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Original Article

Development of a Neurofeedback System for Movement Imagery-Based BCI

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Abstract *- In recent decades, research on Brain-Computer Interfaces (BCIs) based on Electroencephalograms (EEGs) has become a crucial area of study, particularly for enabling real-time control of electric wheelchairs for individuals with disabilities. A most commonly used approach for this purpose is Movement Imagery (MI). Researchers have proposed various techniques to improve classification accuracy, focusing on effective preprocessing and feature extraction methods for real-time classification of movement imagery. This paper investigates the effectiveness of Empirical Mode Decomposition (EMD) as a preprocessing technique to decompose raw EEG signals into Intrinsic Mode Functions (IMFs) and evaluates suitable power spectrum estimation methods. Different rhythmic bands of the raw EEG signals are selected for EMD decomposition. The resulting IMFs are then used to estimate power spectral density using parametric (Burg method) and non-parametric (Welch method) approaches. The analyzed feature is the average power within the rhythmic bands of the selected IMFs. The outcomes of this study have multiple observations. The reported results indicate that the Welch method outperforms the Burg method, achieving overall classification accuracy that is more than 1% higher. Additionally, the proposed methods achieve good classification accuracy on standard movement imagery datasets but fail to match the performance of BCI-illiterate subjects. Based on this analysis, the authors conclude that signal processing and feature extraction methods alone are insufficient to achieve high classification accuracy, emphasizing that users of BCI technology require proper training.*

Keywords *- BCI, EEG, EMG, MI, PSD.*

1. Introduction

The human brain is a complex organ that generates vast amounts of information used to diagnose various diseases. [1] Brain waves recorded on the scalp can be used to develop a neurorehabilitation device to help people with locked-in syndrome. [2] Nowadays, advancements in brain technology help people with motor disabilities. The brain communicates with an external device through advancements in the field of man-machine interfaces, in which the human brain connects with the external world via a computer to control the actions of the external machine. [3] The technology that pertains to the man-machine interface using brain waves is called the Brain-Computer Interface (BCI). [4] It establishes the communication path between the human brain and an external device via a computer, where incoming brain signals are analyzed to infer the brain's state. The electrical activity of the human brain is recorded over the scalp using a 10-20 electrode placement system, which is known as the Electroencephalogram (EEG) signal. [5] There are various methods for recording brain waves, including Magnetoencephalography, Near-Infrared Spectroscopy, and Functional Near-Infrared Spectroscopy (fNIRS). [2] EEG-based BCI system development has been an important topic of research since 1999, the year the first BCI meeting was held, and a formal definition of BCI was proposed. [2] There are two types of BCI systems: Synchronous and Asynchronous. [6] A user performs mental activity in a given time duration, and the electrical activity for those durations is recorded and analyzed to infer the state of the brain, which is called synchronous BCI. The temporal pattern of presenting various commands to the user is referred to as an experimental paradigm. [4, 5] Movement-related patterns, either left or right, are presented within the given time frame in front of the user, and the user imagines the movement of their left and right hands, as indicated by the direction on the computer screen, a paradigm known as movement imagery. [6] Based on the MI-based paradigm, voluminous EEG data were analysed offline to infer the brain's state, and the results were presented to the BCI community as BCI evaluation parameters, including classification accuracy, Cohen's Kappa coefficients, information transfer rate, and mutual information. [7, 8] The ultimate goal of this developed technology is to create an assistive system that helps individuals with motor disabilities. The system should operate in real-time. [9]

A few research works were identified through a literature survey that have developed real-time systems based on movement imagery to control an electric wheelchair. [9] A brain-computer interface based on movement imagery is the most important paradigm for controlling an electric wheelchair. [2, 9] EEG signals are inherently non-linear, non-stationary, and prone to noise, including artefacts from eye blinks, muscle activity, and external electrical interference. [10] The recorded signals are contaminated with these artefacts.

Suitable signal-processing methods are proposed to suppress artefacts and improve the quality of the recorded EEG signal. [11, 12] Traditional signal processing methods, such as the Fourier Transform or wavelet analysis, may not effectively capture the transient and adaptive nature of MI signals. [11, 12] Therefore, advanced signal decomposition and feature extraction techniques are required to enhance the classification accuracy of MI-based BCIs. [13] Depending on the number of channels placed on the scalp, EEG signals can be either single-channel or multichannel. [14, 15] This paper utilizes three-channel EEG signals to identify the discriminative pattern that infers the brain state. This paper proposes a methodology for preprocessing, drawing on literature reports on two situations: offline EEG data analysis for movement imagery detection using EMD, and real-time performance for controlling the joystick of an electric wheelchair. [16-22]

To detect the imagination of movement, one must place the sensor over the sensorimotor area to acquire EEG signals. [23] According to the 10-20 electrode placement system, the AgCl electrodes at C3 and C4 are positioned on the scalp, covering the left and right hemispheres of the brain. EEG signals are noisy, non-stationary, and highly subject-specific, creating challenges for reliable classification. Robust feature extraction and adaptive learning are crucial for achieving enhanced classification accuracy and improved information transfer rates. When a user performs a motor imagery task, the brain produces characteristic changes in neural activity, known as sensorimotor rhythm modulation. [23] These changes occur mainly in the Motor Band (mu) and Beta Frequency Bands.

The phenomenon of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) is observed over the contralateral side of the human brain for left- and right-hand movement imagination. [24-26] Motor-imagery-based brain–computer interfaces work by decoding brain activity during imagined movement, without actually performing the movement. [3] The first stage specific to an MI-based BCI is the motor imagery task itself. The user is instructed to imagine movements such as moving the left hand, right hand, or feet. [27] This imagination must be kinesthetic, meaning the person focuses on the feeling of the movement rather than visualizing it. [21, 27] This modulation of the motor cortex is the fundamental neural phenomenon on which MI-based BCIs rely. [28-30] There are other paradigms, such as the P300-based paradigm for spelling devices and the SSVEP-based paradigm for BCIs. [8, 14, 15] Mi-based BCI differs from stimulus-based BCI in various ways.

