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Enhancing Control with Embedded SSVEP-BCI

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Abstract

Brain–Computer Interface (BCI) technology establishes a direct communication link between the human brain and external devices without relying on muscular activity. Among various BCI paradigms, the Steady-State Visually Evoked Potential (SSVEP)-based approach has gained significant attention due to its high signal-to-noise ratio, minimal user training, and suitability for real-time applications. However, implementing such systems on embedded hardware presents challenges such as limited computational resources, signal noise, and latency in processing This paper focuses on enhancing control performance in an embedded SSVEP-based BCI system through efficient EEG signal processing and system optimization. The proposed framework employs advanced preprocessing techniques, including band-pass filtering to isolate target frequency components and reduce noise interference. Signal optimization algorithms are then integrated to improve classification accuracy and responsiveness. The system's embedded implementation ensures real-time operation, compactness, and portability, making it suitable for low-cost assistive technologies and smart control applications The results demonstrate that optimizing EEG signal processing significantly enhances the detection accuracy of SSVEP responses, leading to faster and more reliable control of external devices. Furthermore, the compact embedded setup reduces overall power consumption while maintaining performance comparable to high-end computational platforms. This work highlights the potential of lightweight embedded BCI systems to provide efficient, real-time, and user-driven control for various applications in neurotechnology, rehabilitation, and human–computer interaction.

Keywords: Brain–computer interface (BCI), electroencephalography (EEG), steady-state visually evoked potential (SSVEP), visual stimuli, human–computer interaction

INTRODUCTION

With technological advancements accelerating, the quest to enable direct communication between the human brain and machines has become increasingly significant. One compelling method in this domain is the Steady-State Visual Evoked Potential-based Brain-Computer Interface (SSVEP-BCI), which empowers users to operate devices by concentrating on specific visual stimuli.

Brain–Computer Interface (BCI) technology is an emerging field that enables direct communication between the human brain and external devices by translating neural activity into control signals. It eliminates the need for any physical or muscular movement, making it highly beneficial for individuals with severe motor impairments. The BCI system primarily relies on the acquisition, processing, and interpretation of brain signals, most commonly recorded through Electroencephalography (EEG) (Figure 1), due to its non-invasive nature, cost-effectiveness, and high temporal resolution.

Among various BCI paradigms, the Steady-State Visually Evoked Potential (SSVEP)-based BCI has gained considerable popularity. SSVEPs are

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periodic responses generated in the visual cortex when a person focuses on a flickering visual stimulus at a specific frequency. These responses exhibit strong frequency components that can be reliably detected in EEG signals, allowing accurate classification of user intent. Compared to other paradigms such as motor imagery or P300, SSVEP offers higher accuracy, minimal user training, and excellent real-time performance, making it well-suited for practical control applications.

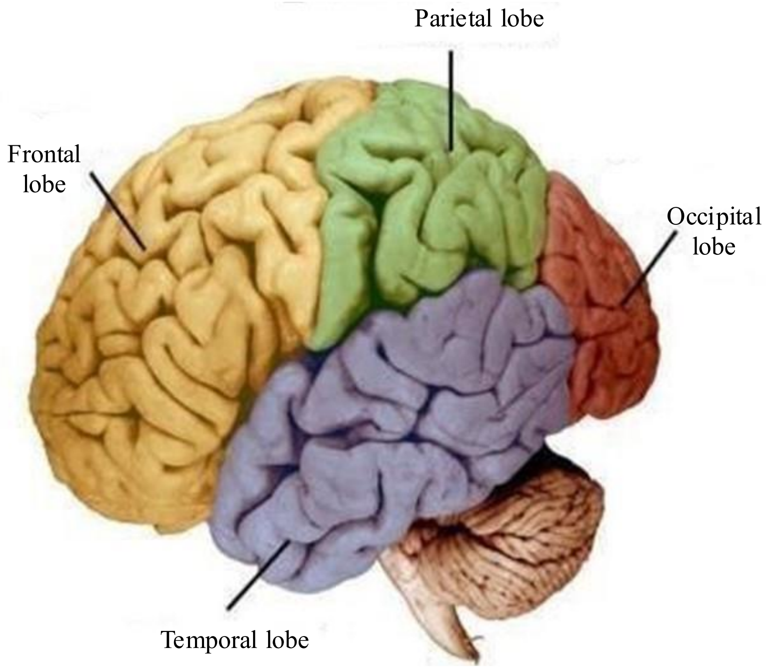


Figure 1. Brain diagram with different lobes.

