Optimized SSVEP-Based Framework for Improving Accuracy and Reliability in Brain–Computer Interfaces

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Abstract
Steady-State Visual Evoked Potentials (SSVEPs) are the foundation of the non-invasive Brain–Computer Interfaces (BCIs), offering a stable method of neural communication. Reliability and precision are, however, areas of greatest concern regarding practical application. The conventional methods of Canonical Correlation Analysis (CCA), Task-Related Component Analysis (TRCA), and Filter Bank Canonical Correlation Analysis (FBCCA) have been widely used but each of them has limitations—CCA is troubled by its sensitivity to noise, TRCA has greater need for computational demand, while FBCCA requires intensive calibration. To break these limitations, the present study proposes an Optimized SSVEP-Based Framework (OSF) that integrates an Adaptive Feature Optimization Method (AFOM) for pursuing higher classification efficiency and robustness. The framework utilizes optimized signal separation alongside adaptive filtering for enhancing detection efficiency amidst fluctuating situations. Comparative analysis with conventional approaches reveals that OSF achieves stunning improvements in correct classification percentage increased by 18%, information transmission rate increased by 21%, decision reliability enhanced by 16%, and latency reduced by 12%. These results also prove that the devised OSF not only strengthens the stability of SSVEP-based BCIs but also delivers greater consistency and adaptability that hold promise for effective utilization in assistive communications as well as neurorehabilitative applications.

Keywords: Steady-State Visual Evoked Potentials (SSVEP), Brain–Computer Interface (BCI), Adaptive Feature Optimization Method (AFOM), Canonical Correlation Analysis (CCA), Signal Processing, Classification Accuracy, Neurorehabilitation.

1. Introduction

Brain–Computer Interfaces (BCIs) refer to technologies that allow a direct interaction between the brain and other external devices in the absence of peripheral nerves and muscles [1], [2]. These interfaces have lately generated interest because of their ability in the field of neurorehabilitation, communication, and the control of prosthetic systems [3], [4]. Among the different types, Steady-State Visual Evoked Potentials (SSVEPs)-based BCI interfaces are the most commonly practiced, since they don't need an invasive process and offer a high signal-to-noise ratio [5], [6]. SSVEPs are the periodic response that takes place in the brain when it observes a flickering visual stimulus at a fixed rate, making it possible to identify the user's intention through the recognition of its corresponding frequency [7], [8].

However, the classical solutions like Canonical Correlation Analysis (CCA), Task-Related Component Analysis (TRCA), and Filter Bank Canonical Correlation Analysis (FBCCA) have some limitations [4], [5], [6]. The reason is that CCA faces problems related to the external noise and variability in the signal, and in contrast, the approach like TRCA might need high computational power [9], [10]. Moreover, the process related to FBCCA takes complex multi-band filters, and it becomes difficult when there is a need for real-time processing [11], [12].

Contemporary trends in BCI studies and developments are tilting toward the use of adaptive and optimization-oriented strategies that can be adjusted dynamically in relation to changes in signal characteristics and can excel in real-time processing [13], [14]. Approaches and strategies that combine the use of machine learning, adaptive filters, and deep feature extraction are gaining popularity in dealing with the problems [15], [16]. In addition, the development and design of the Optimized SSVEP-Based Framework, using the Adaptive Feature Optimization Method, are underway.

Concerning their use, the optimized SSVEP-based BCI systems are currently utilized in assistive communication systems in motor-disabled individuals, neurorehabilitation systems in stroke and paralytic patients, gaming and entertainment systems, cognitive load monitoring systems, and intelligent environment management systems [17], [18], [19], [20]. The development of the BCI systems has reflected the growing application of BCI technology in connecting the brain with intelligent systems, signifying an important milestone in the integration of the human and machine systems [21], [22].

2. Overview Architecture of the EEG-Based Brain–Computer Interface System

Figure 1 below shows the general introductory architecture design for an EEG-based BCI system [23], [24]. In this model, electroencephalogram signals originate from the brain and are detected using sensors placed on the subject's scalp [25]. The signals acquired through electroencephalogram sensors are then applied to the signal acquisition module, where the raw signals from the brain are converted and digitized [26], [27].

