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Analysis of SSVEP component acquisition from EEG signals for efficient target identification

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ABSTRACT

The application of the brain-computer interface (BCI) is massively helpful and advantageous for disabled people. Moreover, BCI is an arrangement of software and hardware interface that provides a direct interaction between the human brain and computer devices. Therefore, in this article, A steady state visual evoked potential (SSVEP)-based BCI system is presented to identify SSVEP components from multi-channel electroencephalogram (EEG) data by minimizing background noise using an adaptive spatial filtering method. Here, the proposed adaptive spatial filtering-based SSVEP component extraction (ASFSCE) model improves reproducibility among multiple trails and identifies targets efficiently by optimizing the Eigenvalue problem. Along with that, the proposed ASFSCE model minimizes computational complexity from $O(G^2)$ to $\mathcal{O}(1)$ to get high target identification accuracy with faster execution. Performance results are measured using the SSVEP dataset. In this dataset, 11 subjects are used to perform experiments and 256-channel EEG data is taken. The efficiency of the proposed ASFSCE model is measured in terms of mean target detection accuracy and mean information transfer rate (ITR) in bits per minute. The average detection accuracy and ITR are evaluated by considering 23 trials for each subject. The obtained detection accuracy is 93.47% and ITR is 308.23 bpm.

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1. INTRODUCTION

Brain-computer interface (BCI) has provided great potential in various applications and recently emerged as one of the best systems to enhance the self-independency of people with severe motor disabilities or for people whose nervous system has stopped functioning properly. BCI is a non-muscular interaction system that is built to establish communication with the outside world using brain activities. This system understands the intentions of a disabled person via directly communicating with his brain. Thus, the BCI system is a communication pathway between a brain and a computer device. This system provides a great medium to connect with people with severe paralysis disease, understands their intentions, and make their life easy by reducing dependency on other people [1]-[4]. BCI system has significant potential and usefulness for disabled people but this system can also assist normal society in many ways, one of the applications is autonomous driving [5]. BCI system is an immensely helpful prospect for disabled people and can be useful in several applications like Electric wheelchairs, spellers, and robot arms [6]-[8]. Thus, the main objective of BCI system utilization is to enhance the quality of life and self-care ability of disabled people through a specific communication gateway in some definite circumstances.

- Furthermore, electroencephalogram (EEG) has gained massive interest from all the research society and experts in the last few decades over BCIs due to their characteristics like non-invasiveness, high temporal resolution, convenience, and cost-reliable.
- EEG is massively important for healthcare applications, biomedical engineering, clinical rehabilitation, and neural engineering. EEG is used in BCI applications for extracting brain events using a brain imaging technique to understand brain intentions and cognitive states by decoding the obtained brain events [9].
- The main objective of adopting EEG in BCI systems is to evaluate neurological conditions in people with neurological disabilities so that brain functions can be analyzed properly.
- Over the last few years, the utilization of EEG signals is heavily used in different applications like sleep monitoring [10], [11], brain-computer interface [12], cognitive research [13], epilepsy diagnosis [14], and other engineering applications. However, acquisition of brain events through EEG is a quite complex and challenging process due to variation, sophistication, and distortion of brain events.

Thus, an understanding of human brain signals or instructions becomes extremely difficult and a proper analysis of different EEG components is quite essential. Moreover, at the time of EEG signal acquisition along with EEG components, there is a strong possibility that background noises are also is added. The reduction of these noise elements from EEG signals is a foremost priority to build an effective BCI system. The components that remain available at the brain scalp are visual evoked potential (VEPs), P-300 event-related potentials, and motor imaginary. Among these components, steady state visual evoked potential (SSVEP) becomes massively popular for varied biomedical applications in associate with BCI systems like dialing a phone call [15], typing [16], and controlling a robotic arm [17] due to their varied capabilities like high communication speed, high information rate, lower variations, lower individual differences, and required less training [18], [19]. SSVEP is referred to as a periodic component inside the EEG signal, which can be generated from the visual cortex area. This visual cortex area remains in synchronization and phase-locked with repetitive visual stimulation.

