and coefficients $d_{1,n}$ and $d_{2,n}$ are utilized for the projection of SSVEP components. Then, SSVEP components are reconstructed using linearized summation of multichannel EEG signals $v(z)$ using (8),

$$X(z) = \sum_{n=1}^{M_g} u_n\, v_n(z) \tag{8}$$

further, the (8) is decomposed in (9),

$$X(z) = \sum_{n=1}^{M_g} \left(u_n d_{1,n} j(z) + u_n d_{2,n} j(z)\right) \tag{9}$$

to get a proper solution for reconstruction of SSVEP components, the linearized summation of correlated and uncorrelated visually evoked potentials is kept as $\sum_{n=1}^{M_g}(u_n d_{1,n}) = 1$ and $\sum_{n=1}^{M_g}(u_n d_{2,n}) = 0$ and then the resultant solution is given by $X(z) = k(z)$. Thus, this solution is obtained by using maximum correlation of inter-trials. Then, the observed EEG signals considering $q-th$ trial is denoted by $v^{(q)}(z)$ and predicted correlated visually evoked components considering $q-th$ trial is indicated by $X^{(q)}(z)$ and q belongs to $q = 1,2, \dots\dots, M_z$. The correlated visually evoked components are predicted in the fixed time interval of $z \in [z_q, z_q + Z]$. Every trial is fixed for the duration Z. Further, the correlation of reconstructed visually evoked components between $q_1 - th$ and $q_2 - th$ trials is given by (10) and (11),

$$G_{m_1 m_2} = Corr\left(X^{(m_1)}(z), X^{(m_2)}(z)\right) \tag{10}$$

$$\boldsymbol{G_{m_1 m_2} = \sum_{n_1,n_2=1}^{M_g} u_{n_1} u_{n_2}\, Corr\left({v_{n_1}}^{(m_1)}(z), {v_{n_2}}^{(m_2)}(z)\right)} \tag{11}$$

all probable trail arrangements are given by (12) and (13),

$$\sum_{\substack{q_1,q_2=1\\ q_1\neq q_2}}^{M_z} G_{y_1 y_2} = \sum_{\substack{q_1,q_2=1\\ q_1\neq q_2}}^{M_z} \sum_{n_1,n_2=1}^{M_g} u_{n_1} u_{n_2} Corr\left({v_{n_1}}^{(m_1)}(z), {v_{n_2}}^{(m_2)}(z)\right) \tag{12}$$

$$\sum_{\substack{q_1,q_2=1\\ q_1\neq q_2}}^{M_z} G_{y_1 y_2} = U^Z K U \tag{13}$$

where, K represents a matrix and expressed by (14)-(17),

$$K = \left(\mathbb{K}_{n_1 n_2}\right)_{1 \le n_1, n_2 \le M_G} \tag{14}$$

$$\mathbb{K}_{n_1 n_2} = \sum_{\substack{q_1,q_2=1\\ q_1\neq q_2}}^{M_z} Corr\left({v_{n_1}}^{(m_1)}(z), {v_{n_2}}^{(m_2)}(z)\right) \tag{15}$$

$$\mathbb{W}\big(X(z)\big) = \sum_{b_1,b_2=1}^{M_g} u_{n_1} u_{n_2}\, Corr\left(v_{n_1}(z), v_{n_2}(z)\right) \tag{16}$$

$$\mathbb{W}\big(X(z)\big) = U^Z Y Z \tag{17}$$

then, the solution for optimization problem is presented by (18),

$$\hat{U} = \arg\max_U (U^Z K U).(U^Z \mathrm{Y} Z\,)^{-1} \tag{18}$$

where, the obtained optimization matrix contains coefficients in form of Eigen values where matrix is denoted as $Y^{-1}K$ and Eigen values are indicated as τ and these values are referred as the cost function for their corresponding Eigen vector $\widehat{U}$. Thus, reproducibility of correlated visually evoked components are measured in terms of costs function. Thus, this process is utilized to efficiently reconstruct SSVEP components for the application of BCIs system. Moreover, the proposed AFCA model enhances signal reconstruction efficiency of SSVEP by reconstructing correlated visually evoked components.