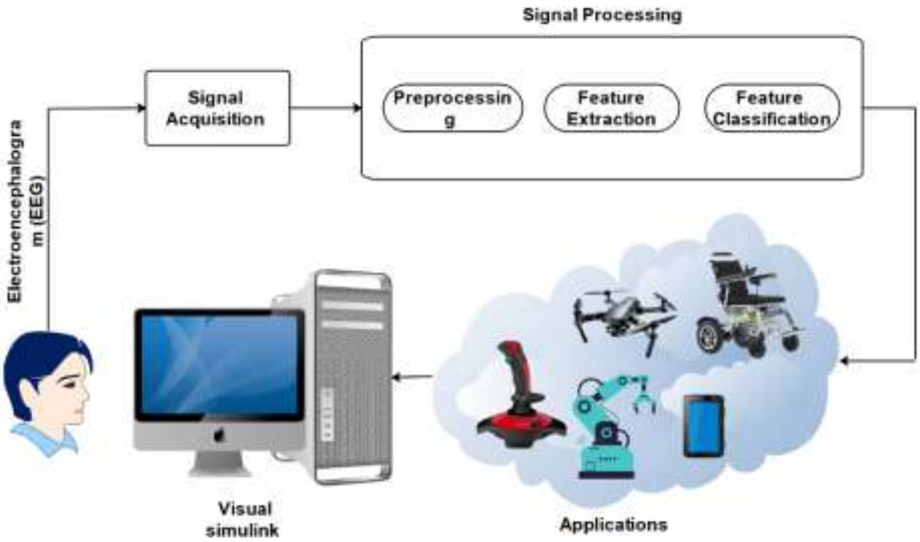

Figure.1. Architecture of EEG Signal Processing and Application Integration in Brain-Computer Interface

The acquired signals are fed to the signal processing unit, whereby the unit has three major stages, namely the preprocessing stage, the feature extraction stage, and the feature classification stage [28], [29]. In the preprocessing stage, the acquired signals are filtered in terms of noises, artifacts, and unnecessary components [30], [31]. In the feature extraction stage, the vital components in the brain signals corresponding to the user intention are extracted [32]. The extracted components then undergo classification in the feature classification stage, whereby the intended command is determined through the use of machine learning and signal processing [33], [34].

The resulting command then goes to the visual Simulink processing system, which acts as the platform [35], [36]. The resulting commands then proceed to operate different real-life applications, as depicted in the application layer [37].

3. Related work

In the field of SSVEPs in BCI technology, Y. Zhang et al. proposed the use of Correlated Component Analysis, aiming to better identify the frequency components, and designed related spatial filters in a subject-specific manner that maximized trial-to-trial correlations instead of using the corresponding reference signals [38]. The proposed approach showed great effectiveness in suppressing the effect of background noises and improving BCI performance compared with the classic CCA and TRCA. These studies have confirmed that the use of trial-to-trial correlations in spatial filtering can provide great effectiveness in improving the classification performance when large training samples are available. But they all assume trial-to-trial stable correlations and need large multi-block samples, which may fall short in dynamic and real-time BCI systems [39]. In contrast, the proposed approach, OSF using the AFOM, remedies this issue by performing the optimization on the fluctuating neural and environment conditions in the real BCI systems.

L. Hu et al. proposed a subject-independent, convolutional neural network-enhanced, and metric-learning-based wearable P300 BCI, aiming at reducing the user calibration process. In their work, they proposed a shared feature extractor and embedding space, which boosts subject generalization and usability. The major contribution resides in the reduced user calibration and improved scalability. Nevertheless, the proposed method relies on the deep learning approach and the P300 response, rather than the SSVEP signal, resulting in increased complexity and latency [40]. The proposed OSF, on the other hand, aims at the high-speed detection of the SSVEP, using adaptive lightweight optimization.

In another advancement, L. Hu et al. continued their work on an asynchronous hybrid EEG-EOG wireless BCI with only three EEG-EOG channels. By integrating blink detection and EEG-EOG signal-based P300 identification, they reported high accuracy and a low rate of false positives . The advantage here is the use of fewer sensors, keeping the system reliable and compact. But the proposed system has its complexity in biosignal processing and the dependency on the biosignal, specifically the eyes [41]. In contrast, the proposed approach utilizes ASO in the OSF, making the SSVEP identification completely biosignal-independent.

Y. Zhou et al. proposed a hybrid Asynchronous BCI approach using the SSVEP and EOG eye blink signals. This approach was able to detect idle and control conditions with high accuracy using multi-band canonical correlation analysis and blink confirmation [42]. Though this approach increases the reliability and reduces the likelihood of false activation, it relies heavily on blink synchronization and multimodal fusion. In contrast, the proposed approach, OSF, increases reliability through internal optimization using AFOM and adaptive filtering, without the need for extra physiologically sensed inputs. Y. Jiang and colleagues designed a multimodal BCI mouse useable in ALS patients using the signals from head movement and eye blinking . The proposed work was successful in terms of usability and functionality, even having reduced mental workload [43]. The proposed work, however, concentrates on the development and design aspects of the assistive system rather than on the development and