SSVEPs can be identified while recording EEG inside the occipital area of the brain considering SSVEP-based BCIs so that phase or frequency properties of brain events can be analyzed [20]. The acquisition of SSVEPs-based BCIs can be categorized into two different categories as frequency-related SSVEP-based BCIs and phase-related SSVEP-based BCIs. In the case of a frequency-related SSVEP-based BCI system, target identification is achieved by the continuous flickering process at different frequencies to analyze user intentions. Whereas, In the case of a phase-related SSVEP-based BCI system, the target detection process is performed by flickering at varied phase differences. However, the objective of this article is to analyze user instructions effectively by continuous flickering at varied frequencies for SSVEP-based BCI system with high classification accuracy and information rate. However, designing a robust, practical, and noise-free SSVEP-based BCI system is a quite complicated task due to the reason that SSVEPs exhibit low signal-to-noise ratios and high noise. The reason for noise occurrence can be spontaneous brain events and task-unrelated activities like eye blinks, eye movements, and interference in the power line. These task-unrelated actions can change voltage and amplitude. Thus, due to the noise and limited SNR results, the practical implementation of the SSVEP-based BCI system becomes limited. Therefore, several researchers have shown great interest in providing solutions to suppress background noise and improve signal acquisition performance. Some of the works of literature are presented below in that regard.

An EEG signal classification method is introduced to analyze SSVEP-based BCI systems using a convolutional neural network (CNN) [21]. The key objective of CNN architecture is an enhancement of classification and validation accuracy with the help of hyper-parameter tuning. A steady-state visual evoked potential classification is performed using a filter bank CNN for improving classification performance in a short-time window [22]. The classification accuracy obtained using FBCNN is 88.36% for a 0.2 sec time window. The impact of training and data length is observed in different categories like inter-individual and cross individual. Karunasena *et al.* [23], a single-channel EEG classification is performed to analyze SSVEP-based BCIs for the application of robot arm control. This technique focuses on controlling motion regarding the wrist and gripper of robot arm control and this technique performs light-emitting diodes (LED) flickering at varied frequencies. Wang *et al.* [24], a novel detection technique is presented to take the benefits of canonical correlation analysis (CCA) and multivariate vibrational mode decomposition (MVMD) to analyze non-linear and dynamic EEG signals in SSVEP-based BCIs systems. This technique focuses on improving classification accuracy and reducing noise artifacts.

The contribution of work can be classified as follows: A SSVEP-based BCI system is introduced to detect SSVEP components in this article by minimizing background noise by analysing EEG signals based on the adaptive spatial filtering method. The proposed SSVEP-based BCI system set up a proper communication gateway between a human brain and a computer system. Here, a visual stimulation process is performed at varied frequencies to detect user intentions. This study focuses on maximizing the reproducibility of EEG signals across trials and subjects. The proposed SSVEP-based BCI system also reduces the eigenvalue and computational complexity problem and shows higher detection results. The obtained brain responses are analysed to evoke SSVEP with the help of visual stimuli. Here, high-dimensional features are obtained using the proposed SSVEP-based BCI system and mapped into the lower-dimensional space. A large public dataset is used to perform analysis and computational complexity is minimized by effective training. A detailed SSVEP detection analysis is performed to get high classification accuracy and information transfer rate (ITR).

This article is presented in the following manner. Section 2, describes the mathematical modeling of the proposed SSVEP-BCI system for the SSVEP signal extraction. Section 3, mentions the experimental results related to SSVEP detection and their comparison with traditional SSVEP detection methods and section 4 concludes the article.

