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BCI Enabled Prosthetic Arm Movement: Signal Processing (Part-1)

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Abstract: This paper has two parts where first part focus on the signal processing and second part will focus on the signal classification and arm movement. This work improves SSVEP detection in EEG-based BCI systems using Empirical Mode Decomposition and FFT. EEG signals recorded with the 10–20 system were broken down into IMFs. IMF2 to IMF4 were identified as key contributors. After averaging and segmenting the data into 2-second windows, FFT-based spectral analysis found SSVEP responses.

We evaluated detection accuracy by classifying segments as true or false. The results show that the suggested EMD-FFT method outperforms the traditional method (85.38%) by increasing average detection accuracy to 88.00%. The construction of an effective control system for upcoming prosthetic arm applications utilizing EEG-driven BCI technologies is aided by this improved accuracy, which fortifies the dependability of SSVEP-based feature extraction.

Keywords: Steady-state visual evoked potential (SSVEP), Brain–computer interface (BCI), Empirical mode decomposition (EMD), Power spectrum analysis (PSA), Intrinsic mode function (IMF), Motor imagery (MI)

I. INTRODUCTION

BCI (Brain-Computer Interface) acts as a channel for human brain to communicate between with a computer system. It allows its users to control external devices which are independent of peripheral nerves and muscles with brain activities. BCI system allows a subject to send commands to an external device by using brain signal.

BCI channel can be considered as the only way through which people affected by motor disabilities can communicate their thoughts. It is very helpful to assist patients with impaired motor functions, such as completely paralyzed patients with amyotrophic lateral sclerosis [1].

For some people with very severe disabilities (e.g., amyotrophic lateral sclerosis or brainstem stroke), a brain–computer interface (BCI) may be the only feasible channel for communicating with others and for environment control. A BCI typically operates by harnessing signals arising from processes within the brain without depending on the brain's normal output pathways of peripheral nerves or muscles. The most common signal employed for this purpose currently is the non -invasive, scalp recorded electroencephalogram (EEG) [2].

What is EEG? Brain is made up of billions of neurons that are communicated by the application of electricity. Simultaneously millions of such signals are sent, which generates an immense amount of electrical activity in the brain. This cumulative operation is rising and dropping like a tide. It is also referred to as brain waves and can be measured by medical instruments such as EEG. It calculates the amount of electricity over the brain scalp region, based on whether the person performing the brain's electrical activity is going to change.

There is a lot of difference between a sleeping person's brainwaves and a person's brainwaves are wide awake. A person's emotional status can be evaluated by studying the rhythm of the brain wave. Highly nervous people emit strong beta waves and people with ADD / ADHD emit sluggish alpha/theta waves [3].

EEG is closely related to Brain–Computer Interfaces (BCI) because it provides the essential input signals used to interpret brain activity. In a BCI system, EEG signals are captured, filtered, and analysed using signal processing and machine learning techniques to detect patterns corresponding to specific thoughts or intentions.

These patterns are then translated into commands that can control external devices, such as prosthetic limbs, wheelchairs, or computer cursor.