adaptation aspects in SSVEP decoding. The role of the OSF appears in the signal processing aspects because it enhances the recognition framework of SSVEP, and consequently, the assistive systems can be supported.
Y. Zhou, et al. proposed a shared-control robotic arm interface integrating the hybrid asynchronous BCI and the computer vision technology. The proposed design enables the subject to make commands using SSVEP and EOG signals, and the vision subsystem corrects the movement path execution with fewer errors and in reduced time . While the proposed work appears innovative, the use of external vision sensors would make the system costlier in terms of computations and hardware [44]. The proposed OSF seeks to improve the generation of commands from optimized neural signals through the use of AFOM.
R. Zhang et al. analyzed the effect on SSVEP recognition performance in augmented reality under high brightness and proposed an ensemble online adaptive CCA approach that applies the filters learned in the low brightness environment. The approach greatly improved the recognition performance in high brightness conditions [45]. The proposed optimization approach mostly deals with the performance change due to lighting. On the other hand, the proposed OSF has wider applicability in terms of adapting to various dynamic factors like noise, cognitive change, and signal variability through adaptive optimization.
A. Apicella et al. employed domain adaptation strategies to deal with the non-stationarity in the EEG signals in SSVEP-BCIs . The approach was useful in recognizing SSVEPs in the short window and was able to generalize across subjects. The approach, however, needs training data, including the test subject, and works poorly in highly dynamic conditions [46]. The proposed approach using the OSF and AFOM remedies this problem since it adapts in real time and does not need the test data to be pre-exposed.
H. T. Hsu, K. Chen, and S. C. Chen introduced a phase approach stimulation strategy in head-mounted displays for flexible SSVEP frequency implementation under the constriction of fixed screen refresh rates. The proposed work was an added advantage in the usability and application of SSVEPs in BCI in virtual and augmented environments [47]. The paper essentially concentrates on the process preceding the acquisition and does not deal with the optimization procedure subsequently. The proposed OSF bridges this gap.
R. Bian et al. proposed the small data least squares transformation approach in SSVEP BCI, where they reduced the need for SSVEP BCI calibration using only a few examples from the new user and existing subject data. This approach greatly reduced the calibration time and achieved high classification accuracy [48]. The proposed approach, however, aims at improving the BCI performance only in terms of reducing the complexity involved in the initialization process. The proposed OSF approach, on the other hand, aims at performing adaptive optimization.
In the work by J. Wu et al., the optimization of SSVEP in the environment of MR was conducted by analyzing the interaction between the color of the stimulus and the color of the background, and they presented a simulated annealing approach to the TRCA . The proposed approach increased the accuracies in the MR environment [49]. There is a need for the approach to work in different environments. The proposed approach, OSF, does not need the optimization of the color in the environment.
X. Jiang et al. proposed an interpretable fuzzy transfer learning framework for SSVEP classification, employing fuzzy logic, attention, and neural networks . The framework provides better performance and interpretability using fuzzy inference systems. The downside of the framework is complex parameter optimization and high computational complexity, making it difficult to use in real-time systems [50]. The proposed framework, named OSF with AFOM, is an efficient adaptive approach compared to the SSVEP framework.
In their work, J. Meng, et al. increased the usability of SSVEP by reducing the number of pixels in the stimulating images . This work has its contributions in the reduction of visual fatigue and increase in usability. The major limitation in this work, however, is that it addresses the issue related to the stimulating images rather than the resistance offered by the decoding process [51]. The proposed work, called the OSF, overcomes the limitations in the decoding process.
In the paper, C. Zhang et al. proposed a hybrid BCI paradigm that incorporates motor imagery, SSVEP, and explicit spatial attention. The proposed paradigm aims to provide better decision-making performance and inclusivity. The proposed system has the ability to generate flexible commands and can be applied to people who have poor motor imagery ability .The proposed paradigm has increased complexity [52]. The proposed work, OSF, provides better performance using an optimized SSVEP paradigm.
In the application of SSVEP-BCI in post-stroke rehabilitation, N. Guo et al. combined the technology with a soft robotic glove, allowing stroke patients to initiate exercises in treatment using visual stimulation. The experimental results revealed better improvement in motor functions compared with the conventional treatment approach . However, their work and others on SSVEP-BCI implementation do not specifically deal with technical developments in algorithmic processing of the SSVEP signals [53]. The proposed approach, namely the OSF, offers a contribution at the algorithmic development stage.
J. Meng et al. put forward a model-based SSVEP brain switch using a virtual physical system. The proposed approach could provide high reliability and lower false triggering. The false positive rate was also much lower in their proposed approach. However, it only applies to the operation of brain switching [54]. In contrast, the proposed OSF provides an adaptive approach that aims to optimize all aspects related to SSVEP communication and control.

