TRANSLATIONAL ENGINEERING IN HEALTH & MEDICINE

NATIONAL TECHNICAL UNIVERSITY OF ATHENS

Course Assignment

EEG Motion Imaginary

MSc Program	Translational Engineering in Health and Medicine
MSc Website	https://masterteam.ntua.gr/
Organiser(s)	National Technical University of Athens (NTUA) School of Electrical and Computer Engineering (ECE) School of Mechanical Engineering (ME)
Course Title	Biosignal Acquisition and Processing
Course Code	bio1003
Academic Year	2024-2025
Professor	George K. Matsopoulos
Assignment Group No#	5
Authors	Ioannis Baresis **(Corresponding Author)** Antonios Lekkas Anastasios Kamenides Ioannis Louloudakis Nikolaos-Andreas Tzovaras
2nd Submission Date	24/01/2025
Revision Date(s)	-

TABLE OF CONTENTS

1 INTRODUCTION

In this project, we focus on analyzing EEG data recorded during motor imagery tasks involving leg movements. Participants are presented with a visual cue that instructs them to imagine moving either both or none of the legs. By decoding the brain's response to these visual stimuli, we aim to explore the potential of using these signals in BCI applications [3].
The main objectives of this project are to explore the preprocessing techniques, feature extraction methods, and statistical validation approaches for EEG signals recorded during motor imagery tasks. The project aims to improve our understanding of how to process, analyze, and extract meaningful features from EEG data to enhance the accuracy and usability of MI-based BCIs. This study will contribute to the advancement of BCI technology and may lead to more efficient systems for controlling external devices through motor imagery [4].

2 BACKGROUND

Electroencephalography (EEG) is widely used for measuring brain activity during MI tasks, providing high temporal resolution and non-invasive recording. EEG is well-suited for capturing the dynamic and rapid changes in brain activity associated with MI tasks [5]. However, raw EEG signals are often contaminated by noise and artifacts, such as muscle contractions, eye blinks, and environmental interference, which can significantly degrade the quality of the data [3]. To mitigate these issues, preprocessing techniques, such as filtering, baseline removal, and detrending, are employed to clean the data and make it suitable for further analysis.

One of the most significant challenges in EEG-based MI studies is the extraction of meaningful features from the raw data. These features need to reflect the underlying brain activity during MI tasks in order to differentiate between different mental states. Power Spectral Density (PSD) is one of the most common feature extraction techniques used in BCI research. PSD quantifies the distribution of power across different frequency bands (e.g., alpha, beta) and provides insights into the brain's oscillatory activity during MI tasks [4].

In addition to PSD, statistical features such as skewness, kurtosis, mean, and variance can also be extracted from the frequency domain, as they provide information about the distribution and variability of the signal [6]. These features are crucial for understanding the neural signatures associated with MI tasks and can help distinguish between different conditions. Moreover, advanced techniques, such as machine learning algorithms, have been increasingly integrated into MI-based BCIs to improve the accuracy of feature classification and signal decoding [7].

While significant progress has been made in MI-based BCI research, challenges remain in achieving robust, generalized systems that work across different individuals and experimental conditions. Variability in EEG signals, low signal-to-noise ratios, and differences in brain anatomy among participants contribute to these challenges [8]. Consequently, further research is needed to refine preprocessing methods, feature extraction techniques, and validation strategies to improve the performance and reliability of MI-based BCIs. This study contributes to this ongoing effort by utilizing advanced signal processing and statistical techniques to enhance the understanding and application of EEG data in motor imagery tasks [9].

3 DATASET DESCRIPTION

The dataset used in this study consists of electroencephalography (EEG) measurements recorded during motor imagery tasks. The tasks involve visual stimuli that ask participants to imagine moving both or none of the legs. Each stimulus shows two soles at the center of the screen with a black background. In the experimental setup, both soles are highlighted in green when participants are asked to imagine moving both legs, while no soles appear in green when imagining no movement. The dataset contains EEG data recorded under two conditions:

- **Imaginary motion**: Visual command to either imagine moving both legs or imagine moving none of the legs.

The EEG signals were recorded from 63 channels, with each channel providing continuous time-series data at a sampling rate of 256 Hz. The dataset consists of recordings from 33 pilots, with each pilot's data corresponding to 20 events per condition (one for each trial). However, data from pilot 13 is missing, resulting in a total of 32 usable pilot datasets.
The channels included in the dataset are as follows:
Fp1, **AF7**, **AF3**, **F1**, **F3**, **F5**, **F7**, **FT7**, **FC5**, **FC3**, **FC1**, **C1**, **C3**, **C5**, **T7**, **TP7**, **CP5**, **CP3**, **CP1**, **P1**, **P3**, **P5**, **P7**, **P9**, **PO7**, **PO3**, **O1**, **Oz**, **Poz**, **Pz**, **CPz**, **Fpz**, **Fp2**, **AF8**, **AF4**, **Afz**, **Fz**, **F2**, **F4**, **F6**, **F8**, **FT8**, **FC6**, **FC4**, **FC2**, **FCz**, **Cz**, **C2**, **C4**, **C6**, **T8**, **TP8**, **CP6**, **CP4**, **CP2**, **P2**, **P4**, **P6**, **P8**, **P10**, **PO8**, **PO4**, **O2**.