2. MODELLING FOR PROPOSED SSVEP-BASED BCI SYSTEM

This section discusses the mathematical representation of target detection by extracting SSVEP components efficiently and performing optimization of the eigenvalue problem and computational complexity. The proposed adaptive spatial filtering-based SSVEP component extraction (ASFSCE) model significantly minimizes computational complexity. Here, Figure 1 shows a graphical representation of the proposed ASFSCE model. The block diagram in Figure 1 contains some building blocks like SSVEP component extraction, pre-processing, feature extraction, feature classification, control, and feedback mechanism. First of all, SSVEP components are extracted from EEG data using the proposed ASFSCE model. Then, there is a high chance that the obtained SSVEP components are noisy. Thus, adaptive spatial filters are utilized to minimize noise and remove background artifacts. Then, high-quality features are obtained and those obtained weights are classified to identify the target using control and feedback mechanism. In the following paragraph, a solution for target identification is proposed. Along with that, optimization of the Eigenvalue problem and computational complexity is also discussed.

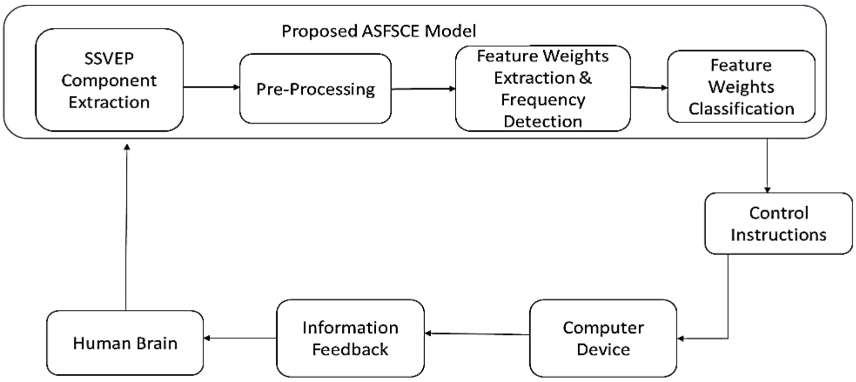

Figure 1. Proposed ASFSCE model

The proposed ASFSCE model is adopted to extract SSVEP components by maximizing the reproducibility of EEG signals across multiple trials. Consider a multi-dimensional signal $y = (y)_{jk} \in \mathbb{D}^{J\times K}$ and the linear vector of coefficients is determined using the proposed ASFSCE model and represented by $\lambda = \mathbb{D}^{J}$. This linear coefficient vector λ is used to maximize the correlation of inter-trials. The projection of inter-trial correlation is represented by $x = \lambda^{R} y$ using the proposed ASFSCE model. The index of EEG data is expressed by j and the number of dimensions is given by J. The total number of samples present in the EEG data is expressed as K and the index of samples is represented by k. The observed SSVEP component from EEG data $x^{(g)}$ for the $g-th$ trial is given by $y^{(g)} = \mathbb{D}^{J\times K}$ where $x^{(g)}$ belongs to $\mathbb{D}^{K}$. Then, the co-variance $L_{n_1 n_2}$ among trials $g_1 - th$ and $g_2 - th$ of EEG data $x^{(g)}$ is represented by the (1) and (2),

$$L_{n_1 n_2} = Corr\left(x^{(g_1)}, x^{(g_2)}\right) \quad (1)$$

$$L_{n_1 n_2} = \sum_{j_1, j_2=1}^{J} \lambda_{j_1} \lambda_{j_2} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \quad (2)$$

where the correlation between two different matrices Y_1 and Y_2 is determined by the (3).

$$Corr(Y_1, Y_2) = M[(Y_1 - M[Y_1])(Y_2 - M[Y_2])^R] \tag{3}$$

Considering that number of trials is G, then all possible combinations for all number of trials are given by the (4) and (5),

$$\sum_{\substack{g_1,g_2=1 \\ g_1 \neq g_2}}^{G} L_{n_1 n_2} = \sum_{\substack{g_1,g_2 \\ g_1 \neq g_2}}^{G} \sum_{j_1,j_2=1}^{J} \lambda_{j_1}\lambda_{j_2} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \tag{4}$$

$$\sum_{\substack{g_1,g_2=1 \\ g_1 \neq g_2}}^{G} L_{n_1 n_2} = \lambda^R N \lambda \tag{5}$$

where the matrix $N = \left(N_{j_1 j_2}\right)_{1 \leq j_1, j_2 \leq J}$ is determined by the (6).