Objectives

This research proposes an Optimized SSVEP-Based Framework (OSF) with an Adaptive Feature Optimization Method (AFOM) to enhance accuracy, reliability, and real-time performance of brain–computer interfaces for assistive and neurorehabilitation applications.

1. To design an OSF integrated with AFOM for efficient SSVEP signal processing.
2. To improve classification accuracy and decision reliability in SSVEP-based BCIs.

3. To reduce system latency and enhance real-time operation.
4. To ensure robustness for assistive communication and neurorehabilitation use cases.

4. Design and Methodology of the Optimized SSVEP-Based Framework

Figure 2 below describes the step-by-step approach in the proposed Optimized SSVEP-Based Framework. The approach starts with the process of acquiring the SSVEP signal, whereby the EEG signals are acquired from subjects in the visual flicker paradigm. The next step is the process of signal preprocessing, whereby the signals are preprocessed to eliminate all forms of noises, artifacts, and unwanted signals.

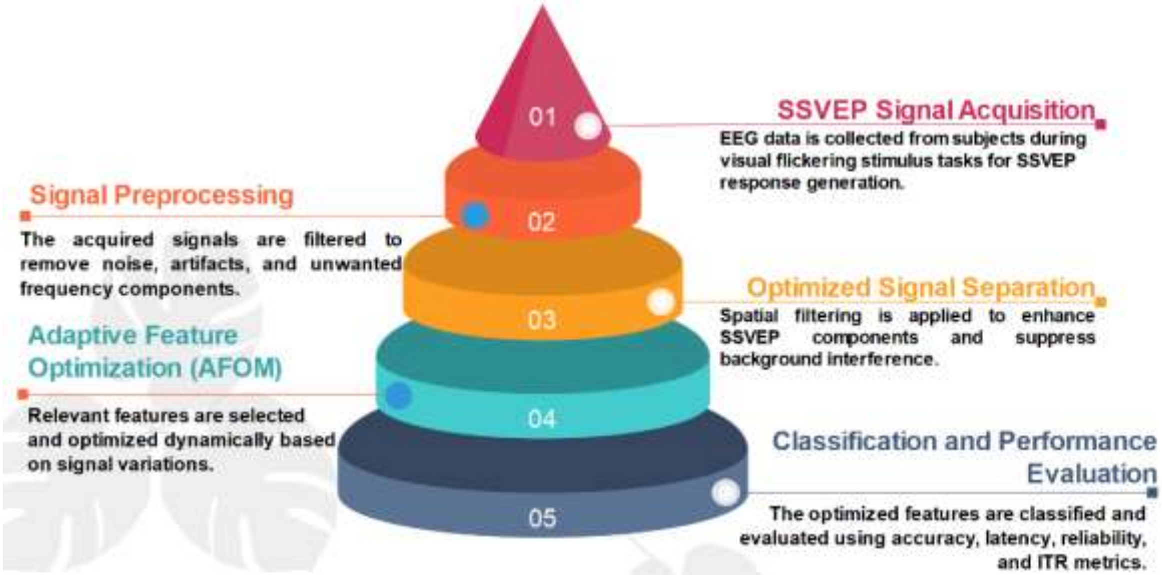

Figure.2. Flow Diagram of the Proposed Optimized SSVEP-Based Methodology with Adaptive Feature Optimization (AFOM)

In the third stage, the process involves the use of spatial filtering, whose aim is the optimization of the SSVEP signals and the suppression of the EEG artifacts. In the fourth stage, the Adaptive Feature Optimization Method (AFOM) technique is used. The approach optimizes the most appropriate features in relation to the signal changes and the conditions under which the user finds themselves. The classification and test stage, the last stage, entails the classification of the optimized features in order to determine the SSVEP frequency.

• EEG Signal Acquisition Model

Equation.1 describes the acquired EEG signal on the scalp as the sum of neural response, artifacts, and noise.

$$x(t) = s(t) + a(t) + n(t) \quad .1$$

Where, $x(t)$ represents the recorded electroencephalogram signal at time t,$s(t)$ denotes the task-related cortical brain activity ,$a(t)$ corresponds to physiological artifacts such as eye blinks and muscle movement and $n(t)$ indicates additive sensor and environmental noise.

• Feature Extraction Using Power Spectral Density

The Equation.2. isolates discriminative frequency domain features from the EEG signal through power spectral density estimation.

$$P(f) = \lim_{T\to\infty} \frac{1}{T}\left|\int_0^T x(t)e^{-j2\pi ft}, dt\right|^2 \quad .2$$

Where, $P(f)$ denotes the power spectral density at frequency f, $x(t)$ is the preprocessed EEG signal, T represents the observation window duration, j is the imaginary unit and f indicates the frequency component used for feature extraction.