The channels are distributed across various brain regions, such as frontal, parietal, occipital and temporal areas, ensuring comprehensive coverage of brain activity.

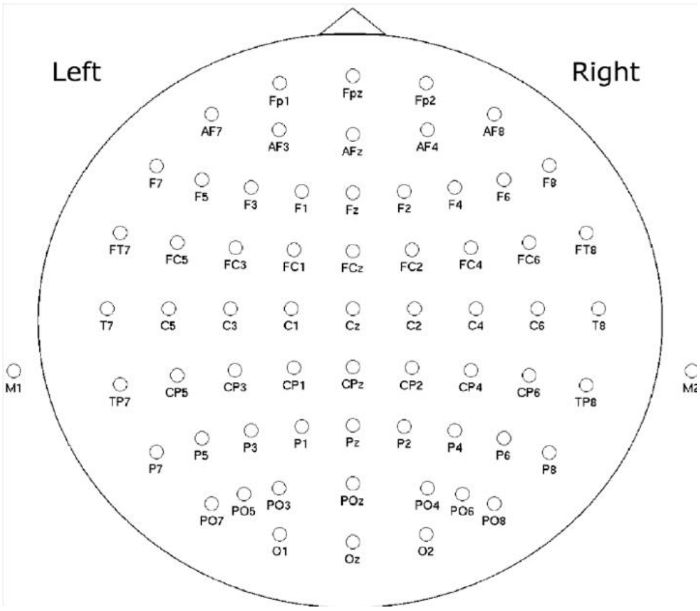

Image 1: Location and nomenclature of a 63-channel cap according to the 5% electrode placement scheme: frontal pole (Fp), antero-frontal (AF), frontal (F), central ©, parietal (P), temporal (T), occipital (O), and mastoid (M). The numbering starts at the midline (z for zero)

increasing with distance. Even numbers indicate right-sided placement with odd numbers on the left [17].

The placement of these electrodes follows the standard electrode positioning system and its extensions to ensure reliable data capture across different cognitive and motor functions. The EEG signals provide insights into brain activity during motor imaginary tasks and are essential for understanding the neural mechanisms underlying such processes.

Each data file corresponds to an individual pilot's EEG signal and includes information for 20 events under either the “both” or “none” conditions. The dataset is provided in CSV format, where each column corresponds to one time point for all 63 channels, and each row corresponds to the signal for a specific channel. The sampling rate of 256 Hz means that each second of recorded data contains 256 samples. This high sampling rate allows for precise time-domain analysis, which is essential for detecting rapid neural dynamics associated with motor imagery tasks.

The primary goal of this dataset is to study brain activity during motor imagery, specifically focusing on distinguishing between the “both” and “none” conditions through feature extraction and validation.

4 STATE OF THE ART

Motor imagery (MI) has been extensively studied for its potential applications in brain-computer interfaces (BCIs), especially in neurorehabilitation and assistive technologies. During MI tasks, the brain exhibits specific oscillatory activity patterns that can be leveraged for BCI control. The alpha (8–13 Hz) and beta (13–30 Hz) frequency bands are particularly important, as they show event-related desynchronization (ERD) and synchronization (ERS) in response to MI, reflecting changes in cortical excitability [1]. These brain rhythms are central to BCI systems that aim to decode motor imagery signals for controlling external devices.

EEG-based MI research relies heavily on effective preprocessing and feature extraction techniques. Raw EEG data is often contaminated by various artifacts such as muscle activity and eye movements, which necessitate robust preprocessing to clean the data. Techniques such as bandpass filtering (1-35 Hz), baseline removal, and detrending are commonly used to isolate the relevant frequency bands and reduce noise [2]. The application of bandpass FIR filters helps to remove unwanted components, such as high-frequency noise and slow signal drift, ensuring the integrity of the data for subsequent analysis.

Power Spectral Density (PSD) estimation is one of the most widely used feature extraction methods, providing a compact representation of brain oscillations during MI tasks. By analyzing the frequency components of EEG signals, PSD helps to identify neural signatures that are essential for distinguishing between different MI conditions [3]. In addition to PSD, statistical features such as skewness, kurtosis, variance, and mean offer complementary insights into the distribution and variability of the EEG signals in the frequency domain, further aiding in the identification of motor imagery states [4].