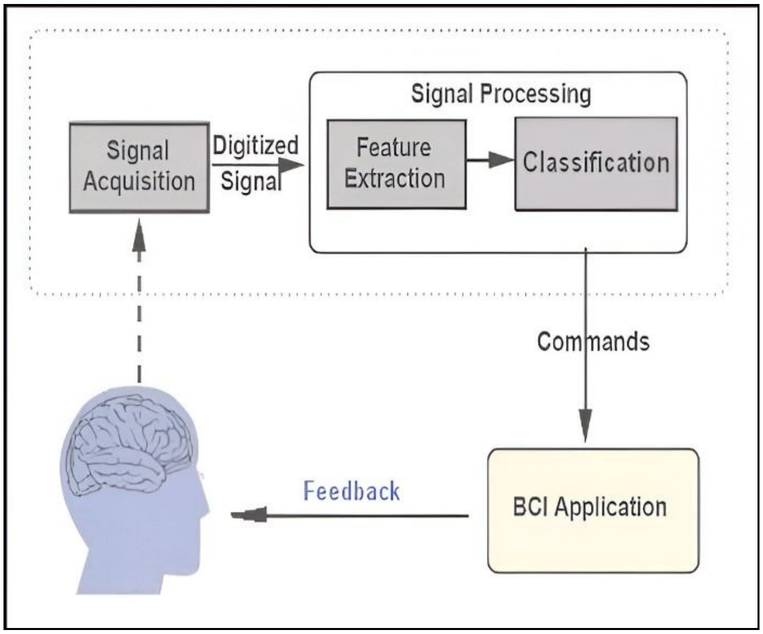

Fig.1 BCI System

The Steady-State Visually Evoked Potential (SSVEP) is an electrophysiological brain response measured by EEG. It occurs when the visual system is excited by a periodic stimulus, such as a flickering light, at a constant rate, typically ranging from 3.5 to 75 Hz. This stimulus entrains the visual cortex to generate sustained oscillatory activity that is "phase-locked" to the exact stimulus frequency and its harmonics. SSVEP signals are strongest over the occipital electrodes (e.g., Oz) and are highly valued for their robust frequency specificity, making them foundational for use in Brain-Computer Interface (BCI) applications for controlling devices.
For data collection we use 10-20 Placement Method. It is the foundational, standardized method for placing electrodes for routine Electroencephalography (EEG). The "10" and "20" signify that the proportional distances between adjacent electrodes are 10% or 20% of the total measured front-back (Nasion-Inion) or right-left (Preauricular) skull distances. This proportional approach ensures reproducible electrode placement across subjects of varying head sizes, which is vital for clinical diagnosis and research consistency. Even numbers (2,4,6,8) refer to the right hemisphere and odd numbers (1,3,5,7) refer to the left hemisphere [1, 4].