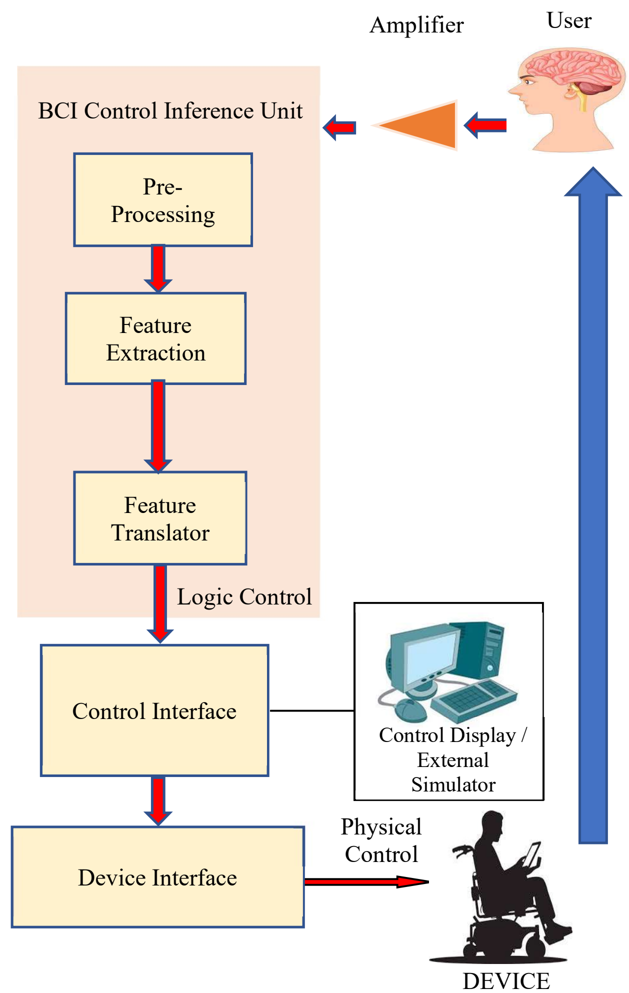

Fig. 1 Block Diagram of BCI System to Control Electric Wheelchair

To develop the BCI system, a crucial component is the BCI inference system. [2] A BCI inference system consists of EEG data acquisition, signal processing, feature extraction, and classification accuracy. A complete BCI system comprises a BCI inference system and a control interface. [2] Electrodes are placed over specific regions of the scalp corresponding to motor areas of the brain. These locations are chosen because they show the greatest changes during motor imagery. Accurate placement is particularly important in MI-based BCIs, as signals from other brain areas are less informative.

After acquisition, the EEG signals undergo preprocessing methods to improve their quality. This includes filtering the signals to retain only the mu and beta frequency bands where motor imagery information is present. [10, 23] The block diagram of the complete BCI system, with different stages controlling the Electric wheelchair, is shown in Figure 1. Noise and artefacts from eye blinks or muscle activity are reduced, as they can mask information related to motor imagery patterns. The processed signals are fed into a feature-extraction block to identify a unique pattern that distinguishes left- and right-hand movement imagery.

Features are subjected to a classifier that predicts the user's intended movement. Classifiers must be fast and efficient to operate in real time (e.g., SVMs, LDA, or low-weight neural networks). [31, 32] Once features are extracted and fed to a classifier, the classifier determines which motor imagery task the user is performing. [31] The classifier learns patterns associated with each imagined movement and converts them into control commands. [33, 34] Because motor imagery signals vary greatly between users and even across sessions for the same user, this stage must handle high variability. Most of the work related to the paradigm mentioned above has achieved outstanding accuracy, ranging from 75% to 90% for offline situations. [17-22] It is based on a database from the Graze Laboratory for BCI competitions, available online. [35]

Empirical Mode Decomposition (EMD) is a signal processing method that is particularly suitable for analyzing non-linear and non-stationary signals, such as EEG. [36, 37] EMD decomposes a complex signal into a set of Intrinsic Mode Functions (IMFs), each representing oscillatory modes at different frequency scales. These IMFs enable precise extraction of signal characteristics such as energy, entropy, and instantaneous frequency. By focusing on relevant IMFs, it is possible to highlight the motor imagery-related components in the EEG, improving classification performance.

Feature extraction in MI-based BCIs is a critical stage. Instead of using raw EEG signals, the system extracts features that highlight differences between imagined movements. [38] The most common approach is to use common spatial filtering methods that employ variance as a feature to distinguish between motor imagery classes. [37] These features represent how brain activity patterns differ when imagining different movements.

The Burg and Welch power spectrum estimation methods were used to identify the feature in the intrinsic mode function obtained from the EMD in the 8-30Hz rhythmic band. [11, 16-22, 36] A unique and important stage in MI-based BCIs is user training and learning. [39] Users must practice motor imagery to generate consistent and distinguishable brain patterns. Some users learn quickly, while others struggle, a phenomenon often referred to as BCI illiteracy. Unlike stimulus-based BCIs, MI-based BCIs depend heavily on the user's ability to learn and adapt. Developing real-time control of electric wheelchairs is a crucial research domain for the BCI community, particularly for individuals in India. [3, 40] The quality of the mental task significantly impacts the system's performance. Many users are unable to generate reliable MI patterns due to a lack of BCI terminology, which users refer to as being BCI illiterate. Training protocols and feedback strategies are developed for improving accuracy. Noise, movement artefacts, and changing environmental conditions make real-world use outside labs challenging, even though wearable technologies continue to improve. [6] Models often outperform on offline benchmarks but tend to drop in accuracy when used online or across multiple sessions, due to variability in users' mental states.

Visual Neurofeedback supports user engagement and helps generate stronger, more consistent MI signals. [9, 41] This approach has shown the most significant performance improvements across sessions. [9] The system provides real-time feedback, usually visual, showing how well the motor imagery is being recognized. [41] This feedback indicates that users should adjust their mental strategies and gradually enhance their performance. Feedback plays a central role in this learning process. Without feedback, motor imagery control is challenging because users are unsure if the system is accurately detecting their brain signals. Neurofeedback trains the user's brain and speeds up learning. Real-time feedback also supports practical applications, like controlling a robotic arm or a wheelchair.

Even though motor imagery, EEG classification, and BCI-controlled wheelchair systems have advanced significantly, there remains a critical research gap in developing low-calibration, infrastructure-adaptive, and reasonably priced BCI wheelchair systems that have been validated with Indian users. [9, 16-18] Large-scale implementation in India is constrained by the lack of Indian EEG datasets, affordable hardware integration, sensitive motor-imagery training, and practical validation in Indian settings. Most of the datasets used are from benchmark datasets that are either Chinese, European, or publicly available (e.g., BCI Competition datasets). Considering differences in BCI literacy, no comprehensive motor imagery EEG dataset has been collected from users. There is a dearth of standardised, annotated Indian motor imagery EEG datasets for wheelchair control research.

Various signal preprocessing methods were applied to offline EEG data analysis. [19-22] EMD is one of the important techniques of signal decomposition. A literature survey reports that EMD and its variants, along with various feature extraction and classification methods, have achieved very high accuracy in offline analysis. [36] As far as novelty is concerned, this paper applied the simple EMD along with power spectral density as a feature extraction method, followed by linear discriminant analysis for movement imagery classification for real-time control of an electric wheelchair, because the combined approach, starting from preprocessing till classification, is simple and computationally fast for movement imagery classification in real time. This paper also considers sub-bands, proposing a small-gap sub-band within the total wide sub-band of 8-30Hz, known as the reactive frequency band. Its application to real-time EEG signal processing is important to investigate because it is fast and computationally efficient, but there are no reported results in the literature using EMD techniques over different reactive frequency bands. Apart from that, it is developing an Arduino-based neurofeedback system to train BCI users, which is crucial for providing feedback based on incoming brain signals. [41] This research paper proposes an Arduino-based neurofeedback system for training BCI users while recording their EEG signals.