Furthermore, the proposed AFCA model is utilized to eliminate background noises from scalp EEG recordings in a SSVEP-based BCIs by using spatial filtering components. Here, proposed AFCA model is employed to exploit spatial filtering components $U_m^{(b)} \in \mathbb{E}^{M_g}$ considering $m-th$ visual stimuli from the distinct standardization information β_m^b. Here, Y evaluated in (17) is acquired in the form of concatenated matrix considering all the trails of training samples β_m^b. The correlation between testing samples and mean training samples is evaluated considering $m-th$ visual stimuli $\bar{\beta}_m^b \in \mathbb{E}^{M_g \times M_k}$ and given by (19),

$$P_m{}^{(b)} = \varphi\left(\left(\bar{\beta}_m^b\right)^{(b)} U_m{}^{(b)}, \left(\mathbb{T}^{(b)}\right)^Z U_m{}^{(b)}\right) \tag{19}$$

where, $\mathbb{T}^{(b)} \in \mathbb{E}^{M_g \times M_k}$ represents test samples of a single trial and $\bar{\beta}_m^b$ represents mean training samples across several trails. Where, function $\varphi(\cdot)$ represents correlation between training samples and testing samples. Further, there are $M_{\mathbb{f}}$ distinct standardization information is obtained with respect to all visual stimuli used in the experiment. Thus, for $M_{\mathbb{f}}$ distinct data, also $M_{\mathbb{f}}$ varied spatial filtering components are obtained. However, all the spatial filtering components consists of some similarity with each other due to similarity between the obtained SSVEP components from EEG recordings. Thus, to ensure high classification accuracy, all these spatial filtering components are combined together by (20),

$$\mathbb{W}^{(b)} = \left[U_1{}^{(b)} U_2{}^{(b)} \dots U_{M_{\mathbb{f}}}{}^{(b)}\right] \tag{20}$$

then, the (19) is rewritten as (21),

$$P_m{}^{(b)} = \varphi\left(\left(\bar{\beta}_m^b\right)^{(b)} \mathbb{W}^{(b)}, \left(\mathbb{T}^{(b)}\right)^Z \mathbb{W}^{(b)}\right) \tag{21}$$

where, function $\varphi(\cdot)$ represents correlation between two samples. At last, optimum features φ_m are acquired by combining all the correlation coefficients with respect to the total sub-band components. Then, target flickering box in a visual stimulation process is detected using (6). In this way, a target flickering box is identified efficiently using proposed AFCA model in a visual stimulation process based on the precise extraction of SSVEP components for the application of BCIs. The proposed AFCA model improves classification accuracy of EEG signals to a great extent.

4. RESULT AND DISCUSSION

In this section, performance is measured by acquisition of SSVEP signals in terms of reconstruction efficiency, classification accuracy and ITR using proposed AFCA model. Here, simulation results are evaluated to enhance efficiency of BCI systems. Further, multiple quality features are obtained using adaptive filters to improve classification accuracy of acquired SSVEP signals. Additionally, spatial filtering components are obtained to detect target flickering box. Besides, a detailed solution for optimization problem is presented using proposed AFCA model. High quality training on large dataset of multichannel EEG signals is adopted to handle BCI system efficiently. Further, SSVEP components are segregating into correlated and uncorrelated visually evoked components. Moreover, combined correlation coefficients provide multiple optimum feature maps based on distinct standardization information. Furthermore, performance results are obtained against varied SSVEP detection techniques in terms of ITR and classification accuracy considering multiple subjects. Background entities are eliminated using adaptive filters in a pre-processing stage. High quality features are evaluated using proposed AFCA model and them; classification accuracy is evaluated based on these features. Finally, efficiency of target flickering box is identified.

4.1. Dataset details

In this section, a large multimedia authoring and management using your eyes and mind (MAMEM) SSVEP dataset is employed to evaluate performance of SSVEP based BCI system using proposed AFCA model. Here, multichannel EEG signals are gathered from 11 subjects. Further, total number of 256 channels are used in EEG signals considering five varied frequencies. Frequencies considered in visual stimulation process are 6.66, 7.50, 8.57, 10.00 and 12.00 Hz. The EEG signals captured at a sampling rate of 250 Hz in a visual stimulation process for controlling BCI system. All the 11 subjects were working staff of Centre for Research and Technology Hellas (CERTH). The number of males and females from out of those 11 volunteer subjects are eight and three, respectively. All the 11 subjects have neither any kind of mental disease nor neurological disorder. In fact, all the 11 subjects are healthy and their age range remains in between 25 to 39 years. These subjects are classified based on the features like thickness and length of hair. These features are characterised by short hair, regular hair and thick hair in which three subjects are categorized by short hair, four subjects are categorized by thick hair and six subjects are categorized by regular hair.