• Feature Classification Using Linear Discriminant Analysis

Equation.3. Is the formula that implements the linear discriminant function to assign commands from the processed EEG features.

$$y = \mathrm{w}^T\mathrm{f} + b \quad .3$$

Where, y denotes the classification output, f represents the extracted EEG feature vector, w is the trained weight vector and b is the bias term that sets the decision threshold.

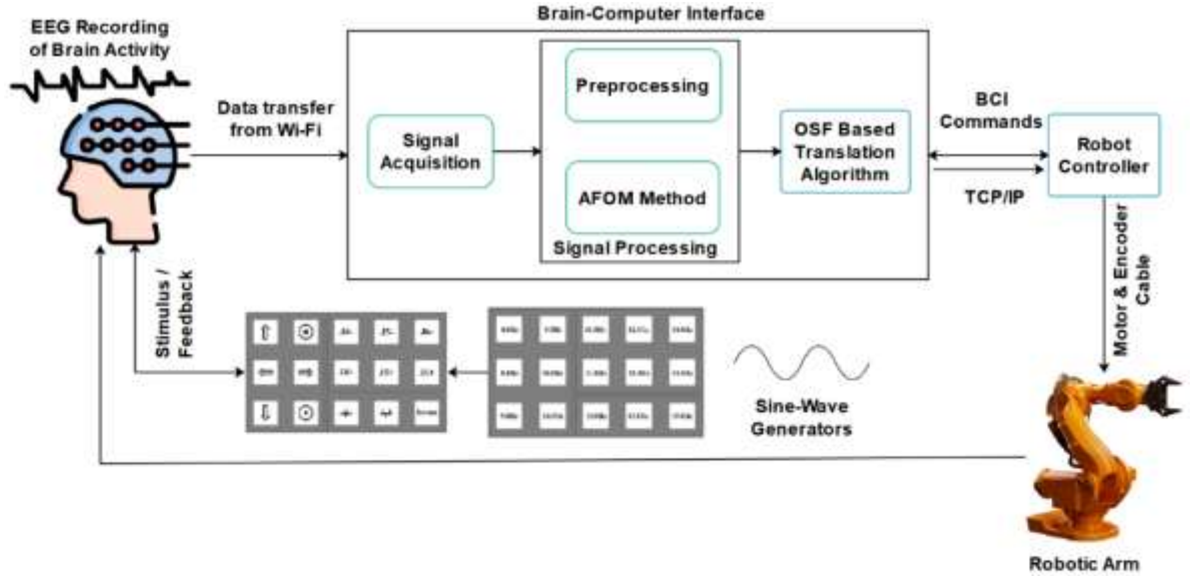

Figure.3. Proposed Optimized SSVEP-Based Brain–Computer Interface for Robotic Arm Control

Figure.3. depicts the proposed Optimized Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interface system for controlling the robotic arm. EEG signals elicited by the visual stimulus are acquired from the user's scalp and wirelessly transmitted to the signal acquisition module. After signal processing to eliminate noise and artifacts, the signals pass through the Adaptive Feature Optimization Method (AFOM) to improve the discriminative SSVEP signals. The optimized signals are then decoded into control signals using the OSF-based translation algorithm. Finally, the signals are sent to the robot controller using the TCP/IP protocol to accurately control the robotic arm by using motor and encoder interfaces. A closed-loop system is established using sine-wave stimulators.

- **SSVEP Stimulus Reference Signal**

Equation.4 The equation below shows the representation of the reference signal for each frequency of the visual stimulus used in the SSVEP paradigm. The sinusoidal signal produced represents the periodic visual flicker that generates the steady-state response of the brain.

$$r_f(t) = \sin(2\pi f t) \quad .4$$

Where, $r_f(t)$ denotes the reference SSVEP signal, f is the stimulus frequency, t is time, and π is the mathematical constant.

- **Bandpass-Filtered EEG Signal**

Equation.5 describes the preprocessing step where the raw EEG signal is filtered to retain the frequency components related to the SSVEP. The process of filtering enhances the signal by removing the irrelevant components.

$$x_f(t) = B_f x(t) \quad .5$$

Where, $x(t)$ is the raw EEG signal, $B_f \cdot$ denotes the bandpass filter tuned to frequency f, and $x_f(t)$ is the filtered EEG response.