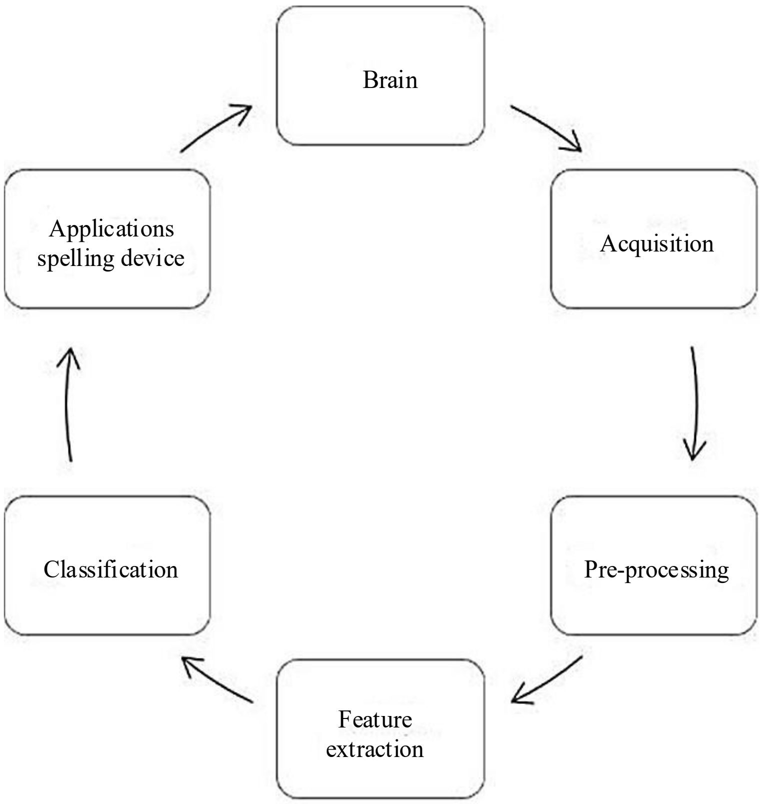


Figure 2. Block diagram.

Despite these advantages, implementing SSVEP-based BCI systems on embedded hardware introduces several challenges. The limited computational capacity of microcontrollers or embedded boards often restricts the complexity of signal processing and classification algorithms. Moreover, EEG signals are inherently weak and prone to noise from environmental and physiological sources, requiring efficient preprocessing for accurate detection.

This paper aims to enhance the control efficiency of embedded SSVEP-based BCI systems by integrating optimized EEG signal processing and real-time implementation techniques. The proposed approach focuses on using band-pass filtering, noise suppression, and feature enhancement to isolate relevant frequency components. By deploying the system on compact embedded hardware, it achieves low latency.

Recent Trends in Electronics Communication System

Acquisition

The first step in the system is signal acquisition, where brain activity is recorded using electroencephalography (EEG). SSVEP-based EEG signals are acquired using specialized EEG equipment. Particular conditions have to be met before acquiring the signal that is the surrounding area should be quiet and no other visual interference should be present in front of the subject as well as minimal to no physical movement is permitted for the subject (Figure 2). There are two types of methods for obtaining signals invasive and non-invasive methods. Invasive methods include placing the electrodes directly onto or inside the brain tissue for which the surgical approach is used on the other hand using a non-invasive approach is much more accessible and practical as no surgical means are used in this process and the electrodes are placed on the scalp to measure he electrical activities of the brain SSVEP- based response from the brain is noted to be maximum near the occipital lobe and the brain's parietal lobe from Table 1.

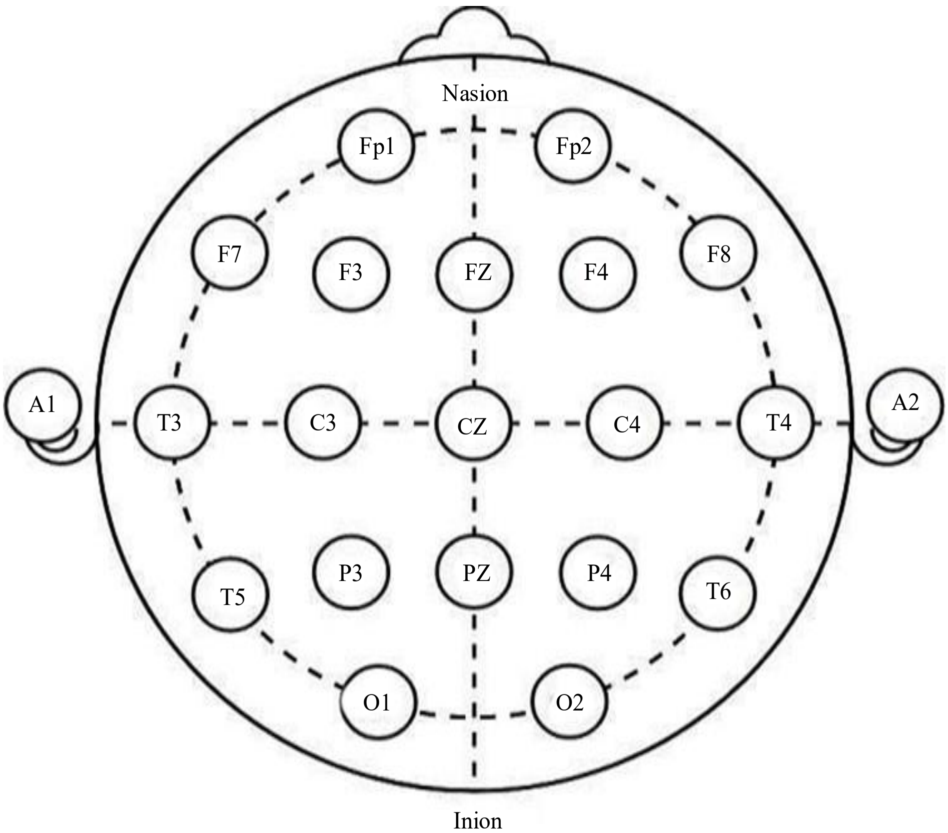


Figure 3. Brain with lobes identification.