Further, visual stimulation projection is carried out through a 22” LCD monitor and the pixel resolution of LCD monitor is 1680×1080 with a refresh rate of 60 Hz. Further, OpenGL programming is employed in Microsoft Visual Studio 2010 for conduction of visual stimulation process. A Nvidia GeForce GTX 860M graphic card is utilized to make processing of frames faster. These multi-channel EEG data are recorded using EGI 300 Geodesic EEG System (GES 300). Thus, a large dataset of EEG signals is obtained and a high-quality training is performed to examine these signals using proposed AFCA model. Here, high training and testing is performed on matlab 2016 to obtain high performance results. Moreover, configurational specifications of desktop device are 8GB RAM, Intel i5 processor, 1TB Hard disk and 2GB Graphics card in a Windows 10 operating system. Five diverse frequencies, which are employed in, are 6.66 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz and 12.00 Hz with black background display while performing visual stimulation process. For any fixed frequency, target box is flickered for 5 seconds. After finishing of this event, there is a pause of 5 seconds and then, again box flickering process is repeated again for next 5 seconds for another frequency and this process repeats till the last frequency. The SSVEP dataset is publicly available in [21] and consists of multichannel EEG signals.

4.2. Comparative analysis

The performance of proposed AFCA model is carried out in terms of classification accuracy and compared against multiple SSVEP signal reconstruction techniques. Moreover, a cross-validation method is utilized to obtain efficient ITR and classification accuracy results. Further, Table 1 shows performance of classification accuracy using proposed AFCA model in comparison with several SSVEP classification methods such as support vector machines (SVM), linear discriminant analysis (LDA), k-nearest neighbor (K-NN) [22], K-NN, C4.5, CNN [23], and SVM along with canonical correlation analysis (CCA) [24], CNN [25] and SVM [26]. The efficiency of proposed AFCA model is evaluated considering classification accuracy. Table 1 shows performance results in terms of mean classification accuracy for all 11 subject and classification accuracy is relatively higher for proposed AFCA model. The obtained classification accuracy is mean of varied data lengths (0.2-0.6). The improvement of classification accuracy using proposed AFCA model against [24] is 0.38% and against [25] is 26.75%, against [26] is 5.85% and against [27] is 15.63%. Thus, proposed AFCA model outperforms all the SSVEP algorithms in terms of classification accuracy.

Besides, 90% data of SSVEP dataset is considered for efficient training purpose and rest of data is utilized for testing purpose. ITR is evaluated in bits per minute for all 11 subjects. Moreover, ITR is immensely higher for almost each subject considering 23 trials and mean ITR results of all 11 subjects are evaluated as 308.23 bpm as demonstrated in Figure 2. Table 1 shows classification accuracy comparison against several traditional classification techniques. ITR results are shown for all 11 subjects separately. Here, subject-2 gives minimum ITR results as 246.99 whereas subject -6, shows highest ITR performance as 339.26. Expect these two subjects, all the other subject shows moderate performance in terms of ITR. This concludes that the performance efficiency is immensely higher considering ITR.

Further, Table 2 demonstrates classification accuracy comparison against different CNN models [27]. Here, means classification accuracy evaluated using proposed AFCA Model is compared against varied CNN models. Here, each CNN model is different with each other in terms of filter size, layer and drop factor. However, their performance is relatively lower than proposed AFCA Model for all the CNN models. Further, mean classification accuracy is improved by 7.46% and 15.40% against two best CNN models such as Sgdm_0.01_0.2_5_2 and Sgdm_0.01_0.5_5. This shows performance of proposed AFCA Model is quite higher than any CCN model.

Table 3 demonstrates classification accuracy comparison against CNN and least absolute shrinkage and selection operator (LASSO) method considering all 11 subjects separately and their mean accuracy is also compared against proposed AFCA Model. Performance results are obtained for each subject from subject-1 to subject-11 considering 23 trails. The average improvement in classification accuracy is obtained as 12.16% against LASSO method whereas against CNN method, the accuracy improvement is 40.26%. For subject-1, the improvement in classification accuracy is evaluated as 27.67% against LASSO method and 7.81% against CNN method. Similarly, for subject S-6, the enhancement in classification accuracy is observed as 12.32% and 41.98% whereas the enhancement in classification accuracy considering subject S-11 against LASSO and CNN is 7.14% and 1%. It is evident from classification accuracy results that performance accuracy is immensely improved using proposed AFCA model. Thus, proposed AFCA Model outperforms both lasso and CNN methods.