Recent advancements have also integrated machine learning algorithms to enhance feature classification and decoding of MI signals. Techniques such as Support Vector Machines (SVM) and deep learning approaches have been employed to improve the accuracy and robustness of MI-based BCIs, achieving higher classification performance compared to traditional methods [6]. Statistical tests, including one-way ANOVA, are often used to validate the significance of the extracted features and to assess the differences between conditions, such as imagining the movement of both legs versus none.

Moreover, research has increasingly focused on the role of brain network features in MI-based BCIs. By analyzing the functional connectivity between brain regions, methods such as coherence or correlation can provide additional insights into the neural mechanisms underlying MI. Brain network analysis has the potential to enhance classification performance by offering a more comprehensive view of brain activity during MI tasks [7]. Additionally, recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated success in automatically extracting hierarchical features from raw EEG signals, reducing the need for manual feature engineering and further improving classification accuracy [8].

Ongoing research focuses on refining preprocessing techniques, feature extraction methods, and machine learning models to address these challenges and create more efficient and adaptable MI-based BCIs [10].

5 METHODOLOGY

The methodology of this project involves several steps, including data preprocessing, feature extraction, and feature validation. The approach is designed to process and analyze the EEG signals in relation to the imaginary motion task, specifically for distinguishing between the two conditions: “both” and “none.” Below, we describe the methods applied to each stage of the project.

5.1 DATA PREPROCESSING

Preprocessing is a critical step in any EEG analysis to improve the quality of the data and remove unwanted artifacts. In this study, the following preprocessing steps were performed:

- **FIR Filter (1–35 Hz):** A bandpass FIR (Finite Impulse Response) filter was applied to the EEG signals to remove noise and artifacts outside the typical frequency range of interest for EEG data related to motor imagery tasks. This range includes typical brain wave frequencies such as Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (30-35 Hz). Filtering helps reduce artifacts caused by high-frequency noise, such as muscle and eye movement artifacts [5].
- **Baseline Removal:** To normalize the data and remove any baseline shifts, baseline correction was performed by subtracting the average of the signal from each time point. This ensures that the EEG signals are centered around zero, removing any drift over time, which is essential for accurate feature extraction [11].
- **Detrending:** To remove any linear or non-linear trends that might bias the data, detrending was applied. This technique helps prevent low-frequency drift that can distort the analysis and feature extraction processes [12].

These preprocessing steps aim to enhance the quality of the data and ensure that the signals used for feature extraction represent the neural activity of interest.