Finally, this system is being integrated with real-time control of electric wheelchair movement. The performance of the proposed method is evaluated over two standard datasets, BCI Competition II and BCI Competition IVb, in different reactive frequency bands. Depending on the classifier and IMF selection strategy, feature extraction techniques based on Empirical Mode Decomposition (EMD) applied to BCI Competition IV-2b generally yield classification accuracies ranging from 75% to 90%. [36, 20-22] While traditional EMD with LDA/SVM typically reports 75–85%, conditional EMD with deep learning techniques can surpass 88–90%. The proposed methods also include EMD with LDA and two power-spectrum estimation methods across different frequency bands, including wide-band motor imagery (8-30Hz), whereas the reported work considers energy as a feature in IMF-3. [37] They have applied various classifiers and reported classification accuracy ranging from 85% to 92%. As for novelty, this paper quantifies the performance of EMD, along with two power spectrum estimation methods, on standard online datasets and on real-time datasets from Indian users across different narrow frequency bands, and assesses its real-time performance.

Regarding the research gap, few studies have reported on real-time control of an electric wheelchair for subjects familiar with BCI. [9, 16-18] The proposed method is being developed to control the movement of an electric wheelchair in real time over an Indian subject who is BCI illiterate. The primary objective of this work is to present the results of the real-time control of the developed joystick interface, which enables the movement of an electric wheelchair. Definitely, the earlier proposed methods on the standard dataset achieved higher classification accuracy, but their performance in real-time degraded. Also, the performance across different frequency bands in offline EEG signal processing has not been reported. The authors aim to develop a real-time system that requires faster decisions to control the movement of an electric wheelchair. It is utmost important to evaluate the performance of the methodology applied to offline EEG signal analysis to ensure the same performance in real-time EEG signal processing and decision-making. This remains pending. It is utmost important to apply offline techniques to an online (real-time) environment to evaluate performance. Keeping the above facts in mind, the authors of this paper propose using the EMD signal processing method as a preprocessing step and evaluate its performance in real time across different rhythmic bands.

Secondly, it contributes to data on illiterate subjects, all of whom are naïve to the BCI application. Thirdly, the authors develop an Arduino-based neurofeedback system to train the user. Developing a neurofeedback system to train BCI users is crucial for providing feedback based on incoming brain signals. [41] This research proposes an Arduino-based neurofeedback system for training BCI users while recording their EEG signals. Finally, this system will be integrated with real-time control of electric wheelchair movement. The proposed method is being developed to control the movement of an electric wheelchair in real time over a subject who is BCI illiterate.

The primary objective of this work is to present the results of the real-time control of the developed joystick, which enables the movement of an electric wheelchair. It acquires and preprocesses EEG signals for motor imagery tasks to enable real-time control of the electric wheelchair. This paper also considers the EMD as a signal decomposition method and the power-based features extracted by both power spectrum estimation methods. [36] This paper also considers LDA as a classifier for classifying movement-related EEG data.

The performance of a real-time BCI inference system for controlling an electric wheelchair by a BCI-illiterate user is presented. [9] The objective of this paper is categorized into two sub-objectives: to develop a neurofeedback system based on signal processing methods to display the decision while recording is in progress, and to compare the results with the standard online dataset when the same feature extraction and signal processing methods are applied. [10] Additionally, focus on developing a control interface to operate the joystick of an Electric wheelchair. Finally, the developed neurofeedback and joystick controller will be integrated to control the electric wheelchair [9]. The Arduino-based neurofeedback system, which trains the user while recording, is depicted in Section 2.

The paper is organized as follows: Section 2 illustrates the experimental setup and the proposed methodology, which includes EEG acquisition, preprocessing, EMD decomposition, feature extraction, and LDA classification. Section 3 presents the results and performance analysis, followed by a discussion, conclusions, and a section on future work.

2. Proposed Methodology

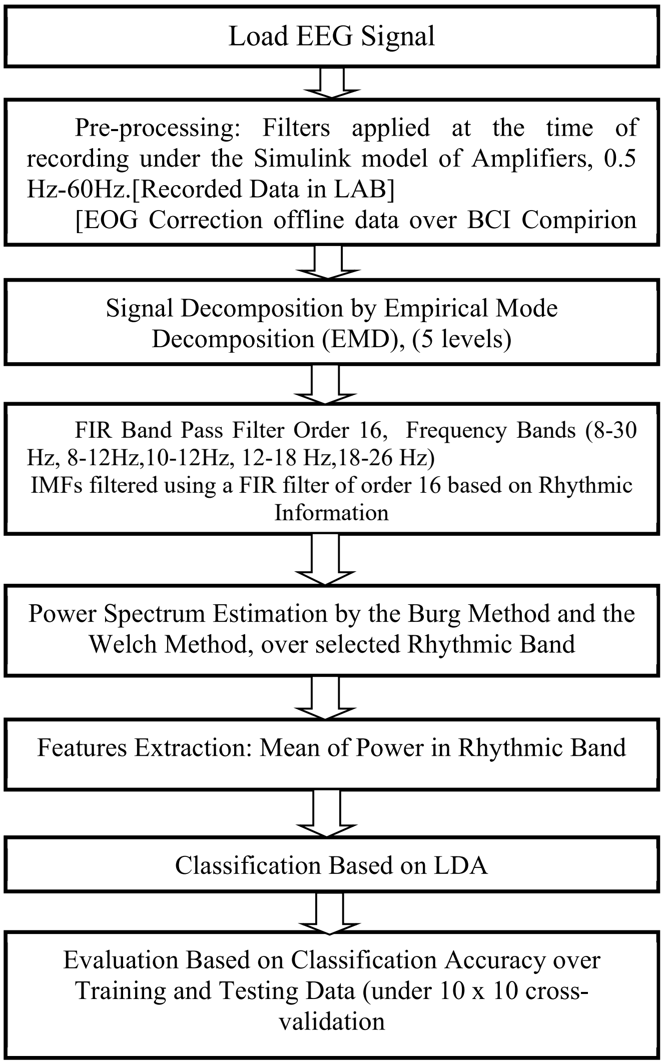

Fig. 2 Flow chart of proposed methodology for EEG signal processing to develop a real-time BCI inference system

The mental simulation of movement without actual physical movement is called Motor Imagery (MI). [9] MI-based BCIs interpret brain activity during imagined movements (of hands, feet, and tongue) to control external systems, such as robotic limbs, Functional Electrical Stimulation (FES), wheelchairs, or virtual environments. This paradigm is non-invasive and widely used in neurorehabilitation and assistive technology research. Motor imagery-based BCIs often utilize EEG signals because they are non-invasive and provide rapid data acquisition. Hz), which is suppressed around the sensorimotor cortex during real or imagined movement. Beta rhythm (13–30 Hz): This rhythm also shows suppression during motor imagery. The aim is to extract features from EEG signals that can distinguish between different imagined movements. Imagining movement produces real, detectable changes in brain rhythms, which can be used to control things or study the brain. Despite the above, the author divides the broad 8-30Hz frequency band into smaller interval subbands to examine rhythmic changes and establish the reactive frequency band, as shown in Figure 2. Figure 2 depicts the signal processing flowchart and classification algorithm. The different rhythmic bands are selected using a FIR bandpass filter [9] with a narrow frequency band of order 16.