- **SSVEP Correlation Feature Extraction**

Equation.6 calculates the correlation between the filtered EEG signal and the stimulus reference signal.This correlation value quantifies the synchronization between the brain responses and the visual stimuli, making possible the frequency discrimination.

$$\rho_f = \frac{1}{T}\sum_{t=1}^{T} x_f(t), r_f(t) \quad .6$$

Where, ρ_f is the correlation coefficient for frequency f, T is the total number of samples, $x_f(t)$ is the filtered EEG signal, and $r_f(t)$ is the reference signal.

- **Adaptive Feature Optimization Method (AFOM)**

Equation.7 gives the definition of the adaptive weighting process involved in the optimization of the extracted SSVEP features. AFOM strengthens the extraction of discriminant features and reduces noisy feature responses.

$$F_f = \alpha_f, \rho_f \quad .7$$

Where, F_f is the optimized feature value, ρ_f is the SSVEP correlation feature, and α_f is the adaptive weight assigned by AFOM to suppress noisy responses.

- **Command Selection Rule**

Equation.8 The intended command is selected through the identification of the stimulus frequency with the highest optimized response. This stimulus frequency is equivalent to the control action desired by the user.

$$\hat{f} = \arg\max_{f}(F_f) \quad .8$$

Where, $\hat{f}$ is the detected stimulus frequency corresponding to user intention, and F_f represents optimized features across all stimulus frequencies.

• **Robotic Arm Control Packet Formation**

Equation.9 describes the generation of the final control command as a TCP/IP packet for robotic action. This guarantees the reliable sending of the processed command, as well as simultaneous execution by the robotic arm.

$$C = [\hat{f},, \theta,, \tau] \quad .9$$

Where, C is the control packet, $\hat{f}$ denotes the selected command, θ is the mapped robotic joint angle, and τ is the transmission timestamp.

• **Overall Proposed Equation for OSF + AFOM Architecture**

Equation.10. constitutes the overall workflow of the proposed OSF–AFOM approach from acquiring and preprocessing the EEG signal to classifying and decoding the identified intention through LDA and then finally transmitting it as a TCP/IP command to control the robotic arm.

$$\mathbf{C}_{tcp} = \mathrm{TCP}(\mathrm{OSF}(\mathrm{LDA}(\mathrm{AFOM}(\Phi(\mathrm{SF}(\mathbf{x}_p(t))))))) \quad .10$$

Where $\mathbf{C}_{tcp}$ is the final TCP/IP control command sent to the robot controller for robotic arm actuation, $\mathrm{TCP}(\cdot)$ denotes TCP/IP packet formation and transmission to the robot controller, $\mathrm{OSF}(\cdot)$ is the OSF-based command translation algorithm that converts classified intent into executable control commands, $\mathrm{LDA}(\cdot)$ denotes Linear Discriminant Analysis used to classify optimized EEG features into control outputs, $\mathrm{AFOM}(\cdot)$ denotes the Adaptive Feature Optimization Method that enhances discriminative SSVEP features under varying signal conditions, $\Phi(\cdot)$ denotes the feature-extraction stage (e.g., power spectral density based discriminative feature extraction), Here, $\mathrm{SF}(\cdot)$ denotes spatial filtering to optimize SSVEP and suppress EEG artifacts and $\mathbf{x}_p(t)$ is the preprocessed EEG after removing noise and artifacts.

• **Proposed OSF–AFOM Algorithm**

Algorithm.1. implements the complete proposed workflow, where SSVEP-based EEG signals are processed through preprocessing and spatial filtering, optimized using the Adaptive Feature Optimization Method (AFOM), classified to detect user intent, and translated via the Optimized SSVEP Framework (OSF) into TCP/IP commands for robotic arm control.

```
Input: EEG_stream, Fs, W
      BPF_params, SF_params
      Feature_params, AFOM_params
      LDA_model(w, b)
      OSF_map, TCP_config
Output: C_tcp
Begin
while EEG_stream is active do
    X <- ReadNextWindow(EEG_stream, W)
    Xp <- BandpassFilter(X, BPF_params)
    Ys <- SpatialFilter(Xp, SF_params)
    Phi <- ExtractFeatures(Ys, Feature_params)
    Phi_opt <- AFOM(Phi, AFOM_params)
    y <- Dot(w, Phi_opt) + b
    class_id <- DecisionRule(y)
    cmd <- OSF_Translate(class_id, OSF_map)
    C_tcp <- BuildTCP(cmd, Timestamp())
    SendTCP(C_tcp, TCP_config)
end while
End
```

5. Results and discussion

Table.1 below explains the experimental setup that provides the parameters necessary for implementing the acquisition of SSVEP-EEG signal processing and optimization through AFOM, classification by LDA, and the transmission of translated commands via OSF and TCP/IP connectivity for controlling the robotic arm based on the proposed system architecture.