$$N_{j_1 j_2} = \sum_{\substack{g_1,g_2=1 \\ g_1 \neq g_2}}^{G} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \tag{6}$$

Then, SSVEP components can be obtained by maximizing the (5) using the optimal coefficient $\hat{\lambda}$. Then, summation of the variance for EEG data $x^{(g)}$ can provide a finite solution as (7)-(10),

$$\sum_{g=1}^{G} Var\left(x^{(g)}\right) = \sum_{g=1}^{G} Var\left(\lambda^R y^{(g)}\right) \tag{7}$$

$$\sum_{g=1}^{G} Var\left(x^{(g)}\right) = \sum_{g=1}^{G} \sum_{j_1,j_2=1}^{J} \lambda_{j_1}\lambda_{j_2} Corr\left(y_{j_1}^{(g)}, y_{j_2}^{(g)}\right) \tag{8}$$

$$\sum_{g=1}^{G} Var\left(x^{(g)}\right) = \lambda^R A \lambda \tag{9}$$

$$\sum_{g=1}^{G} Var\left(x^{(g)}\right) = 1 \tag{10}$$

where the matrix $A = \left(A_{j_1, j_2}\right)_{1 \leq j_1, j_2 \leq J}$ is determined by the (11).

$$A_{j_1, j_2} = \sum_{g=1}^{G} Corr\left(y_{j_1}^{(g)}, y_{j_2}^{(g)}\right) \tag{11}$$

Then, the solution for the optimization of the eigenvalue is given by the (12),

$$\hat{\lambda} = \arg\max_{\lambda} \frac{\lambda^R N \lambda}{\lambda^R A \lambda} \tag{12}$$

the eigenvector of the matrix $A^{-1}N$ gives the optimal coefficient vector. Then, the linear filter is chosen based on the eigenvector with respect to the largest eigenvalue $\hat{\lambda}$ to extract SSVEP components.

The computational cost in traditional SSVEP extraction methods is drastically enhanced due to numerous cross-variance updates or calculations when the number of trials increases. For an instance, two trials $n1 - th$ and $n2 - th$ are used to demonstrate computational complexity reduction using the proposed ASFSCE model, and the correlation between these two trials is represented by $L_{n_1 n_2}$. In the traditional methods, all the elements of the matrix which represent the correlation between two trials are evaluated except diagonal elements A and their summation will provide a correlation matrix N. Then (6) will be simplified as (13),

$$N_{j_1, j_2} = \sum_{g_1=1}^{G-1} \sum_{g_2=g_1+1}^{G} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) + \sum_{g_2=1}^{G-1} \sum_{g_1=g_2+1}^{G} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \tag{13}$$

where the first summation part in (13) represents the upper triangular part in the matrix N and the lower triangular part is represented by the second summation part in (13). Thus, the (13) can be reformulated as,

$$N = N^{(Upp)} + N^{(Low)} \tag{14}$$

where $N^{(Upp)}$ and $N^{(Low)}$ are defined as (15) and (16).

$$N_{j_1, j_2}^{(U)} = \sum_{g_1=1}^{G-1} \sum_{g_2=g_1+1}^{G} Corr\left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \tag{15}$$

$$N_{j_1,j_2}^{(U)} = \sum_{g_2=1}^{G-1} \sum_{g_1=g_2+1}^{G} Corr\ \left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \quad (16)$$