Table 1. Frequency bands.

Frequency band	Range of frequency in Hz
Delta	0–4
Theta	4–8
Alpha	8–12
Beta	12–30
Gamma	>30

Electrodes are strategically positioned on the scalp to detect the brain's electrical signals. This stage is responsible for capturing and digitizing the SSVEP responses generated when the user is exposed to periodic visual stimulai [1, 2].

Therefore the electrodes used to acquire EEG signal data are placed near the occipital and parietal lobe. In our research, we place five electrodes on PO3, POz, PO4, O1, and O_2, respectively, three on the Parietal conductivity between the electrodes and the scalp by reducing impedance and giving a stable signal. lobe and two on the occipital lobe of the brain. A saline conductive gel is used to improve the electrical conductivity between the electrodes and the scalp by reducing impedance and giving a stable signal (Figure 3).

Signal Processing

Signal processing plays a vital role in the functionality of BCI systems, especially those using SSVEP responses. Since raw EEG recordings often contain disturbances caused by muscle motion or eye blinks (Figure 4), applying proper filtering and artifact removal techniques is essential to ensure the integrity and clarity of the data for subsequent analysis [3, 4] signal processing critical for accurate interpretation.

1. Band-Pass Filtering.
2. Artifact Removal.
3. Spatial Filtering [2].

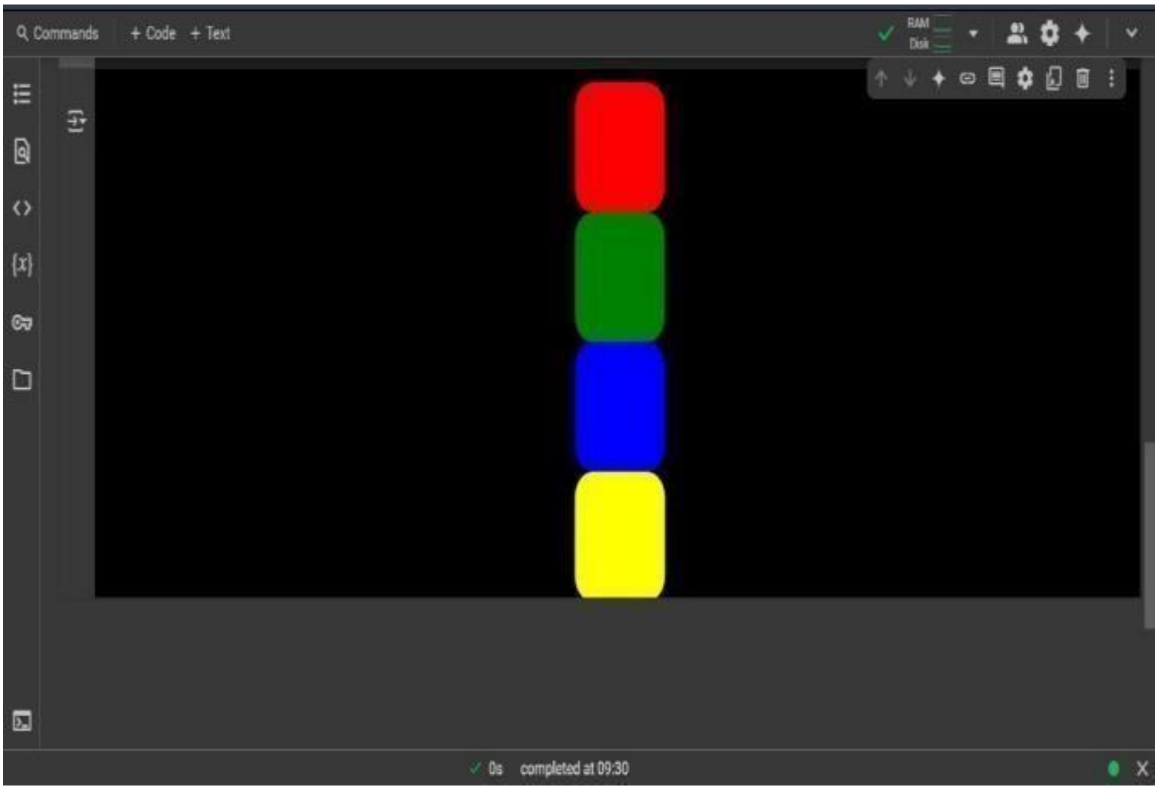


Figure 4. Color cascade.