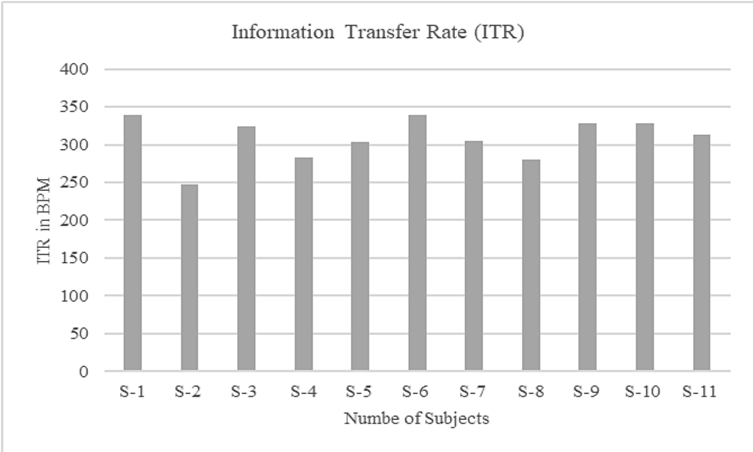

Figure 2. ITR results using proposed AFCA model

Table 1. Classification accuracy comparison against several traditional classification techniques

Classification techniques	Classification accuracy
SVM, LDA, K-NN, [22]	79.47%, 64.11%, 49.40%
K-NN, C4.5, CNN [23]	46.17%, 49.41%, 69.03%
SVM along with CCA [24]	93.11%
CNN [25]	73.74%
SVM [26]	88.3%
CNN+LOSO [27]	69.75%
CNN [27]	80.83%
Proposed AFCA Model	93.48%

Table 2. Classification accuracy comparison against different CNN models

Classification techniques	Classification accuracy
Sgdm_0.01_0.1_5 [27]	79.38%
Sgdm_0.01_0.2_5_2 [27]	86.98%
Adam_0.01_0.001_5 [27]	79.43%
Sgdm_0.01_0.5_5 [27]	80.99%
Sgdm_0.01_0.1_5 [27]	75.00%
Sgdm_0.01_0.2_5_7 [27]	80.16%
Sgdm_0.01_0.5_5 [27]	80.78%
Proposed AFCA Model	93.48%

Table 1. Classification accuracy comparison against CNN and LASSO method considering all 11 subjects separately

Subject ID	CNN (%)	CNN +LASSO (%)	AFCA (%)
S-1	92.75	78.36	100
S-2	80.43	74.97	83.48
S-3	44.93	89.66	97.11
S-4	57.61	86.91	90.22
S-5	27.39	86.50	92.18
S-6	70.43	89.03	100
S-7	61.30	82.91	90.44
S-8	28.26	81.11	82.61
S-9	96.09	79.12	98.27
S-10	78.26	78.82	98.27
S-11	95.65	89.28	95.66
Mean accuracy	66.64	83.33	93.48

Here, Figure 3 shows a graphical representation of performance efficiency obtained using proposed AFCA model against CNN+LASSO model considering all 11 subjects. The performance results in Figure 3 shows much better performance than its counterpart, especially in case of Subject-3, Subject-5 and Subject-8. Mean classification accuracy using proposed AFCA model is 93.48% whereas using CNN+LASSO model is 69.75%. Thus, the mean classification accuracy improvement is 34% against CNN+LASSO model. Furthermore, considering subject-1, the improvement in classification accuracy is evaluated as 3.75% against CNN+LASSO method. Similarly, considering subject S-4, the enhancement in classification accuracy is observed as 33.85%. It is evident from classification accuracy results that performance accuracy is immensely improved using proposed AFCA model. Thus, proposed AFCA Model outperforms CNN+ LASSO model.

Here, Figure 4 demonstrates a graphical representation of classification accuracy acquired using proposed AFCA model against varied SSVEP classification methods such as Adaboost, C4.5 sequential forward selection (SFS), support vector machine with genetic algorithm (SVMG), Long short-term memory network (LSTM), Naïve Bayes, linear discriminant analysis (LDA), k-nearest neighbour (k-NN) SFS [22], [23] considering all 11 subjects. The performance results in Figure 4 shows higher performance than its counterpart, especially in case of Naïve-Bayes, k-neural network (k-NN) SFS and C4.5 SFS. Mean classification accuracy using Adaboost is 66.67, C4.5 SFS is 52.36, SVMG is 65.13, LSTM is 66.89, Naïve Bayes is 35.46, LDA is 58.59 and k-NN SFS is 51.03. Furthermore, improvement in classification accuracy against k-NN SFS is 83.16% and C4.5 SFS is 78.51%. Thus, proposed AFCA Model outperforms all traditional SSVEP classification techniques.