The computational complexity of matrix N for the number of trails $2\binom{G}{2} = G^2 - G$ is given by $\mathcal{O}(G^2)$. The final correlation matrix is also evaluated by subtracting A from $\widetilde{N}$ as shown in the (17),

$$N = \widetilde{N} - \tilde{A} \quad (17)$$

where $\tilde{A}$ is represented as the sum of diagonal elements and $\widetilde{N}$ is represented as the summation of all correlation elements. Then, the matrix $\widetilde{N}$ is defined as (18)-(21),

$$\widetilde{N}_{j_1,j_2} = \sum_{g_1=1}^{G} \sum_{g_2=1}^{G} Corr\ \left(y_{j_1}^{(g_1)}, y_{j_2}^{(g_2)}\right) \quad (18)$$

$$\widetilde{N}_{j_1,j_2} = \sum_{g_1=1}^{G} \sum_{g_2=1}^{G} C^{-1}\ \left(y_{j_1}^{(g_1)} - \Psi_{j_1}^{(g_1)}\right)^T\ \left(y_{j_1}^{(g_1)} - \Psi_{j_1}^{(g_1)}\right) \quad (19)$$

$$\widetilde{N}_{j_1,j_2} = C^{-1} \sum_{g_1=1}^{G} \left(y_{j_1}^{(g_1)} - \Psi_{j_1}^{(g_1)}\right)^T \sum_{g_2=1}^{G} \left(y_{j_1}^{(g_1)} - \Psi_{j_1}^{(g_1)}\right) \quad (20)$$

$$\widetilde{N}_{j_1,j_2} = Corr\left(\bar{y}_{j_1}, \bar{y}_{j_2}\right) \quad (21)$$

where $\Psi_j^{(g)}$ is the mean of $y_j^{(g)}$ across multiple samples in EEG data and $\bar{y}$ is the sum of $y^{(g)}$across multiple trials and represented by the (22) and (23).

$$\Psi_j^{(g)} = C^{-1} \sum_{k=1}^{C} y_{jk}^{(g)} \quad (22)$$

$$\bar{y}_j = \sum_{g=1}^{G} y_j^{(g)} \quad (23)$$

The steps from (18) to (21) show that $\widetilde{N}$ can be evaluated as the auto-correlation of $\bar{y}$ and its computational cost does not rely upon the number of trials used. Thus, the computational cost of the matrix N can be minimized to $\mathcal{O}(1)$ from $\mathcal{O}(G^2)$ using the proposed ASFSCE model. However, the computational cost in traditional SSVEP extraction methods remains the same as $\mathcal{O}(G^2)$. In this way, optimization of the Eigenvalue problem and computational cost is achieved for faster execution and saves training time to get better SSVEP extraction results.

3. RESULT AND DISCUSSION

This section provides details of experimental results to determine the target identification accuracy by extracting SSVEP components efficiently with the help of continuous flickering of visual stimuli. Here, adaptive spatial filtering is employed to remove background artifacts and noises. The adaptive spatial filters are used to extract correlated visually evoked SSVEP components from EEG data at a specific frequency. The proposed ASFSCE model to optimize the Eigenvalue problem and minimize computational complexity. The performance of the proposed ASFSCE model is measured in terms of target detection accuracy and ITR based on the obtained feature.

A SSVEP-based EEG dataset is utilized to get the simulation results for target identification. In this dataset, a total number of 11 varied subjects [25] are used to obtain the simulation results by gathering multi-channel SSVEP components from EEG data. In the EEG signals, a total number of 256 channels are present. In this dataset, SSVEP components are gathered at a 250 Hz sampling frequency from EEG data. All the 11 subjects who participated in this experiment are working in a research center named as centre for research and technology hellas (CERTH). Among all those 11 volunteers, the total number of 8 participants are male and the rest are female. All the volunteers are aged between 25 to 39 years.

The process of visual stimulation is performed considering various frequencies and those frequencies are 6.66 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz, and 12.00 Hz. All the extracted SSVEP components from EEG data are obtained from the SSVEP dataset and this dataset is publically available in [25]. A detailed quantitative and graphical analysis is provided to perform a comparison between traditional SSVEP extraction methods and the proposed ASFSCE model in terms of target detection accuracy and information transfer rate.