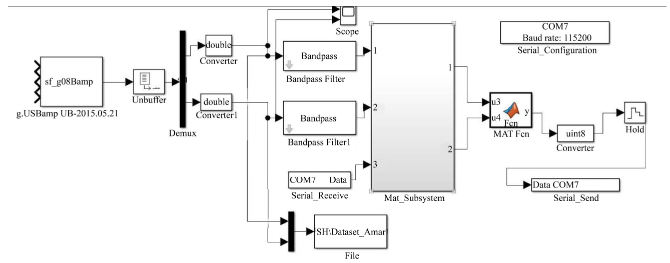

Fig. 3 MATLAB Simulink model to real-time implementation of the neurofeedback system

Figure 3 illustrates the steps involved in real-time data acquisition through MATLAB Simulink. Each sub-band signal is decomposed by the EMD technique to obtain the vibratory components, known as the Intrinsic Mode Functions (IMFs). [25] IMF selection is based on an error and trial procedure. Each selected IMF is processed using the power spectral estimation method to obtain its frequency spectrum, and the mean spectrum across sub-bands is treated as a feature. These features are further applied to the linear classifier to classify the movement imagery task. Figure 3 illustrates the steps involved in real-time data acquisition through MATLAB Simulink. EEG data is recorded by placing electrodes on the scalp using the 10-20 electrode placement system. The EEG signal over the channels is derived from the amplifier's bipolar setting. The sampling frequency was 256Hz. The notch filter is activated for 50Hz. The amplifier's bandpass filter was set at 0.5Hz to 60Hz. The data obtained is also processed in real time using a MATLAB function implemented within a simulation model and stored in a MATLAB file.

Fig. 4 Physical model developed for real-time control of an Electric wheelchair

To validate the performance of the proposed system, a standard database (BCI Competition II and BCI Competition IV 2b) for movement imagery classification has been utilized. [30] The proposed methodology for developing the BCI inference system is illustrated in Figure 3. Figure 3 depicts the EEG data acquisition system, which utilizes a g.tec amplifier. The incoming brain signals are recorded according to the paradigm shown in Figure 11. The proposed methodology is implemented as a MATLAB subsystem, which is illustrated in Figure 4. Based on the incoming brain signals, decisions are made and fed back to the user as input. The same concept is applied to control the movement of an electric wheelchair. Figure 4 depicts the proposed real-time system for controlling the electric wheelchair.

In this research, an Arduino-based control interface is developed to operate the joystick of an electric wheelchair, as illustrated in Figure 4. The classifier weight parameter is estimated after the offline analysis of the EEG data. This same weight parameter is then applied during testing in the MATLAB Simulink model to provide real-time feedback to the user. The classifier weight parameter reflects the user's state of mind after analyzing and classifying the incoming brain signals, as illustrated in Figure 2.

3. Results and Discussions

The proposed methods are applied to two standard datasets available online. For the same paradigm, this paper reports results from seven subjects, recorded in the lab during real-time control of the electric wheelchair joystick, who are BCI illiterate. Figures 5 and 6 show the raw EEG signal recorded over the central region of the motor cortex using the bipolar setting of the amplifier. The sensor is placed over the motor cortex, specifically over regions C3 and C4, as per the 10-20 electrode placement system. The recorded EEG signal is processed using the EMD technique, and the resulting IMF is then passed through different band FIR filters. It is found that IMF-1 of channels C3 and C4 in different rhythmic bands shows better classification accuracy.

The proposed methodology is applied to evaluate the performance of subjects who are BCI illiterate. The EEG signals recorded during motor imagery tasks were subjected to a 5-level EMD to extract IMFs. Figures 7 and 8 show the decomposition of a sample EEG channel C3 during left-hand motor imagery. The decomposition yielded five IMFs along with a residual component. The obtained IMFs are subjected to an FIR bandpass filter, and the rhythmic band IMFs are subjected to power spectral density estimation using both parametric and non-parametric methods. It is plotted in Figures 9 and 10 for different movement imagery tasks. Event-related synchronisation (ERS) and Event-Related Desynchronization (ERD) are observed as the power difference in the frequency band 8- 30 Hz. This power-difference uniqueness can be considered a key feature for classifying incoming brain signals. Additionally, this paper considers the different rhythmic bands for feature extraction, as shown in the table below. These smaller frequency subbands are called the reactive frequency band. From the reported results on the BCI competition datasets IV 2b and II Graze laboratory, we found that the classification accuracy under 10-fold cross-validation is approximately 70% or higher for both power spectral estimation methods. The results are presented in Tables 1, 2, and 3, utilizing the Burg and Welch methods of power spectrum estimation. [16, 17] While performing the experiment on BCI-illiterate participants, the same classification accuracy has not been achieved as with the standard dataset. Table 3 shows the classification accuracy for subjects trying to move the joystick of the electric wheelchair. The average classification accuracy is very poor, and individual subject accuracy in a few subjects is approximately 60% in both the training and test datasets.