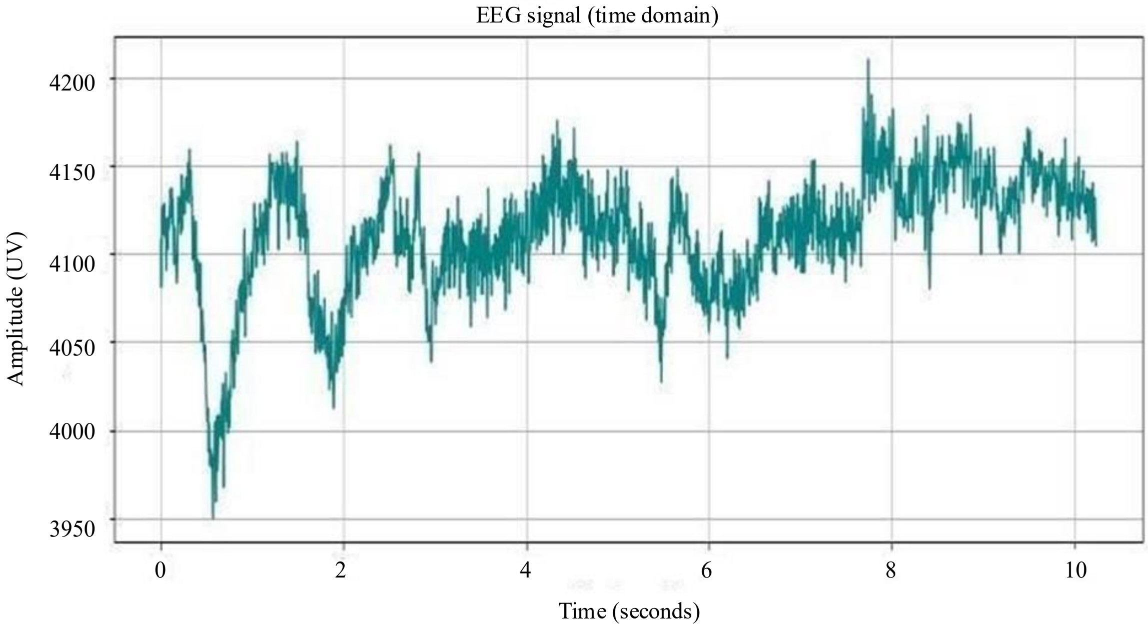


Figure 5. Signal representation in time domain.

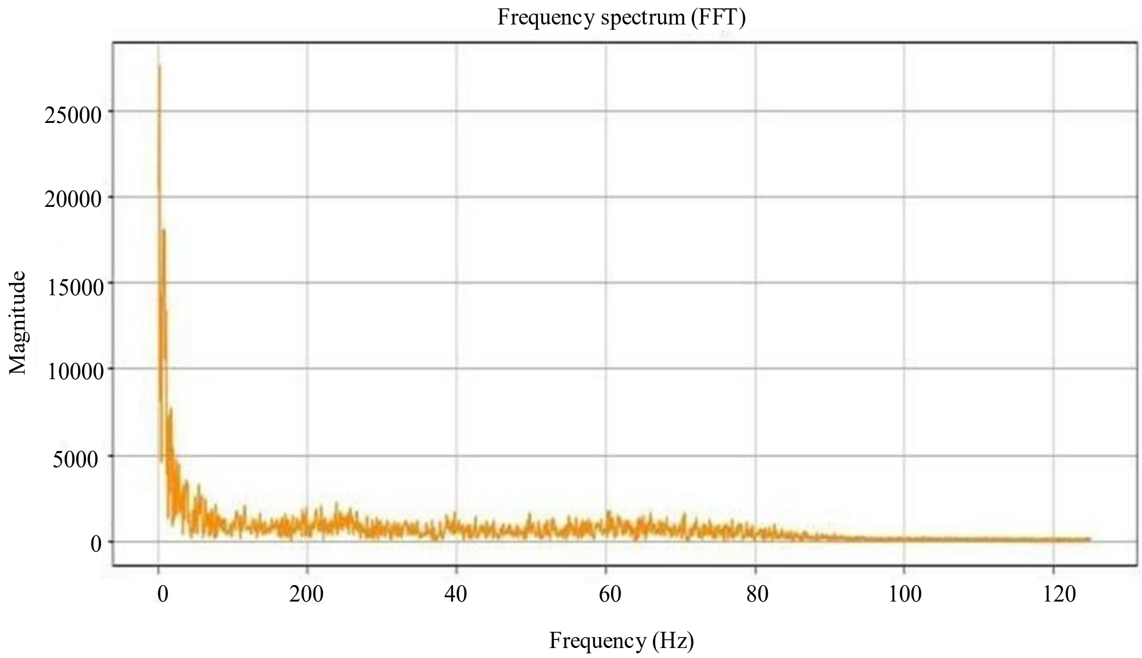


Figure 6. Signal representation in frequency domain.

"The above graph represents the EEG signal in the time domain, recorded from the O_2 electrode. The plot shows variations in amplitude over time, capturing the brain's electrical activity in response to visual stimuli (Figure 5). Despite the presence of some noise, underlying patterns and fluctuations are clearly visible, indicating potential SSVEP responses [5, 6].

"The above plot shows the frequency spectrum of the EEG signal obtained using Fast Fourier Transform (FFT). A prominent peak is observed at lower frequencies, indicating the presence of SSVEP components corresponding to the visual stimulation frequency (Figure 6). The sharp drop in magnitude beyond 30 Hz suggests the signal is mainly concentrated in the lower frequency bands, as expected in typical SSVEP responses."

Feature Extraction

Extracting features from the processed EEG signals is crucial for effectively distinguishing between brain responses triggered by various visual stimuli frequencies. The characteristics obtained can differ depending on electrode placement; for instance, signals from electrodes on the occipital lobe will differ from those on the parietal region.