These traditional methods extract SSVEP based on convolutional neural network architecture and their different variants. Here, a quantitative analysis considering all 11 subjects is presented in Figure 2 in terms of target detection accuracy and compared against different CNN variants for SSVEP component extraction. There are a total number of 23 trials are conducted for each subject from S1 to S11 to get efficient target detection accuracy. Then, the mean target detection accuracy is measured by evaluating the average of accuracy of 23 trials for each subject individually. Figure 2 results are quite superior to the traditional SSVEP extraction methods for all 11 subjects. The detection accuracy for subject S-1 is enhanced by 8%, and for the subject S-6 is 42%, and the performance improvement for subject S-10 is 26% in terms of target detection accuracy. Thus, the performance of detection accuracy is massively increased using the proposed ASFSCE model against traditional CNN architecture.

Furthermore, mean target detection accuracy results for all 11 subjects are presented in Table 1 using the proposed ASFSCE model against different SSVEP extraction methods such as LDA, CNN, CNN with LASO, SVM, and KNN [26]. The least target detection accuracy is observed as 46.17% using the KNN SSVEP extraction method among all the SSVEP acquisition methods and the best performance is observed using the proposed ASFSCE model as 93.47%. It is evident from all the performance results that the proposed ASFSCE model outperforms all the other SSVEP acquisition methods using EEG data.

Table 2 shows ITR results in bits per minute obtained using the proposed ASFSCE model. All the results related to ITR are gathered using all 11 subjects. The mean ITR results for each subject are evaluated by taking an average of all 23 trials of ITR results. Most of the ITR results are quite superior, specifically for subjects S-3, S-6, S-9, and S-10. The mean is evaluated considering all 11 subjects as 308.23 bpm. All the results such as target detection accuracy and ITR obtained using the proposed ASFSCE model show satisfactory quantitative results.

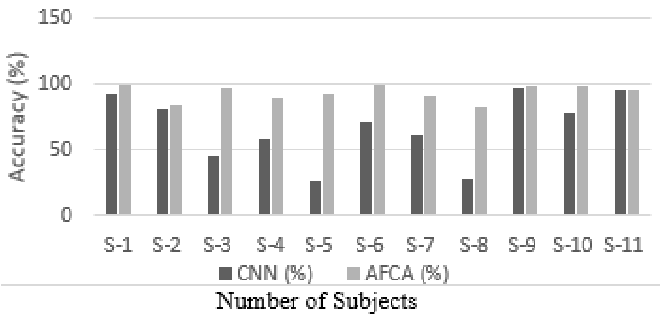

Figure 2. Comparison of SSVEP detection accuracy for each subject against CNN architecture

Table 1. Mean target detection accuracy comparison

Target detection methods	Detection accuracy (%)
KNN	46.17
SVMG	65.13
LSTM	66.89
SVM	79.47
CNN	80.83
ASFSCE	93.47

Table 2. Information transfer rate in bpm for all 11 subjects

Subject ID	ASFSCE (bpm)
S-1	339.267
S-2	246.991
S-3	323.583
S-4	282.738
S-5	303.466
S-6	339.267
S-7	304.503
S-8	280.264
S-9	328.742
S-10	328.742
S-11	312.955

4. CONCLUSION

The SSVEP component acquisition from EEG data is massively important and necessary for the application of BCIs. However, SSVEP-based BCIs are a complicated and challenging process. Thus, in this article, the acquisition process of SSVEP components from multi-channel EEG data is discussed to enhance target detection accuracy based on the adaptive spatial filtering method. Here, the target is identified based on the continuous flickering of visual stimuli at varied frequencies, and detection accuracy is enhanced by eliminating background activities using the proposed adaptive spatial filters. Comprehensive mathematical modeling for the identification of correlated visually evoked SSVEP components is discussed. Here, a detailed solution for target identification and optimization of the Eigenvalue problem is presented. In addition, a comprehensive solution for the optimization of computational complexity is discussed. Here, high-quality feature weights are generated from the multi-channel EEG data, and the reproducibility of EEG signals across multiple trials is maximized using the proposed ASFSCE model. In this article, the SSVEP dataset is adopted to measure target detection results and information transfer rate. The mean target detection accuracy obtained using the proposed ASFSCE model is 93.47% and the mean ITR results in bits per minute are 308.23 considering all 11 subjects.

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