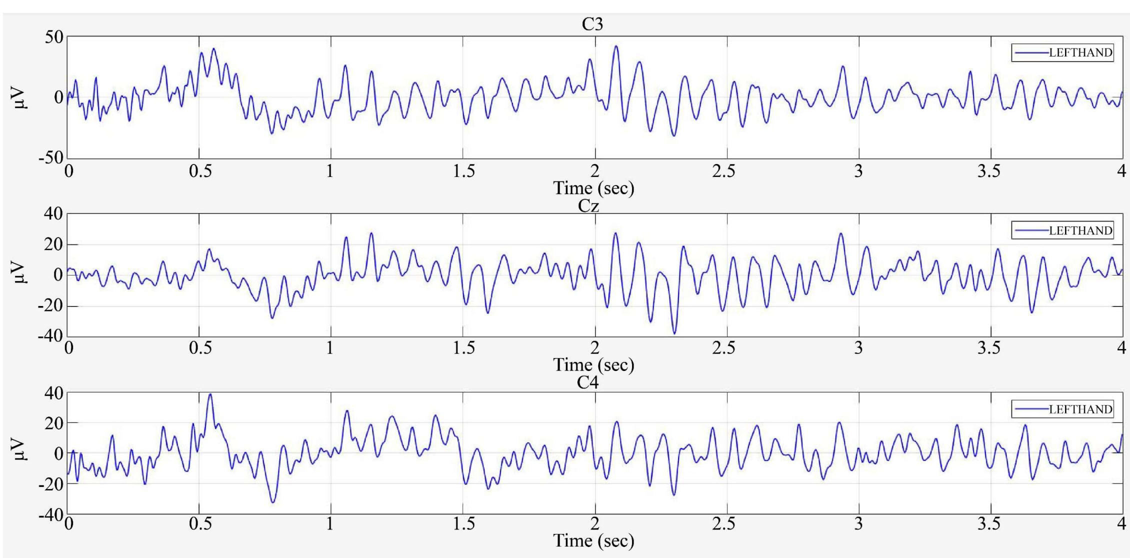

Fig. 5 Raw EEG Signal recorded for the Left-hand MI

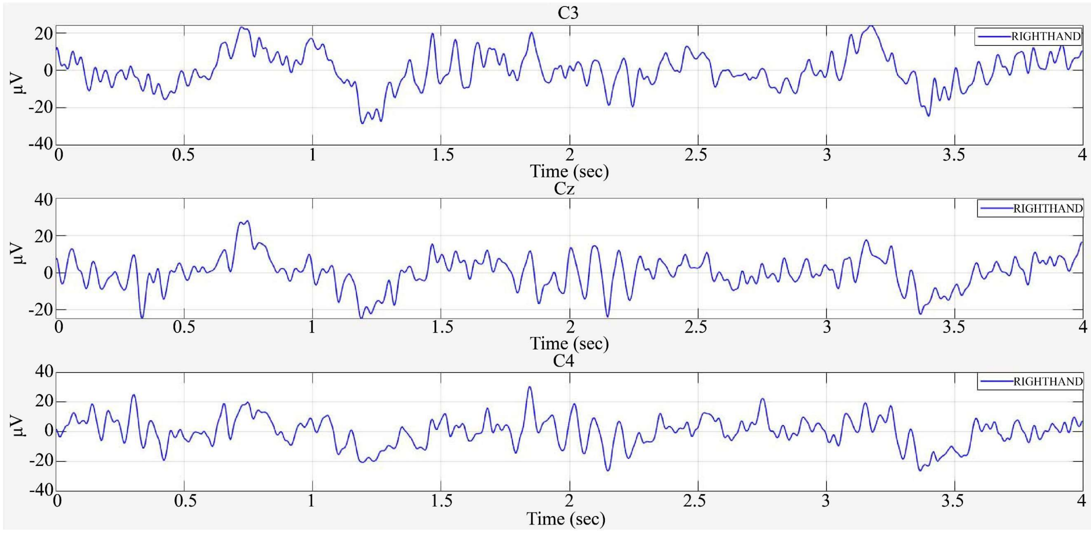

Fig. 6 Raw EEG Signal recorded for Right-hand MI

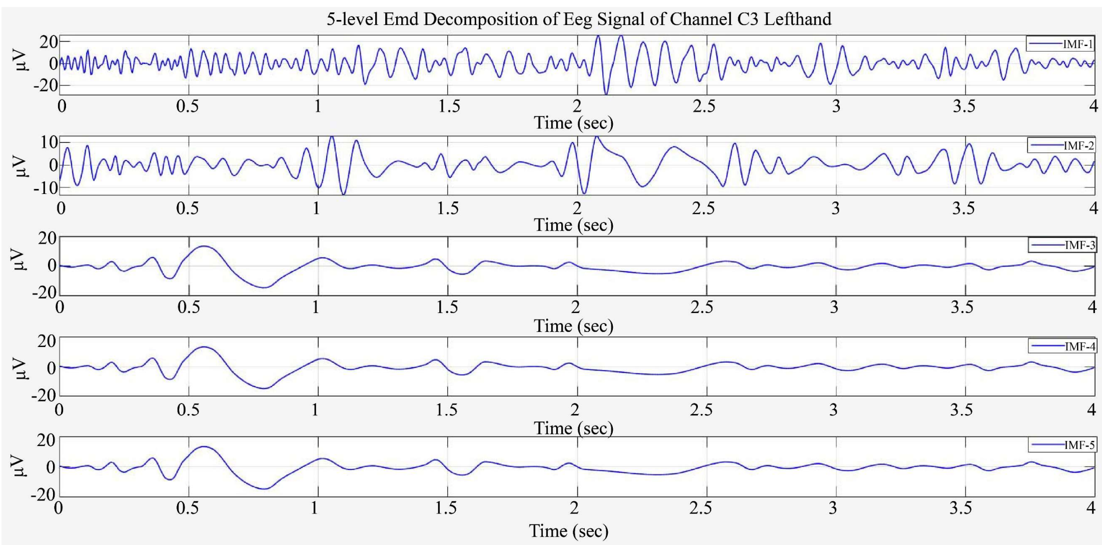

Fig. 7 IMF (Using EMD) of Recorded Signal for Left Hand MI of Channel C3

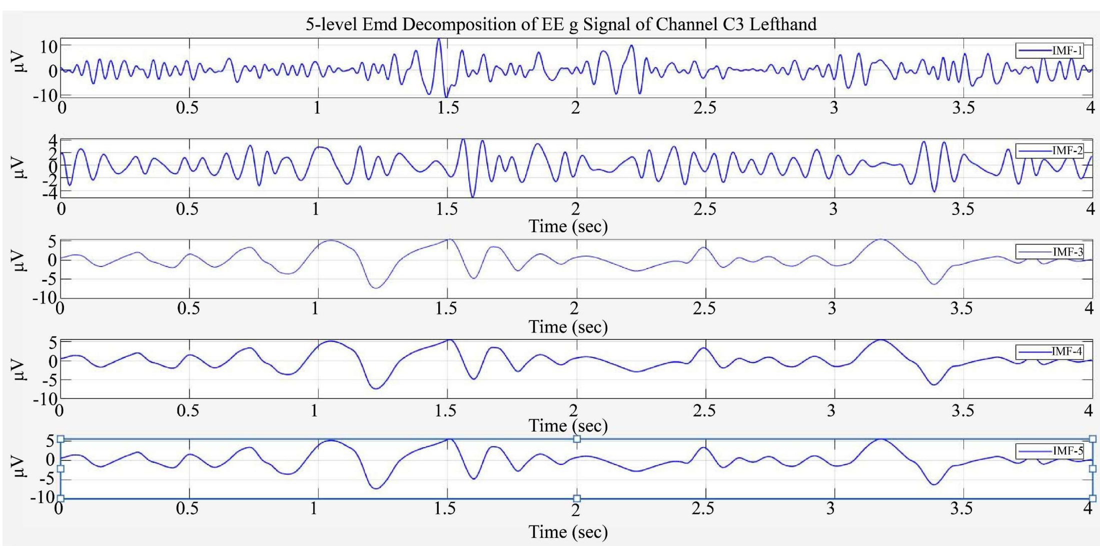

Fig. 8 IMF (Using EMD) of Recorded Signal for Right Hand MI of Channel C3

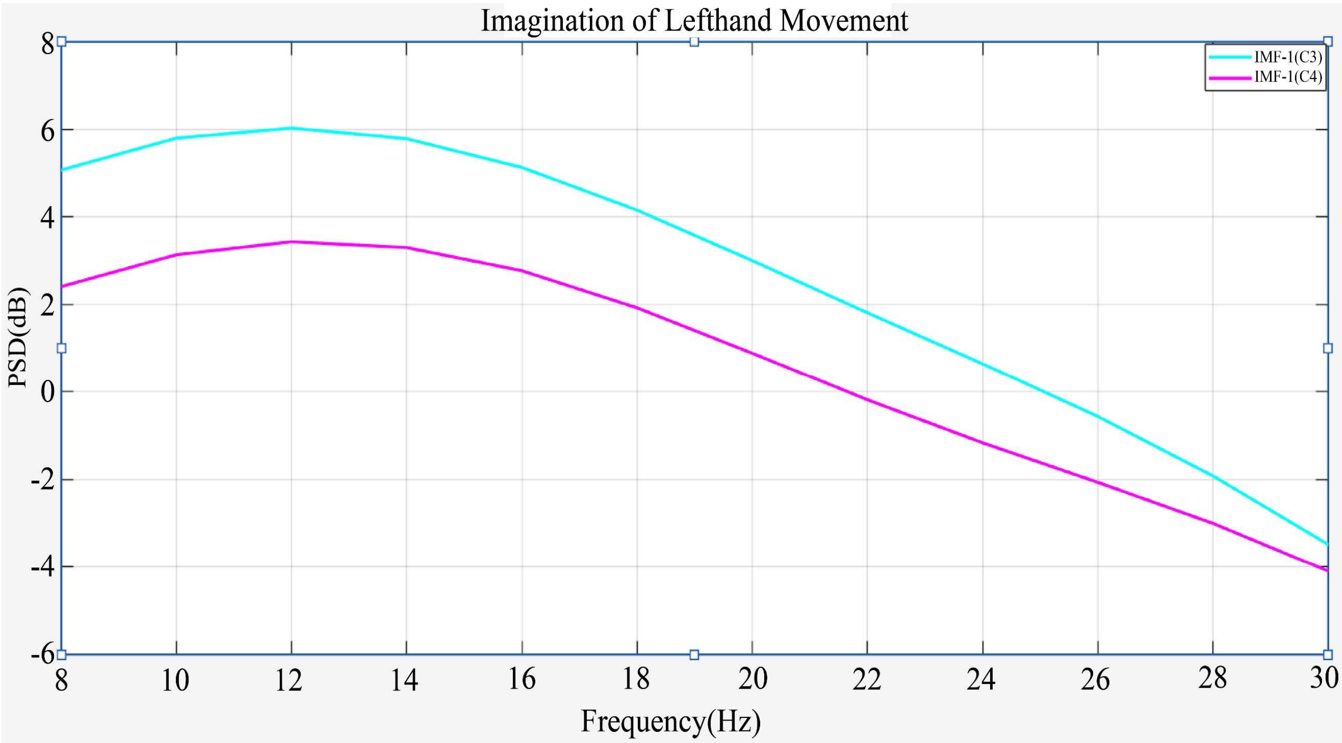

Fig. 9 PSD of IMF1Channel C3andC4 for Left-hand Movement Imagery

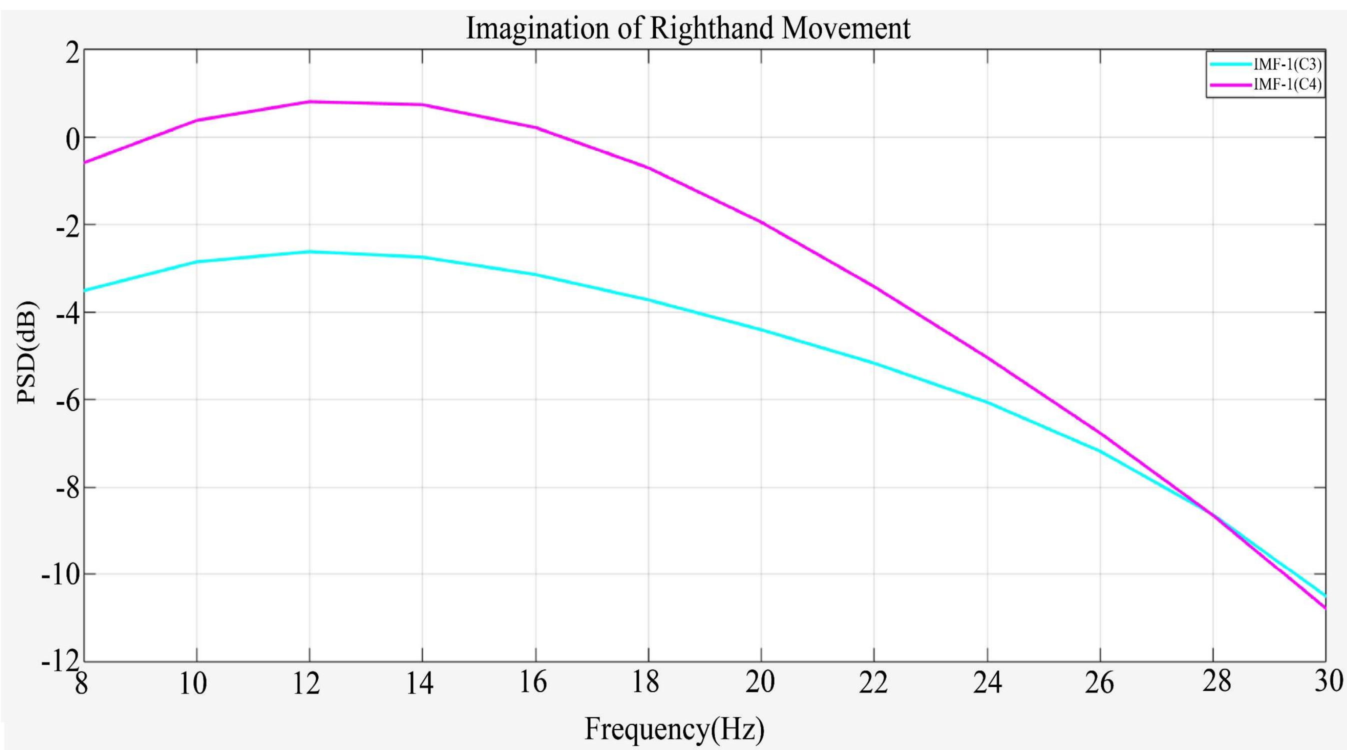

Fig. 10 PSD of IMF1Channel C3 and C4 for Right hand Movement Imagery

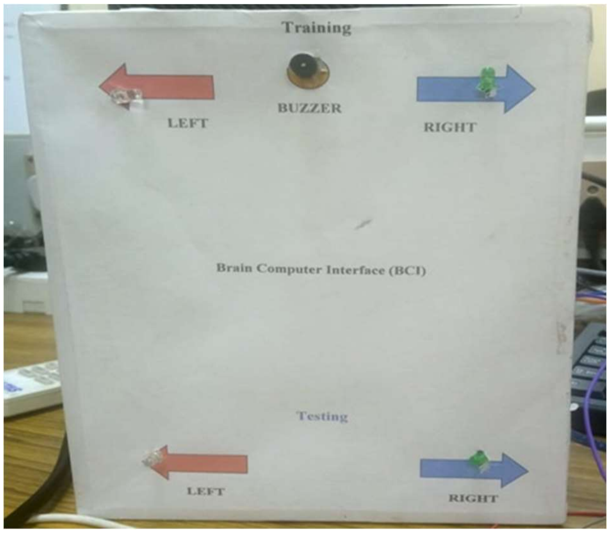

Fig. 11 Arduino-Based Neurofeedback System

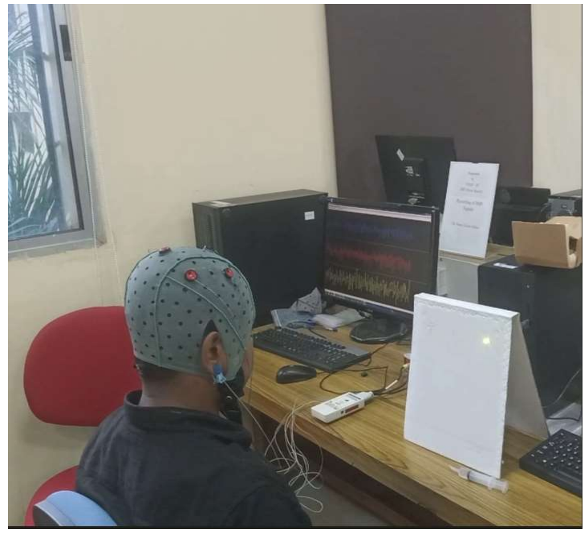

Fig. 12 Testing of Neurofeedback Development.

Fig. 13 Designed a control interface to control the joystick of the Electric wheelchair

By comparing the results, the authors have identified several key points that require further attention. Firstly, the subjects participating in the experiment are completely naïve. They have heard the term' brain-computer interface' for the first time. The proposed signal processing and feature extraction methods have achieved very good classification accuracy on standard datasets; however, with BCI illiterate subjects, they fail to achieve a similar level of accuracy.

This indicates that the user must be trained multiple times to improve classification accuracy. Another point to consider is that the ERD and ERS phenomena are not consistently observed across trials, as shown in Figures 9 and 10 for left- and right-hand movement imagery; accuracy does not improve. Finally, MI-BCIs require ongoing adaptation. Brain signals are not stable over time, so the system must update or recalibrate its models to maintain accuracy. This adaptation may occur automatically during use and is especially important for long-term or real-world deployment. To generate output for the user, this paper first develops an Arduino-based neurofeedback system, as illustrated in Figure 11.