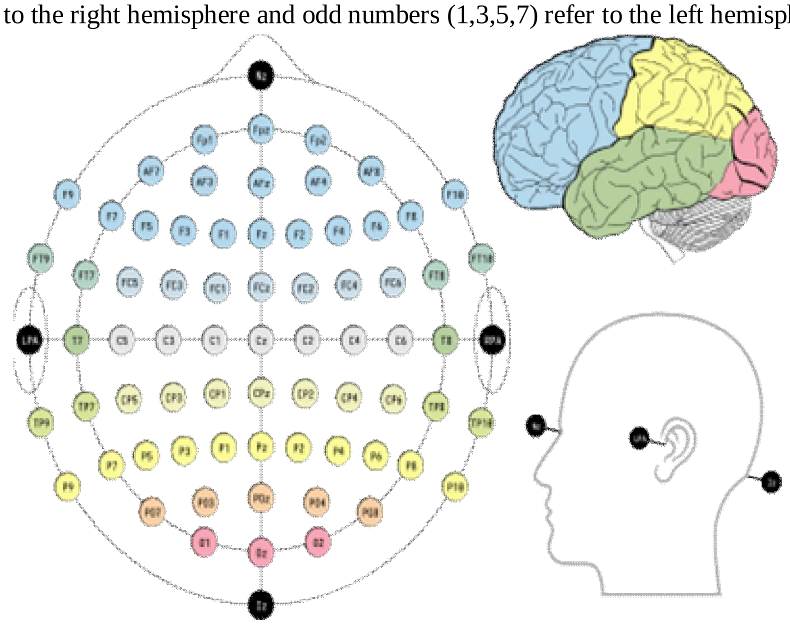

Fig.2 10-20 Placement Method

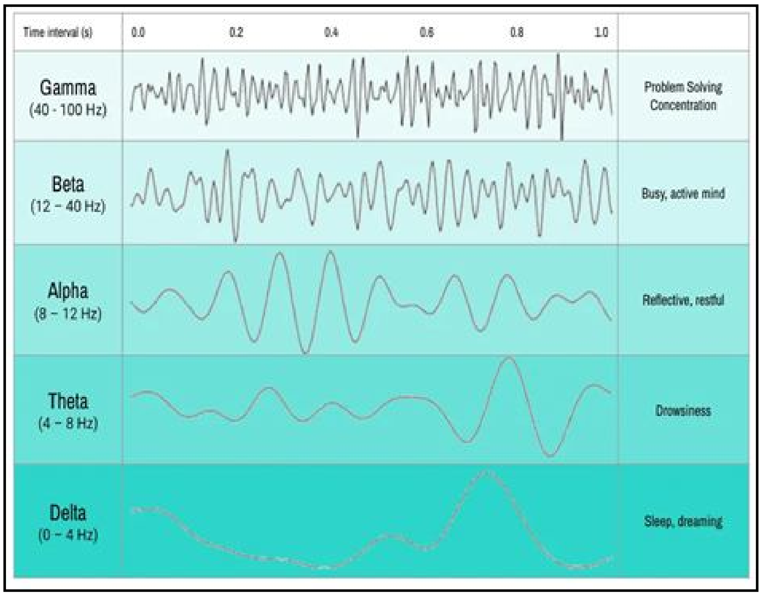

Fig.3 Different human brain waves [1].

TABLE 1. Different Brain Rhythms **[1].**

BRAIN WAVE	FREQUENCY	CONDITION
Delta	0.5–4 Hz	Deep sleep
Theta	4–8 Hz	Drowsiness, meditation
Alpha	8–13 Hz	Relaxation, eyes closed
Beta	13–30 Hz	Active thinking, focus
Gamma	30–100 Hz	High-level cognition

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II. LITERATURE REVIEW

Early work in this field used motor imagery (MI), P300, and SSVEP signals to generate control commands. According to Palumbo et al. (2021), a lot of progress has been made in MI-based wheelchair control, with many studies reporting accuracies between 70–80%. However, issues like noise in EEG signals, user fatigue, and slow command generation are still common. Saichoo et al. (2022) showed that if the training is customized for each user, the performance improves significantly.

Research on prosthetic arms also shows promising results. Diwakar et al. (2014) built a low-cost robotic arm controlled directly using EEG signals. Their study proved that even simple EEG features can be used to control prosthetics. Later, Pancholi et al. (2021) applied deep learning to predict hand movements from EEG signals, which helps in creating smoother and more natural control for robotic hands.

Hybrid BCI systems are becoming popular because they combine multiple signals. For example, Huang et al. (2019) used EEG together with EOG signals to control both a wheelchair and a robotic arm. This made the system more reliable and allowed more control options for the user.

A. Recent Developments (2023–2025)

A lot of recent studies have made practical improvements. Basit et al. (2025) introduced *Cognitive Arm*, a real-time EEG-controlled prosthetic arm that uses lightweight machine learning models. Since the processing is optimized for embedded devices, the arm responds very quickly.

Thapa et al. (2025) used a deep learning model combining Bi-LSTM and Bi-GRU to control wheelchair navigation from EEG motor imagery signals. They achieved better Accuracy than many older systems.

Zhang et al. (2024) developed a user-friendly and intelligent wheelchair that uses EEG signals for control along with safety features and improved user comfort.

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One recent study from 2024/2025 showed that a normal electric wheelchair can be converted into a "thought-controlled wheelchair" using a low-cost EEG device that costs around $600. This makes BCI systems more accessible for real-life use.

Hybrid systems from 2023–2024 combine EEG with eye-tracking and computer vision, allowing robotic arms to perform reaching and grasping tasks more accurately. A 2024 review in *Applied Sciences* highlighted how machine learning and deep learning models are improving prosthetic control, rehabilitation, and real-time movement prediction.

III. PROBLEM STATEMENT

People who have lost control over parts of their body due to paralysis, spinal cord injury, or limb amputation often find it difficult to perform basic daily activities. Traditional assistive devices depend on muscle movement or manual control, which are not useful for individuals with severe disabilities. A BCI based EEG signals offers a way to help such individuals by using their brain activity to control external devices like prosthetic arms or wheelchairs. EEG records the brain's electrical signals through electrodes placed on the scalp, which can then be analysed to understand a person's intentions. However, EEG signals are often weak and mixed with noise, making it difficult to detect accurate commands. Therefore, the main problem is to develop a reliable and efficient EEG-based BCI system that can accurately recognize brain signals and convert them into control commands for prosthetic or assistive devices, helping disabled individuals regain movement and independence.