Time-domain statistical features such as mean, variance, and standard deviation offer fundamental insights, while advanced metrics like skewness and kurtosis provide deeper signal characterization [2].

Features from different domains are extracted from the preprocessed EEG data these features will help us understand the signals better and benefit us in differentiating between different frequency-stimulation signals. Features can also vary from electrode to electrode meaning if one electrode is placed on the occipital area of the brain and the other is placed on the parietal side of the brain these signals will have different features [7, 8]. Statistical time domain features that we are concerned with are mean, variance, and Standard deviation. Higher-level features like skewness and kurtosis are also used to analyze and further classify such signals. In frequency domain analysis, power spectral density (PSD) serves as a primary method for extracting features. In this study, the periodogram technique is employed to estimate power spectral density. However, the application of FFT extends beyond the extraction of EEG sub-bands; it also proves valuable in extracting statistical features such as spectral centroid and spectral energy. A features matrix is then prepared in which all the features are arranged in such a manner that they can be differentiated based on the frequency with which the subject was stimulated so that the classifier learner will be able to differentiate between these EEG signals which are obtained via different SSVEP based frequency stimulation to the subject. Data labeling is done after the creation of the feature matrix according to the frequency of the visual stimulus it corresponds. For example, if we have a stimulus frequency at 10 Hz, 12 Hz, 8.5 Hz and 7.5 Hz label each trial accordingly.

Classification

The extracted features are used as input for the classification stage. Machine learning algorithms, such as Support Vector Machines (SVM), k- Nearest Neighbors (k-NN), or deep learning models like Convolutional Neural Networks (CNNs), are commonly applied to classify and identify the user's intended action or target from the SSVEP responses. The classification stage aims to accurately detect and decode the user's intended command based on the extracted.

The dataset, comprising feature matrices and their corresponding labels, is partitioned into training and testing subsets. The training subset facilitates the Classification classifier's training process, while the testing subset is utilized to assess its performance. Several machine- learning algorithms utilized for the classification of signals. Commonly used algorithms for EEG classification include Support Vector Machines (SVM), k- Nearest Neighbors (k-NN), and Random Forests.

We can also use different types of SVM, such as:

1. Cubic SVM.
2. Fine Gaussian SVM.
3. Linear SVM.
4. Quadratic SVM.
5. Non Linear SVM.

LINEAR SVM

Support Vector Machine with Radial Basis Function (RBF) Kernel is particularly effective in modeling complex, non-linear boundaries in high-dimensional EEG feature spaces. It works by mapping the input feature vectors into a higher-dimensional space where a separating hyperplane can be constructed. This is especially useful when using FFT or wavelet-based features that show non-linear separability. However, implementing non-linear SVMs on embedded systems requires careful optimization, as kernel- based methods can be computationally expensive. To address this, some systems use pre-trained SVM models with reduced feature sets or support approximate SVM algorithms. The selected training dataset is to be trained in the classifier where the algorithm learns to map the feature vectors to the corresponding labels as discussed before. Evaluation of the data based on features is done by the classifier for which various evaluation metrics are considered like accuracy and Information Transfer Rate (ITR). In which the classifier determines how accurately the algorithm can differentiate between signals that are acquired using different frequencies using the extracted features and feature matrix. The classifier learner provides us with a scatter plot, and confusion matrix for a more detailed analysis of the classification.

LITERATURE REVIEW

Many researchers have explored Brain-Computer Interfaces (BCIs) to help people interact with machines using brain signals. Among the different types of BCIs, SSVEP-based systems are popular because they offer faster and more accurate responses. These systems rely on how the brain reacts to flashing visual stimuli at certain frequencies. Studies have shown that using EEG signals from the occipital region of the brain gives strong SSVEP responses. To improve the quality of these signals, researchers often apply preprocessing steps like band-pass filtering and artifact removal. Some works also use machine learning algorithms like SVM or CNN to classify the brain signals and turn them into useful commands Recent developments have focused on making BCI systems faster, more reliable, and easy to use in real-time scenarios. Many studies also aim to reduce the hardware size and improve the comfort of users during operation. Our project builds on these ideas by refining the signal processing pipeline and using a pre-recorded dataset to create a more efficient, responsive, and user-friendly BCI system [9, 10].

Features from different domains are extracted from the preprocessed EEG data these features will help us understand the signals better and benefit us in differentiating between different frequency-stimulation signals. Features can also vary from electrode to electrode meaning if one electrode is placed on the occipital area of the brain and the other is placed on the parietal side of the brain these signals will have different features. Statistical time domain features that we are concerned with are mean, variance, and Standard deviation. Higher-level features like skewness and kurtosis are also used to analyze and further classify such signals. In frequency domain analysis, power spectral density (PSD) serves as a primary method for extracting features. In this study, the periodogram technique is employed to estimate power spectral density. However, the application of FFT extends beyond the extraction of EEG sub-bands; it also proves valuable in extracting statistical features such as spectral centroid and spectral energy. A features matrix is then prepared in which all the features are arranged in such a manner that they can be differentiated based on the frequency with which the subject was stimulated so that the classifier learner will be able to differentiate between these EEG signals which are obtained via different SSVEP based frequency stimulation to the subject. Data labeling is done after the creation of the feature matrix according to the frequency of the visual stimulus it corresponds. For example, if we have a stimulus frequency at 10 Hz, 12 Hz, 8.5 Hz and 7.5 Hz label each trial accordingly.