The real-time implementation is depicted in Figure 12. Finally, the joystick control has been developed and is shown in Figure 13. In summary, MI-BCIs are built around imagined movement, sensorimotor rhythm modulation, motor-area EEG recording, specialized signal processing, intensive user training, continuous feedback, and adaptive learning. These stages make MI-BCIs fundamentally different from other BCI paradigms that rely on externally evoked brain responses. [11] As per the reported result over experienced BCI users, the earlier proposed methods for real-time control of an electric wheelchair achieve classification accuracy above 40%-60%. [16] Some papers reported above 90%, but they noted that the users were highly trained. [17, 18]

Table1. Classification Accuracy over the nine subjects of BCI Competition IVA (Burg Method & Welch Method)

IMF 2 of C3 and IMF 2 of C4 Channel using Burg Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18 Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub- 1	68.80	72.50	58.80	63.75	70.00	75.00	66.90	66.87	65.60	65.00
Sub-2	50.80	50.83	45.80	52.50	49.20	49.17	50.80	54.17	47.50	55.83
Sub-3	48.10	51.88	33.10	48.13	40.60	46.88	55.60	53.12	38.10	48.75
Sub- 4	92.50	91.25	88.10	89.38	91.20	90.00	88.10	80.00	88.80	86.25
Sub-5	72.50	59.38	63.10	55.63	61.30	58.13	76.90	59.38	61.30	57.50
Sub-6	71.90	73.12	53.10	57.50	66.20	66.87	61.90	74.38	55.60	58.75
Sub- 7	71.20	61.88	68.10	58.75	72.50	65.00	68.80	61.88	66.90	60.62
Sub-8	79.40	83.75	82.50	75.00	78.80	83.13	71.90	75.00	76.90	68.13
Sub-9	76.20	80.63	67.50	72.50	66.90	75.62	81.20	76.88	68.10	73.12
Total Average	70.15	69.46	62.23	63.68	66.30	67.75	69.12	66.85	63.20	63.77

IMF 2 of C3 and IMF 2 of C4 Channel using Welch Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub- 1	75.00	72.50	65.60	61.88	68.80	70.63	68.80	70.63	63.10	63.75
Sub- 2	46.70	55.83	46.70	46.67	46.70	53.33	48.30	55.00	49.20	48.33