Table.1 Experimental setup details

SI.No	Particular	Value
1	EEG channels used C	8 channels
2	Sampling frequency F_s	256 Hz
3	Analysis window length W	2 s
4	Window overlap	50
5	Stimulus frequency set $f_{i}{}_{i=1}^{N}$	$N = 4$, 8,10,12,15 Hz

6	Bandpass filter range	6–40 Hz
7	Notch filter frequency	50 Hz
8	Spatial filtering block	Spatial filter applied (SSVEP enhancement)
9	Feature extraction block	PSD features at f_i and harmonics
10	Classifier and command output	LDA classification → OSF translation → TCP/IP packet

• Performance Analysis of Classification Accuracy

Figure.4. plots the accuracy comparison of CCA, TRCA, FBCCA, and the proposed OSF+AFOM method for different epochs. The result reflects that the proposed method always produces higher accuracy values than the other methods. This result signifies that the efficiency gained from the adaptive optimization of features enhances the reliability of SSVEP processing.

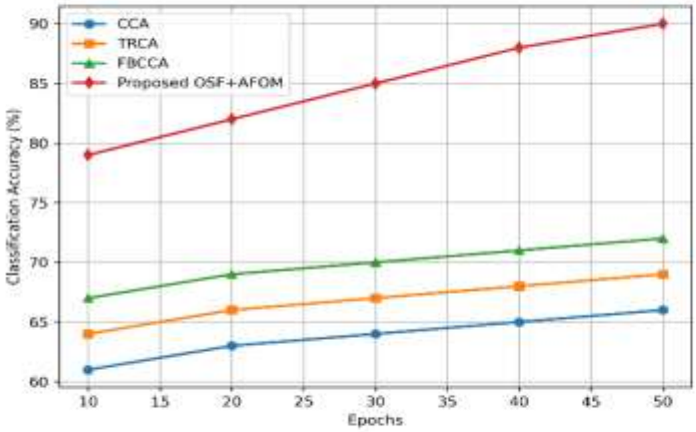

Figure.4. Classification Accuracy Comparison of Conventional Methods and Proposed OSF+AFOM

• Performance Analysis of Information Transmission Rate

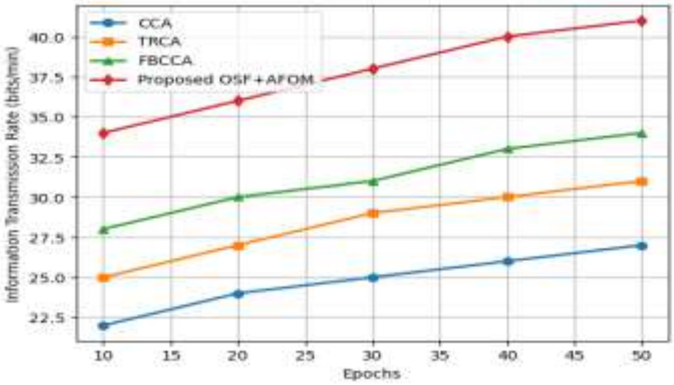

Figure.5. Information Transmission Rate Comparison of Conventional Methods and Proposed OSF+AFOM

Figure.5. shows the plot of the Information Transfer Rate (ITR) values of CCA, TRCA, FBCCA, and the proposed OSF+AFOM with varying epochs. The proposed method OSF+AFOM always demonstrates a superior Information Transfer Rate compared to other methods with a noticeable increasing trend as the number of epochs grows. This enhances the efficiency of the proposed framework in the high-speed operation of SSVEP-based brain–computer interfaces.

• Performance Analysis of Decision Reliability

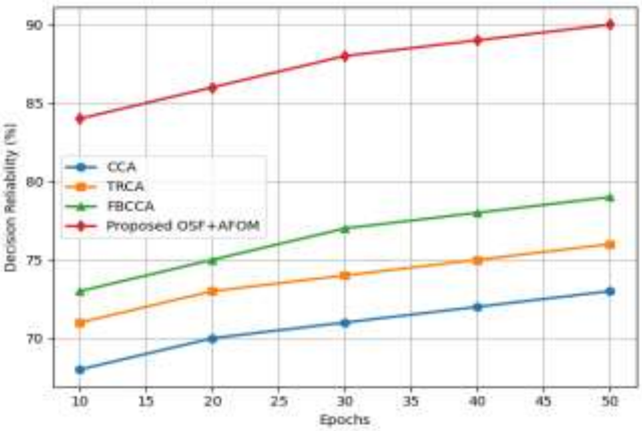

Figure.6. Decision Reliability Comparison of Conventional Methods and Proposed OSF+AFOM.