A. Objective

1) To detect cognitive or mental states

Identify states such as:

- Attention
- Fatigue
- Stress
- Workload

This helps in applications like driving assistance or training systems.

2) To improve FFT Technique for better Detection Accuracy

We will try to upgrade FFT Filter (Fast Fourier Transform) to convert time domain signal which is difficult to understand and study. Previous FFT Filter has less Detection Accuracy for recognising different state of mind. This FFT Filter will have better Detection Accuracy than Previous Filter.

IV. METHODS

A. Signal Acquisition

Four healthy volunteers participated in this study. The data consists of single-channel EEG recorded primarily from the Oz electrode, which is situated over the posterior (occipital) region of the brain. Healthy subjects were exposed to visual stimuli flickering at multiple distinct frequencies, often including a set of five frequencies such as 6 Hz, 6.5 Hz, 7 Hz, 7.5 Hz and 10 Hz. This dataset allows researchers to analyse real-world SSVEP responses and develop detection and classification algorithms.

3 times each frequency was recorded for the 30 s at the sampling frequency 512 Hz [1,5,6].

The data is collected with the help of 10-20 Placement method.

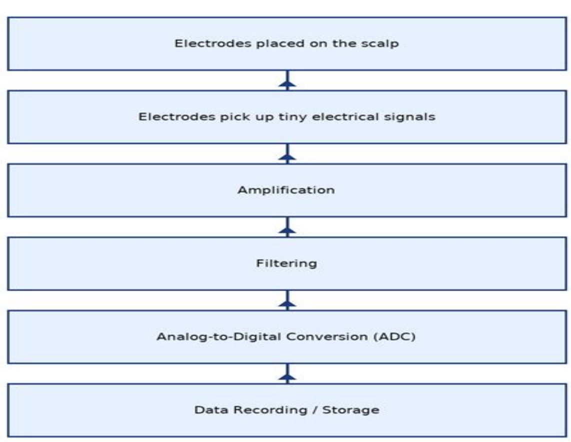

Fig.4 Block Diagram of signal acquisition

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B. Pre-Processing Of Eeg Signals

Pre-processing of EEG signals is a crucial step that prepares raw brain data for analysis in Brain–Computer Interface (BCI) systems. Raw EEG recordings often contain various artefacts such as eye blinks, muscle movements, power-line interference, and environmental noise, which can distort the signal. Pre-processing aims to clean and enhance the data to improve accuracy and reliability. The process usually begins with filtering, including band-pass filters (0.5–40 Hz) to retain useful brain rhythms and notch filters (50Hz) to remove power-line noise [1]. Segmentation is then performed to divide the signal into short, stable time windows. Artefact removal techniques such as Independent Component Analysis (ICA) or adaptive filtering help eliminate unwanted components like EMG and EOG artefacts. Normalization and baseline correction may also be applied to stabilize signal amplitude. Overall, pre-processing ensures that only meaningful neural information is preserved, enabling effective feature extraction and classification in BCI applications [1,5,6,7].

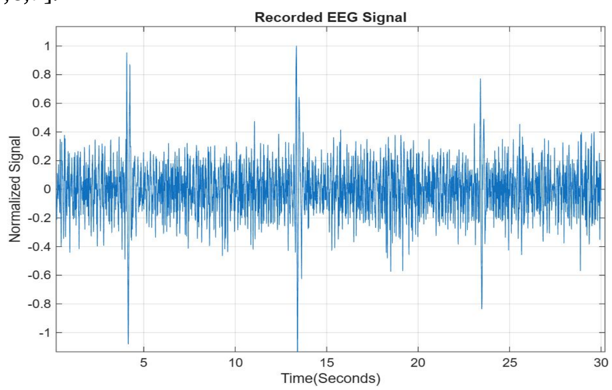

Fig.5 Raw data of 10 Hz frequency.