WORK DONE

While performing this research we have done the following steps:

- A microcontroller board with at least three LEDs to simulate flicker frequencies.
- EEG electrodes for capturing brain signals.
- An EEG machine for signal acquisition.
- EEG data acquisition software, such as BT Traveler Acquisition and BT Traveler Analysis applications.
- MATLAB for signal processing, feature extraction, and classification.
- Jupyter Notebook for SVM model.

SIGNAL ACQUISITION

In the signal acquisition stage, instead of recording new data, we used an available EEG dataset containing brain responses to visual stimuli (Figure 7). This saved time and allowed us to directly focus on processing and analyzing the signals for BCI control.

Figure 7. Neuro pulse 24.

SIGNAL PRE-PROCESSING

In signal preprocessing, we cleaned and prepared the EEG data to make it easier to understand. We applied a band-pass filter to keep only the useful frequency range, removed unwanted noise and artifacts, and adjusted the signals to a common baseline. This helped improve the accuracy of brain signal analysis.

FEATURE EXTRACTION

After cleaning the EEG signals, the next step was feature extraction – this means picking out the most useful information from the brain signals that can help us understand which visual stimulus the person is focusing on. Think of it like this: the brain responds differently to different flashing lights (like 10 Hz, 12 Hz, etc.). We need to capture those differences in a measurable way, and those measurements are called features.

Frequency-Domain Features

Since SSVEP signals appear at specific frequencies, we used Fast Fourier Transform (FFT) to convert the EEG signal from time-domain to frequency-domain From this, we extracted the power (or amplitude) at the stimulus frequencies (e.g., 10 Hz, 12 Hz). Statistical Features:

We also used simple math-based features like mean, standard deviation, and signal power, which help represent the overall signal.

CLASSIFICATION

In this research, we focus on enhancing device control using an embedded SSVEP-based Brain-Computer Interface (BCI). The core of the system relies on the classification of EEG signals collected in response to visual stimuli of specific frequencies. A pre-recorded dataset containing EEG signals corresponding to multiple stimulus frequencies is used for training purposes (Table 2). The signals are initially pre-processed using a Notch filter to remove power line interference, typically at 50 Hz, and band-pass filtered to isolate the SSVEP frequency range.

The filtered EEG data is then processed in Python using Jupyter Notebook, where we apply signal analysis techniques such as Fast Fourier Transform (FFT) to extract frequency-specific features. These features are fed into a classification algorithm (such as SVM, KNN, or a neural network), which is trained on the labeled dataset to learn the correlation between the brain's response and the visual stimulus frequency.

Table 2. Statistical and spectral features used for signal analysis.

Time domain features
Mean Median Mode Standard Deviation (std) Variance (var) Minimum (min) Maximum (max) Range Skewness Kurtosis Root Mean Square (RMS) Energy Zero Crossings
Frequency domain features
FFT Mean FFT Std Spectral Entropy Max Frequency Mean Frequency

This trained model is saved and later embedded into the control system. During real-time operation, the system uses the trained model to classify live EEG signals and generate corresponding control commands. Since the model is already trained, the embedded system only needs to process incoming data and match it with the trained frequency classes for fast and accurate control output.

This approach ensures low-latency control, higher classification accuracy, and a practical path toward real-world implementation of SSVEP-BCI systems for assistive technology.

KERNAL SVM

In this project, we use a Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel. The RBF kernel is chosen because it effectively handles non-linear relationships in EEG signal data. It transforms the input features into a higher-dimensional space, allowing the SVM to find an optimal hyperplane that separates different classes corresponding to distinct visual stimulus frequencies Figure 8(a) and (b). This improves the model's classification accuracy, especially when the EEG signal patterns are not linearly separable.