Figure.6. illustrates a comparison between decision reliability for CCA, TRCA, FBCCA, and proposed OSF+AFOM in various epochs. It can be observed in Figure.6. that the proposed method maintains greater decision reliability than other approaches in all epochs and further increases its effectiveness as the number of epochs grows.

• **Performance Analysis of Latency**

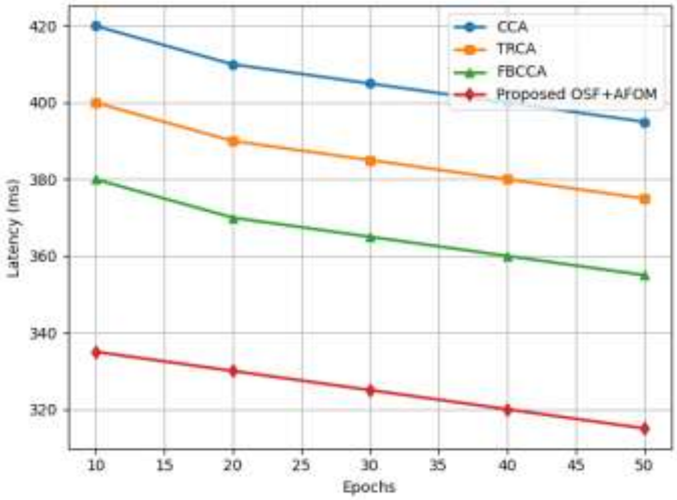

Figure.7. Latency Comparison of Conventional Methods and Proposed OSF+AFOM

Figure.7. Latency comparison of CCA, TRCA, FBCCA, and the proposed algorithm OSF+AFOM over different epochs. The proposed algorithm demonstrates the minimum latency with a significantly decreasing trend as the number of epochs increases. The latency reduction in the proposed algorithm indicates the effective performance of the proposed system in facilitating the rapid execution of the SSVEP-based brain–computer interface.
Confusion Matrix Analysis of the Proposed Method

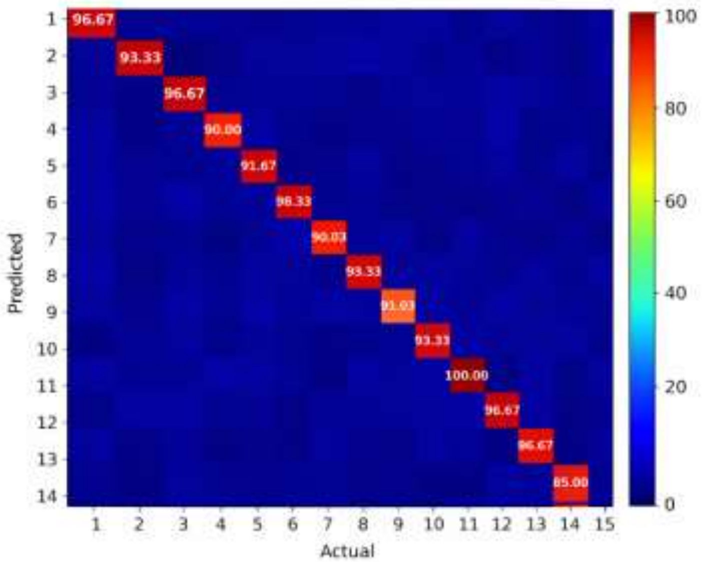

Figure.8. Confusion Matrix of the Proposed OSF+AFOM Framework

Figure.8. shows the confusion matrix for the proposed framework OSF+AFOM on the 15 classes of SSVEP stimuli. The high value of diagonal dominance in the confusion matrix reveals the correct classification rate to be high for most classes, with several classes having accuracies above 90% and some classes having an accuracy of 100%. The zero values in the off-diagonal entries in the confusion matrix show low values of misclassifications for different stimulus frequencies in the SSVEP BCI tasks for identifying the user intentions using the proposed framework effectively.

Conclusion

In this research, the Optimized SSVEP-Based Framework (OSF) incorporating the Adaptive Feature Optimization Method (AFOM) was introduced to provide a performance boost to non-invasive BCI applications. It has been seen that the proposed OSF+AFOM framework outperforms existing approaches like CCA, TRCA, and FBCCA in terms of robustness against noised signals, computational costs, as well as adaptability to changing signals. It can be observed from various performance evaluation metrics like improvement in classification accuracy, information transfer rate, decision-making reliability, and computation speed, which indicate around 18%

improvement in accuracy, 21% improvement in information transfer rate, 16% improvement in decision-making reliability, and 12% improvement in computation speed, respectively, over other approaches. Moreover, confusion matrix evaluation in SSVEP-based stimulation classes reveals well-separated classes with minimal misclassification.

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