C. Feature Extraction

A feature represents a unique property. Emotion recognition from EEG signals allows the direct assessment of the “inner” state of a human, which is considered as an important parameter in Brain-Computer-Interface [1]. After preprocessing the signal is fed into one or more type of feature extraction algorithms. This component extracts features in the time domain and frequency domain that encode messages or commands [5]. Wide varieties of feature extraction methods are used in BCI system. We use FFT (Fast Fourier Transform). All signals that are collected from the brains are in time domain which is Analog signal ad to obtain the feasible data from the Analog signal is very difficult and hard to understand. So, FFT is used to convert time domain signal into frequency domain signal. Frequency domain signal is easy to understand and we can collect the feasible data.

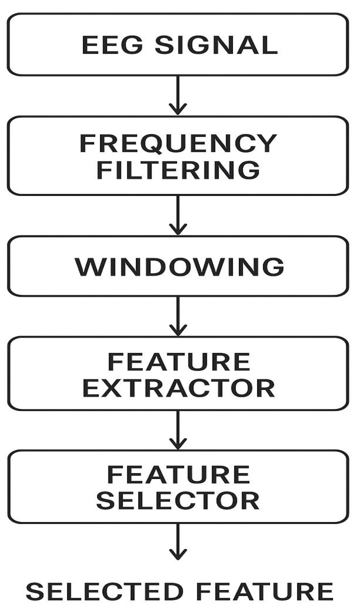

Fig.6 Process involved in feature extraction

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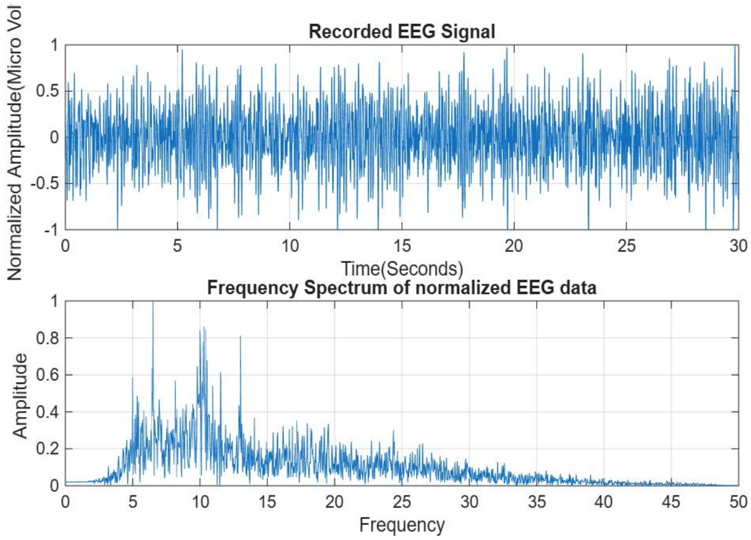

Fig.7 10 Hz Frequency is extracted

D. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is an adaptive signal analysis technique for processing non-linear and non-stationary sequences [6,8-10].

It decomposes a signal into a set of Intrinsic Mode Functions (IMFs). The computation relies on an iterative sifting process.[3] In each step, the algorithm identifies the local extrema, constructs the upper and lower envelopes, and calculates the local mean m_t, which is then subtracted ($h_K = h_{K-1}$-m_k). This iterative filtering continues until the resulting component meets the criteria to be designated as an IMF [6,8].

Low-frequency elements present in IMF and should satisfy two conditions. (a) The number of extreme & zero-crossing must be similar or may have a difference of one. (b)The mean maximum and minimum envelope should be zero [6,8].