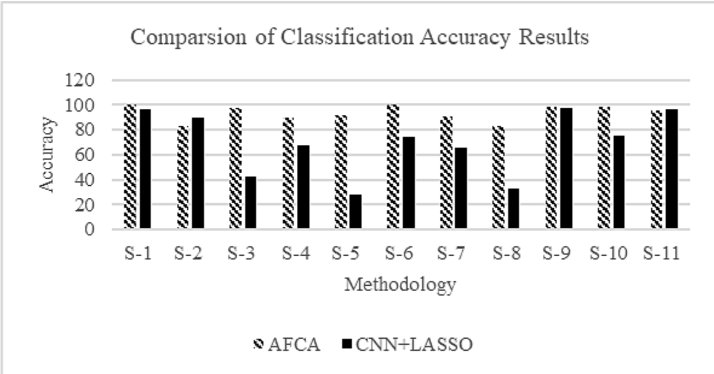

Figure 3. Comparison of classification accuracy obtained using proposed AFCA model against CNN+LASSO model

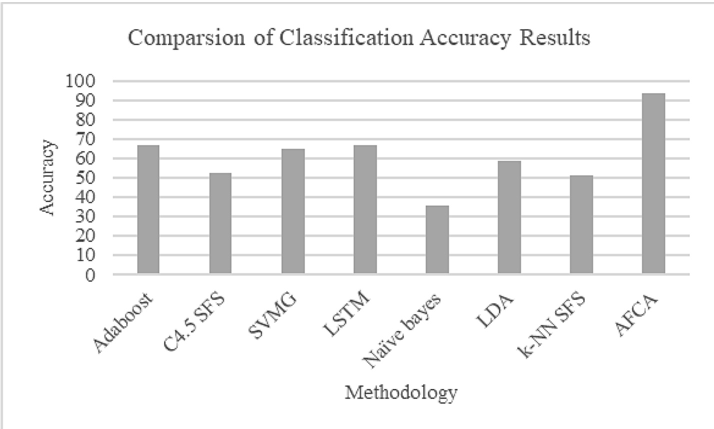

Figure 4. Comparison of classification accuracy obtained using proposed AFCA model against various SSVEP classification methods

Additionally, ITR results are evaluated considering all 11 subjects with respect to varied data length, which ranges from 200 ms to 600 ms. Interval is considered as 100 ms as demonstrated in Figure 5. It is observed from Figure 5 that for data length as 300 ms, the ITR performance is relatively higher with respect to ITR results obtained considering other data lengths.

Furthermore, classification accuracy results are evaluated considering all 23 trials with respect to varied data lengths. This ranges from 200 ms to 600 ms as demonstrated in Figure 6 and with 100ms interval. It is observed from Figure 6 that for data length as 500 ms, the classification accuracy performance is relatively higher for all the trials.

Furthermore, mean classification accuracy results are obtained considering all 11 trials with respect to varied sub-bans. This ranges from 1 to 5 as demonstrated in Figure 7. It is observed from Figure 7 that, the classification accuracy performance is relatively higher when higher number of sub-bans are utilized.