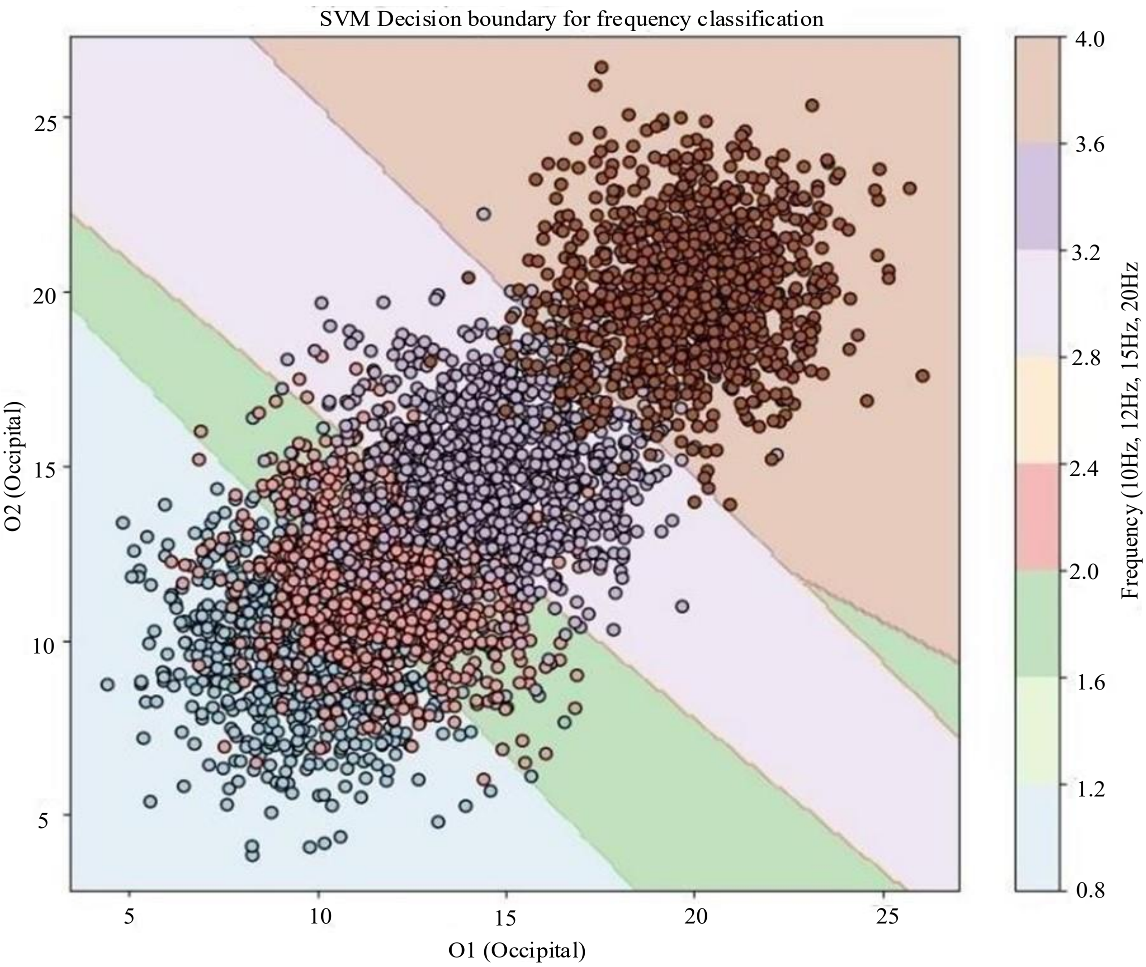
RESULT TABLE

The proposed system, which integrates an embedded SSVEP-based Brain Computer Interface (BCI) with an ESP32 microcontroller for real-time motor control (Figure 9), successfully demonstrated its ability to decode user intentions through visual stimuli and translate them into precise motor actions. The experiment involved users focusing on flickering stimuli at distinct frequencies (10 Hz, 12 Hz, 7.5 Hz, and 8.5 Hz), each representing a specific control command: move forward, turn left, and turn right, respectively.

The matrix illustrates the performance of an SVM classifier applied to EEG data across four frequency classes: 10 Hz, 12 Hz, 7.57 Hz, and 8.57 Hz. Each class is perfectly classified, as indicated by the values of 1 along the diagonal and 0 elsewhere. This results in a perfect accuracy score of 1.00 (or 100%), showing that the model successfully identified each EEG signal's frequency without any misclassifications. The results suggest that the EEG features used were highly discriminative and that the SVM model was effectively trained for this classification task.

FUTURE SCOPE

As the field of neuroscience and machine learning continues to advance, there are numerous exciting avenues for future research in the domain of Visually Evoked Potentials (VEPs). The research paper focuses on the SSVEP-based EEG signal application of Brain–Computer Interface (BCI) where numerous medical as well as automation opportunities present and which lay the foundation for several promising directions for further exploration and enhancement.