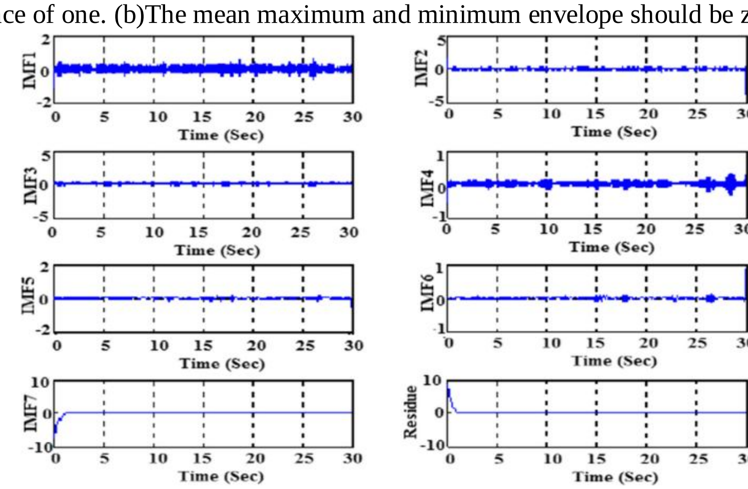

Fig.8 Different IMFs using EMD

For a given data of time series x(t), an EMD algorithm is outlined as under;

1. Identify all maxima and minima of the data set x(t)
2. Obtain upper envelope u(t) and lower envelope l(t) of x(t) by joining all maxima and minima points.
3. mean value is computed by averaging upper along with a lower envelope

$$m(t)=\frac{u(t)+l(t)}{2}$$

4. The first component is obtained by subtracting mean value from the original time series data using

$$G_1(t)=x(t)-m(t)$$

5. If g1(t) satisfied the condition (a) and (b) then it is an IMF, and that is given by

$$h1(t)=g1(t)$$

Otherwise, repeat the above steps until the $g_1(t)$ becomes an IMF.

6. Compute the residual by subtracting IMF h1(t) from the time-series data

$$r1(t) = x(t)-h1(t)$$

7. Consider 1(t) residual as a new data

$$\delta_1 (t)=r1(t)$$

8. The above process is repeated on every subsequent residual till every residue satisfies the stopping criteria, the obtaining results are

$$R_2(t)=r_1(t)-g_2(t)\ldots r_n(t)=r_{n-1}(t)-g_n(t)$$

9. In the last, original signal x(t) is equal to the sum of IMFs and a residual which is given as follows

$$x(t)=\sum_{i=1}^{n} h_i(t) + \delta_n(t)$$

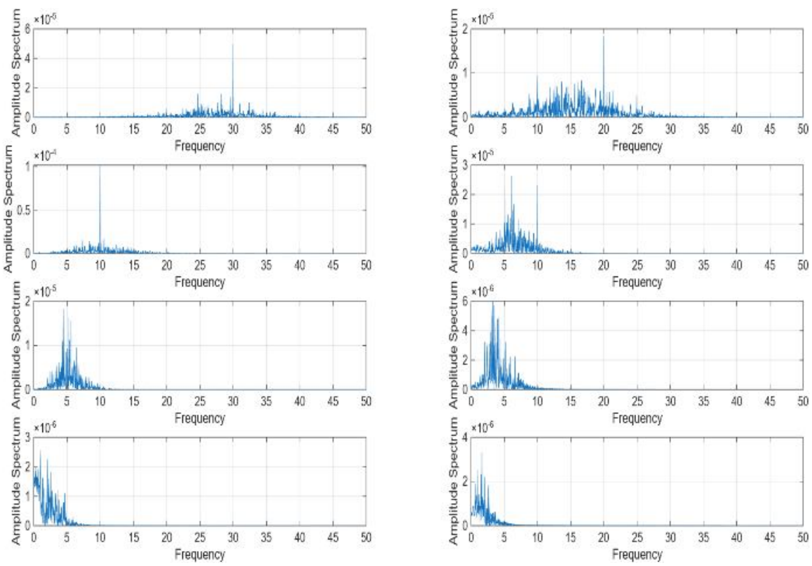

Fig.9 Normalized power spectrum analysis of IMF1-IMF7 and residue using FFT of stimulus frequency 10 Hz of subject-4 [6].

V. RESULT

A single channel AVI SSVEP data set is used to test the suggested approach. 512 Hz was the sampling frequency. The recorded EEG signal, which includes the shadow of a periodic waveform of the SSVEP response or target frequency and its harmonics, is analysed using MATLAB software. Pre-processing, feature extraction, and detection accuracy comprise the overall frequency detection process. To demonstrate the efficacy of the EMD approach, we compare our findings with the most recent PSA. Initially, the normalized recorded data of frequency 10 Hz is decomposed into oscillating components using EMD. The decomposed components are shown in Table 2.