Sub- 3	47.50	53.12	31.20	49.38	35.60	50.62	55.60	59.38	30.60	50.00
Sub- 4	91.90	88.75	89.40	91.25	91.20	88.75	91.20	81.25	88.80	90.62
Sub- 5	68.10	58.13	63.10	59.38	63.70	57.50	80.60	62.50	62.50	60.00
Sub- 6	71.90	72.50	59.40	65.00	64.40	66.87	65.00	74.38	58.10	65.62
Sub-7	69.40	61.88	77.50	62.50	71.90	58.75	68.80	59.38	79.40	64.38
Sub- 8	78.10	86.25	83.10	78.75	80.00	82.50	76.20	81.25	82.50	78.12
Sub-9	76.20	81.25	70.00	76.25	65.00	80.63	81.20	79.37	69.40	78.12
Total Average	69.42	70.02	65.11	65.67	65.25	67.73	70.63	69.23	64.84	66.54

Table 2. Classification Accuracy over the Single Subject of BCI Competition II (Burg Method & Welch Method)

IMF 1 of C3 and IMF 1 of C4 Channel using Burg Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18 Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub-1	72.1	70.71	78.6	70.71	67.9	67.86	62.1	64.29	70.70	72.14
IMF 1 of C3 and IMF 1 of C4 Channel using Welch Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18 Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub-1	79.3	75	77.1	75.71	79.3	73.57	70	71.43	75.70	75.71

Table 3. Classification Accuracy over the seven subjects of the recorded EEG Signal in the lab (Burg Spectrum)

IMF 1 of C3 and IMF 1 of C4 Channel using Burg Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**	**Training (%)**	**Testing (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18 Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub-1	47.14	58.57	51.43	60	57.14	60	47.14	48.57	41.43	57.14
Sub- 2	34.29	38.57	45.71	47.14	38.57	52.86	41.43	48.57	48.57	48.57
Sub-3	54.29	54.29	58.57	41.43	61.43	44.29	44.29	52.86	42.86	40
Sub- 4	48.57	65.71	55.71	54.29	48.57	64.29	51.43	64.29	51.43	58.57
Sub-5	48.57	65.71	55.71	54.29	48.57	64.29	51.43	64.29	51.43	58.57
Sub-6	58.57	52.86	61.43	52.86	64.29	58.57	44.29	50	55.71	48.57
Sub- 7	50	47.14	42.86	52.86	47.14	58.57	55.71	55.71	41.43	51.43
Total Average	48.78	54.69	53.06	51.84	52.24	57.55	47.96	54.90	47.55	51.84