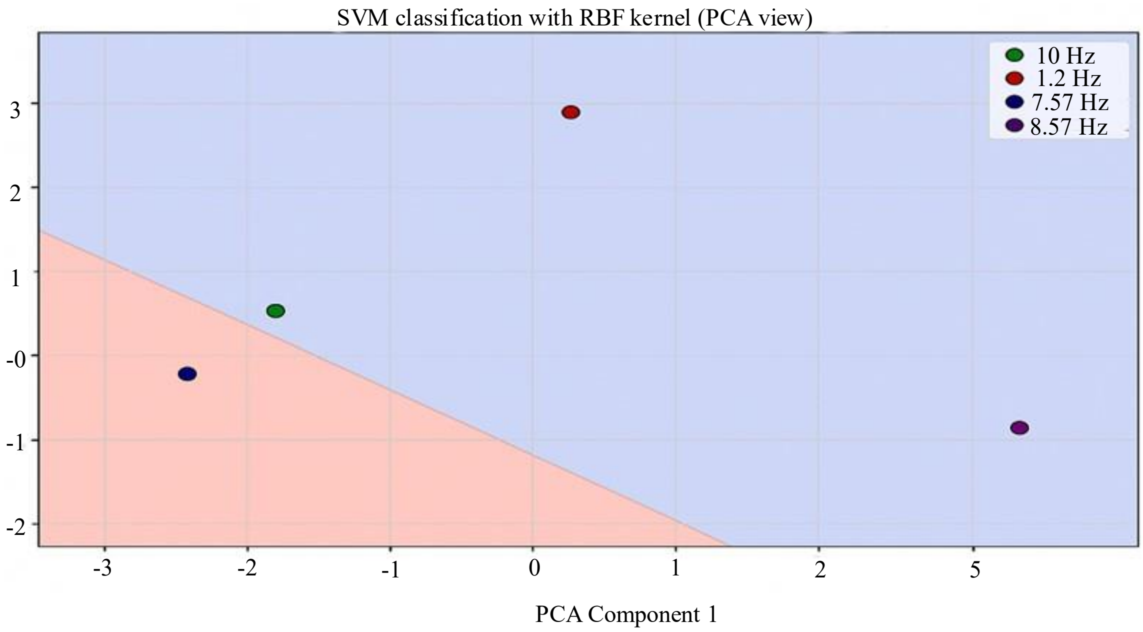


Figure 8. (a) and (b): SVM classification with RBF kernel (PCA view).

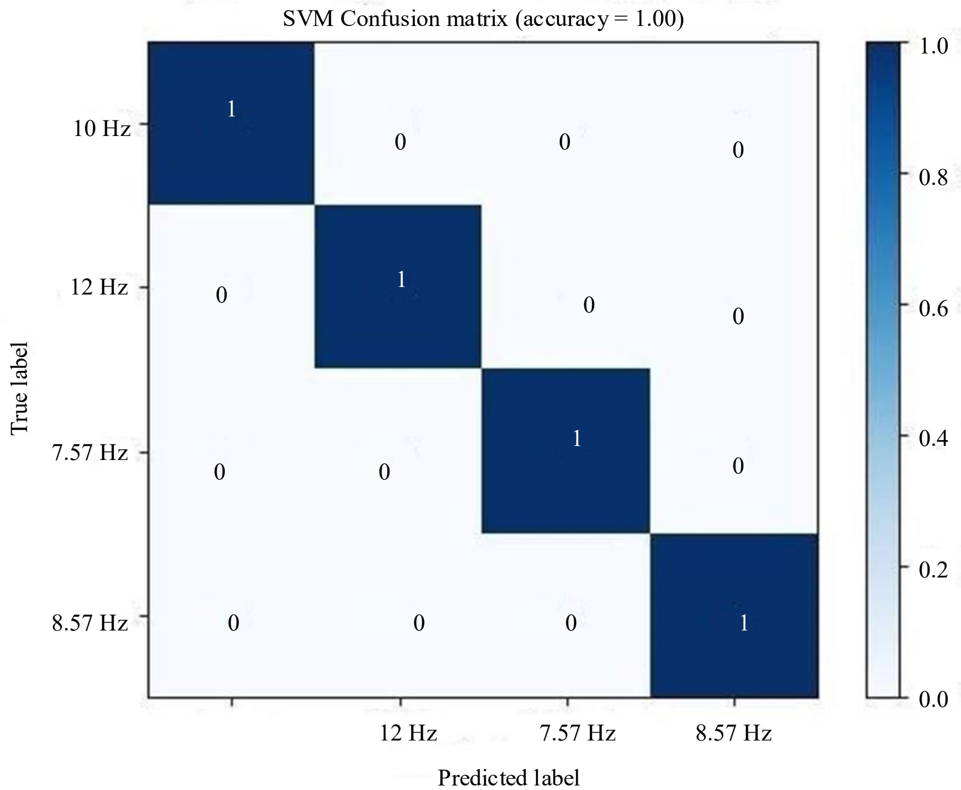


Figure 9. SVM confusion matrix (accuracy).

The following future scope outlines potential areas of SSVEP-based EEG signals used for BCI purposes:

Medical Applications

SSVEP-based BCIs can enable individuals with severe motor disabilities, such as those with locked-in syndrome or advanced ALS, to communicate. By focusing their attention on different visual stimuli, users can generate specific brain responses that can be translated into commands or messages. These systems can also be used to control several assistive devices such as wheelchairs, robotic arms, or smart home appliances. This allows disabled individuals to regain a level of independence by controlling their environment and performing tasks that would otherwise be challenging or impossible.

Entertainment and Gaming Industry

SSVEP-based BCI system can enhance the gaming experience by providing a more immersive and interactive interface for the users.

Personalized BCI Systems

In the future BCI systems may adapt to the user's unique brain signal by incorporating adaptive learning techniques which could continuously receive feedback from the users and adapt accordingly providing a more personalized experience.

CONCLUSION

In this paper, we deal with visually stimulating the user and then acquiring EEG signal from the user using various frequencies from alpha and beta frequency bands, We introduce this type of visual stimuli using a checkeredboard that flickers with alternating light and dark squares to which the brain produces a natural response called Visually Evoked Potential (SSVEP) at specific frequencies. The acquired signal is then preprocessed and important time and frequency domain features arextracted. A feature matrix is prepared and labeled according to different frequencies. We have mainlyfocused on integrating modern machine learning methods with EEG(electroencephalography). With the use of modern classification techniques, we were able to gain new insights as well as determine the accuracy with which the system can differentiate between signals from different frequencies. Such SSVEP-based BCI systems can be integrated and used in numerous medical and other applications.

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