In our research we use 5 different types of frequency which is shown in Fig 10.

The IMFs that exhibit peak energy at the desired frequency—primarily IMF2, IMF3, and IMF4—are recognized as contributing elements. After ensemble-averaging these IMFs, FFT-based power spectrum analysis is used to identify the SSVEP response. Detection accuracy, which counts segments with power above a threshold as true positives, is used to gauge how well the algorithm works. Accuracy is computed as:

$$\text{Detection Accuracy} = \frac{T_P}{T_P + T_F}$$

Where T_P = True Segment and T_F = False Segment

The ensemble-averaged IMF components are split into 2-second segments, and the power spectrum of each segment is analysed. Detection accuracy is then computed as the ratio of correctly identified segments to the total number of segments across all trials for the given stimulus (target) frequency.

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Here we can clearly See that the conventional Technique to find detection accuracy is 85.38% and by using our method and improved algorithm of FFT and EMD our detection accuracy is increased to 88.00% which is more than then the conventional technique. This is the first part of our research where we try to improve the detection accuracy and feature extraction process for our next part which is Controlling a Prosthetic arm using BCI system and EEG signal.

TABLE 2. Result And Comparison

Stimulus Frequency	Conventional (%)	Proposed Design (%)
6 Hz	82.20	80
6.5 Hz	84.40	80
7 Hz	88.90	93.3333
7.5Hz	86.60	100
10 Hz	84.80	86.6667
Average	85.38	88.00

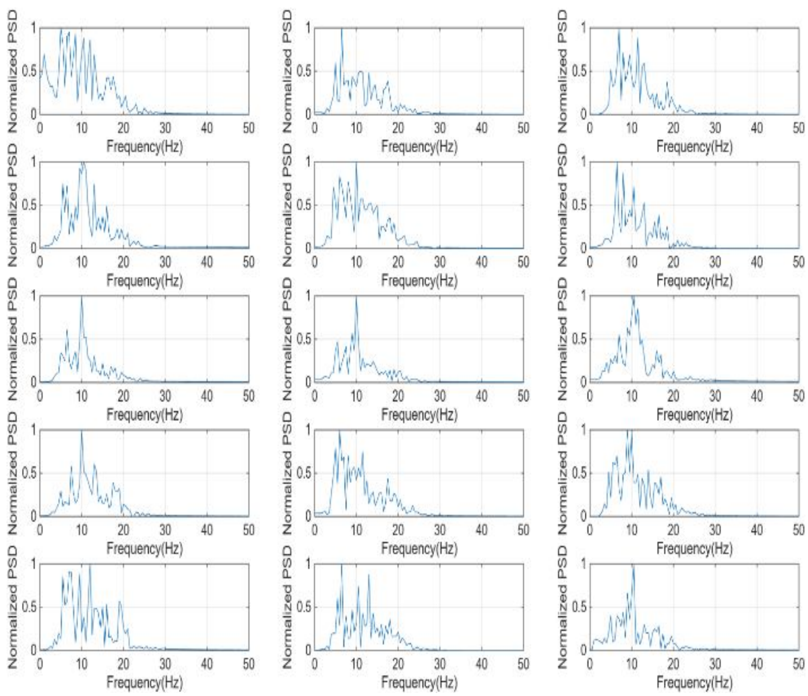

Fig.10 Power Spectral Analysis using FFT

VI. CONCLUSION

The integration of Brain-Computer Interface (BCI) technology with prosthetic arms demonstrates significant potential in restoring motor functions and independence for individuals with disabilities. Research on Steady-State Visual Evoked Potentials (SSVEP)-based BCIs highlights advantages such as high signal-to-noise ratio, rapid response time, and minimal training requirements, making them highly suitable for real-time prosthetic control. By decoding neural responses elicited from visual stimuli, SSVEP-based systems can provide reliable and efficient communication pathways between the brain and prosthetic devices. The Detection Accuracy using FFT is important for motor imagery and mental task classification which is increasing as the day pass by.