The others' real-time control of electric wheelchairs claims a success rate of 70%-80% with different signal processing methods and classification techniques. The proposed methodology achieves classification accuracy approximately equal to, and slightly lower than, the reported result in the mentioned references. [16, 17] By analysing EEG data, some users achieve success rates above 60% with the Welch and Burg methods. It is well known that EEG signals exhibit a narrow frequency band, the rhythmic band. It is also essential to report classification accuracy across different rhythmic bands to identify the user's reactive frequency band. All users have different frequency bands, achieving better classification accuracy than the state of the art reported in the literature. [16] The authors consider the concept of the reactive frequency band; their results indicate that not all users share the same rhythmic band for reaction. It is also essential to identify the most reactive band in the training data, and the same band can be used for validation and testing accuracy. It is found that classification accuracy is consistent across training and test data, highlighted in red for both spectrum estimation methods in Tables 3 and 4. Some existing state-of-the-art systems achieve better real-time classification accuracy due to BCI literacy and extensive training, as claimed in the reported work. After reviewing the EEG data analysis, BCI literacy is a major factor in enhancing accuracy and information transfer rate. [18] The real-time results presented in this paper are from subjects who have heard the term BCI for the first time. A verbal instruction was given regarding the experimental paradigm. The authors agree that familiarity with the BCI is important, as is Neurofeedback, which is essential for user training. To this end, we have developed an Arduino-based neurofeedback system to train users to improve classification accuracy.

Table 4. Classification Accuracy over the seven subjects of the recorded EEG Signal in the lab (Welch Spectrum)

IMF 1 of C3 and IMF 1 of C4 Channel using Welch Method										
User	**Training (%)**	**Testing (%)**	**Training (%)**	**Testin g (%)**	**Training (%)**	**Testin g (%)**	**Training (%)**	**Testin g (%)**	**Training (%)**	**Testin g (%)**
	8-30 Hz	**8-30 Hz**	**8-12 Hz**	**8-12 Hz**	**12-18 Hz**	**12-18 Hz**	**18-26 Hz**	**18-26 Hz**	**10-12 Hz**	**10-12 Hz**
Sub-1	51.43	58.57	54.29	58.57	61.43	62.86	54.29	58.57	57.14	60
Sub- 2	41.43	48.57	44.29	48.57	34.29	48.57	44.29	48.57	42.86	48.57
Sub- 3	58.57	60	55.71	42.86	60	44.29	55.71	42.86	61.43	42.86
Sub-4	51.43	62.86	48.57	58.57	57.14	64.29	48.57	58.57	47.14	58.57
Sub-5	51.43	62.86	48.57	58.57	57.14	64.29	48.57	58.57	47.14	58.57
Sub- 6	47.14	55.71	62.86	54.29	57.14	54.29	62.86	54.29	61.43	55.71
Sub- 7	50	60	45.71	51.43	47.14	55.71	45.71	51.43	45.71	51.43
Total Average	50.20	58.37	51.43	53.27	53.47	56.33	51.43	53.27	51.84	53.67

In future work, the authors will report classification accuracy and provide feedback to the user to correct the imagination and improve classification accuracy. As reported, the proposed methods using Burg and Welch power spectrum estimation techniques achieve classification accuracies of 75% to 80% across different rhythmic frequency bands over the standard dataset, BCI Competition II Graze data set. The methods adopted for movement imagery classification differ slightly from the reference work, in which the signal is decomposed into epochs, the energy spectrum is calculated, and the results are fed to different classifiers. Definitely, the earlier proposed methods on the standard dataset achieved slightly higher classification accuracy, but their performance across different frequency bands in offline EEG signal processing has not been reported. The authors aim to develop a real-time system that requires faster decisions to control the movement of an electric wheelchair. The methodology applied to offline EEG signal analysis, as well as its performance in real-time EEG signal processing and decision-making, remains pending. It is utmost important to apply offline techniques to an online (real-time) environment to evaluate performance. Keeping the above facts in mind, the authors of this paper propose the same signal processing methods and evaluate their performance in real time. Secondly, it contributes to BCI illiterate subjects, where all subjects are naïve to the BCI application. This paper presents preliminary results from the development of the real-time BCI inference system. The user does not have extensive training. As reported in the literature, classification accuracy exceeds 90% in a few subjects, but training time is extensive, as mentioned in the reference. [18] This indicates that users need training for better accuracy. The authors will address the results of EEG data recorded during training, with the user providing the Neurofeedback in the next paper. This paper presents the novel performance of the existing methods for offline EEG time series analysis, whose performance on the standard dataset is high, whereas the same algorithm shows degraded performance in real time. Also, this paper presents the performance of EMD, along with two power spectrum estimation methods, on standard and real-time datasets from subjects across different narrow frequency bands. The reported results indicate that the Welch method outperforms the Burg method, achieving an overall classification accuracy that is more than 1 % higher. The Welch method is appropriate for estimating the power spectral density of EEG time series. The Burg methods of power spectrum estimation rely heavily on autoregressive models. Whether the EEG time series data follows the same AR model remains to be seen.

In a nutshell, this paper contributes to the BCI research community by showing that real-time control of an electric wheelchair requires training, as reported results across a standard dataset and a naïve dataset differ significantly for the proposed signal processing methods and feature extraction method.

4. Conclusion

The results presented in Tables 3 and 4 are based on the recorded dataset from Indian participants. The outcomes are below expectations, with only a few subjects achieving classification accuracy exceeding 60%, which are highlighted in red. The average accuracy on the standard dataset ranges from 60% to 80%, depending on the rhythmic band. In contrast, the average accuracy of our recorded dataset during real-time joystick control is quite low, at approximately 50%, which is almost equal to the reported result in [16]. This analysis highlights the need to train users, as they were inexperienced and unfamiliar with the paradigm and BCI. Additionally, there is a need for user training and a session-wise evaluation of the system's performance. Reactive frequency bands are the EEG rhythms that “react” to imagined or real movements, mainly mu (8–13 Hz) and beta (13–30 Hz), and they are the key signals used in motor imagery BCIs. The real-time performance, as well as the offline analysis of the recorded dataset, has not met the standard dataset result, indicating a need to train the user. Furthermore, the authors will report the implications observed during this experiment, as well as the analysis of the real-time data.

5. Study Limitations and Future Study

While working on a real-time BCI inference system, the authors encountered numerous problems. First of all, managing subjects for recording is a very difficult task. EEG data recording is a time-consuming process. Secondly, multichannel data are important for brain signal recording. Placing the electrode on the scalp at multiple positions is a time-consuming process. To accelerate EEG recording, a minimum number of channels is used to capture EEG signals over a limited scalp area. Another limitation is a universal feature. All users are reactive in different frequency bands. Before using the real-time system, the user's EEG data must be used to train the classifier. The parameters obtained from the classifier are used to classify the incoming brain signals and generate commands to control the electric wheelchair. Development of a real-time system is very challenging. Offline-reported results obtained using a different methodology cannot guarantee that the same result can be obtained in a real-time system. Additionally, working with a real-time buffer size is a significant issue. The algorithm should be computationally efficient and make decisions quickly. In the future, the authors will aim to train users and make them BCI-literate by providing Neurofeedback. There is a need to explore session-wise accuracy and investigate the effect of feedback on classification accuracy.

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