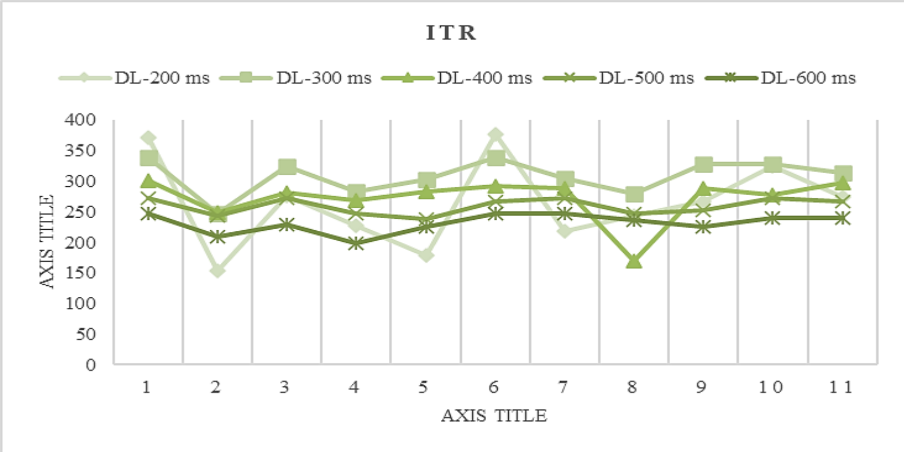

Figure 5. ITRs results across all 11 subjects considering varied data lengths

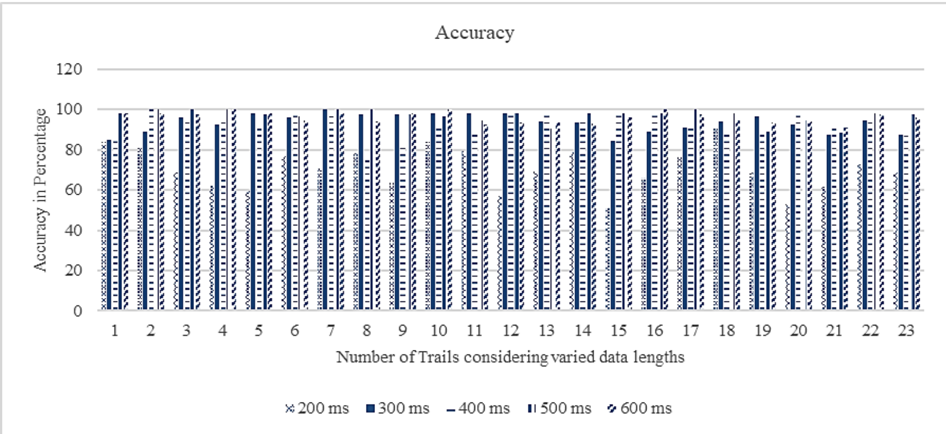

Figure 6. Classification accuracy results across all 23 trials considering varied data lengths

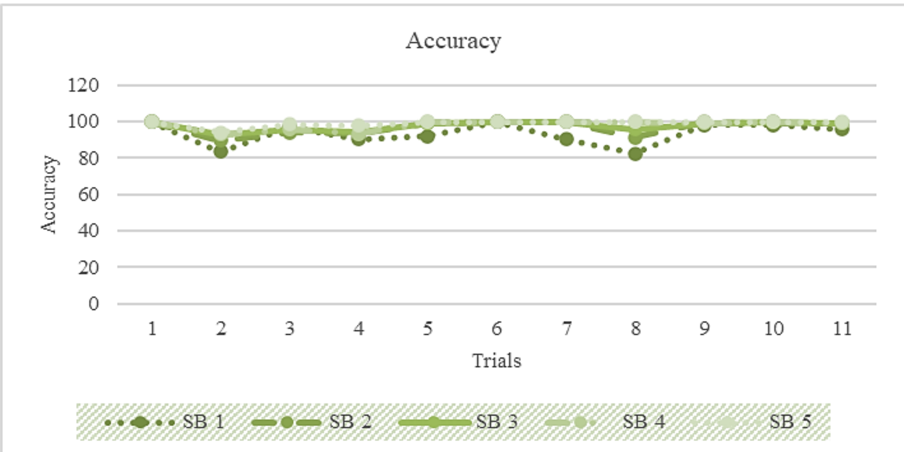

Figure 7. Mean classification accuracy across all 11 subjects for varied sub-bands

5. CONCLUSION

This study provides an assessment of SSVEP-based BCI system based on the obtained reconstructed EEG signals from MAMEM SSVEP dataset. This study provides efficient control on brain-computer-interface using SSVEP signal extraction from brain surface and detection of target flickering box is achieved at varied frequencies using proposed AFCA model. A detailed literature review is carried out on SSVEP based BCI systems and several researchers have mostly focused on classification accuracy enhancement and have tried to study the ITR for controlling BCI systems. Furthermore, a comprehensive mathematical modelling to efficiently extract SSVEP signals and improve classification accuracy. Here, adaptive filters are utilized to eliminate background noises to enhance performance efficiency. A large MAMEM SSVEP dataset is employed to evaluate performance of SSVEP based BCI system using proposed AFCA model for all 11 subjects considering 256 EEG channels. Further, multiple quality features are obtained and simulation results are evaluated based on these extracted features. Experimental results are carried out using proposed AFCA model and compared against varied SSVEP extraction techniques in terms of classification accuracy and ITR. Mean classification accuracy using proposed AFCA model is 93.48%. Further, the mean classification accuracy improvement is observed as 34% against CNN+LASSO model. Thus, proposed AFCA Model outperforms all traditional SSVEP classification techniques.

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