However, challenges remain, including signal variability, user fatigue, and the influence of noise and artifacts, which must be addressed through advanced signal processing, spatial filtering, and adaptive algorithms. Hybrid approaches that combine SSVEP with other modalities, such as motor imagery or deep learning-based classifiers, may further enhance accuracy, robustness, and user comfort.

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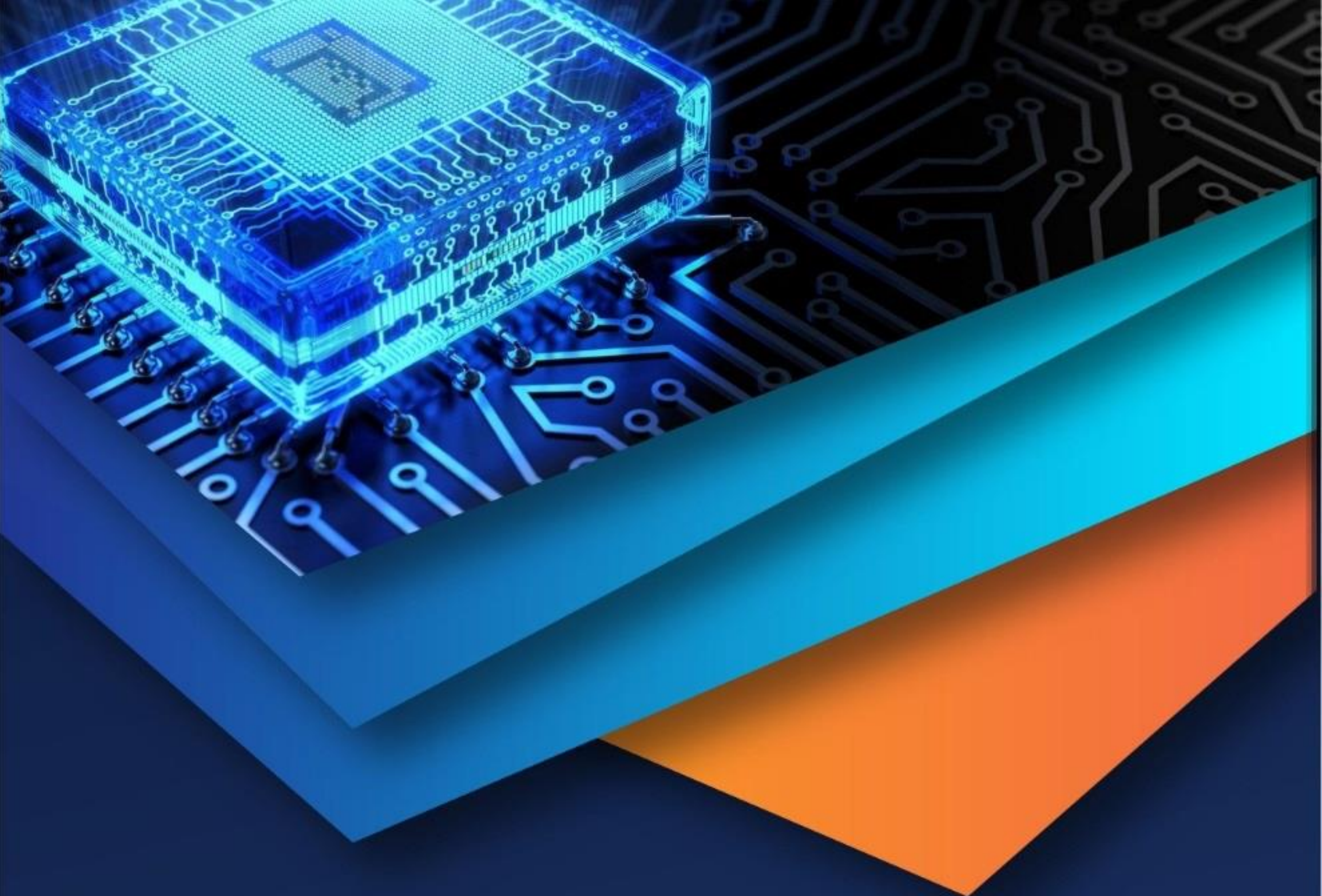

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