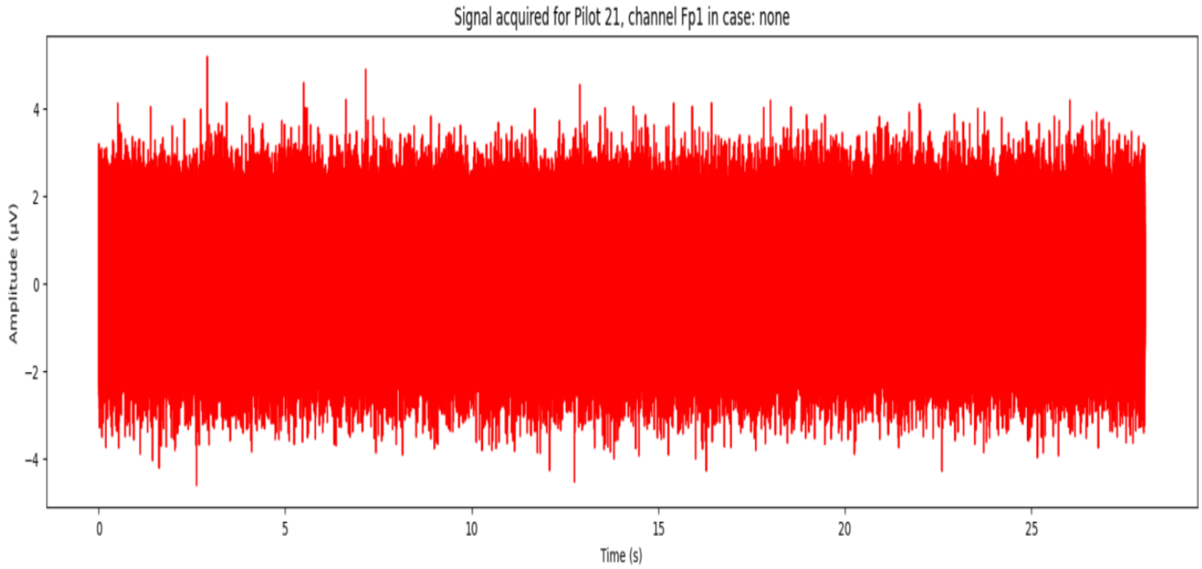

Image 2: EEG signal of channel Fp1 from pilot 21 in "none" case before filtering

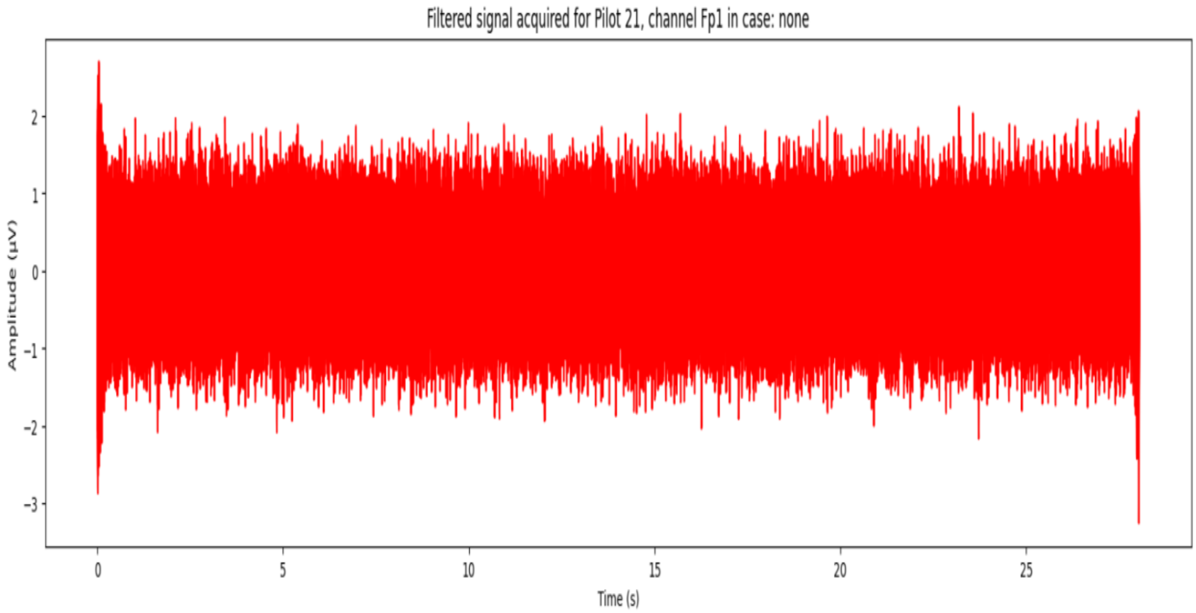

Image 3: EEG signal of channel Fp1 from pilot 21 in "none" case after filtering

5.2 FEATURE EXTRACTION

Once the data was preprocessed, the next step was feature extraction. The goal of feature extraction is to transform the EEG signals from the time domain into a more informative representation in the frequency domain. This is done by using the **Fourier Transform** to obtain the **Power Spectral Density (PSD)**.

- **Fourier Transformation & PSD Calculation:** The EEG signals were first converted from the time domain to the frequency domain using the **Fast Fourier Transform (FFT)**. This transformation allows the analysis of the frequency components of the signals and provides a clearer understanding of the neural oscillations that occur during the task. The PSD was then calculated for each EEG channel. The PSD provides insights into the power distribution of the EEG signals across various frequency bands, which are often linked to different cognitive and motor processes [5].
- **Frequency Bands of Interest:** The key frequency bands analyzed were Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (30-35 Hz). These bands are commonly used in motor imagery tasks, as they reflect different neural processes. For example, the Alpha band has been associated with relaxed states, while the Beta band is associated with motor planning and movement preparation [13].
- **Skewness, Kurtosis, Mean, and Variance:** In addition to PSD, additional statistical features such as skewness, kurtosis, mean, and variance were extracted for each frequency band. These statistical measures provide further insights into the distribution and variability of the EEG signals. Skewness describes the asymmetry of the signal distribution, while kurtosis measures the "tailedness" of the distribution. The mean and variance provide information about the central tendency and spread of the signal's power, respectively [14][15].

By extracting these features, we aim to capture the distinctive characteristics of the EEG signals under the two experimental conditions ("both" vs. "none"), which can later be used for statistical analysis and potential classification.

5.3 FEATURE VALIDATION

To validate the significance of the extracted features, a **One-Way Analysis of Variance (ANOVA)** was performed between the two conditions ("both" and "none"). ANOVA is a statistical method used to determine if there are any statistically significant differences between the means of multiple groups. In this case, it helped assess whether the features extracted from the EEG data showed significant differences between the two experimental conditions.

- **ANOVA for PSD and Statistical Features:** One-way ANOVA was applied separately for each feature (PSD, skewness, kurtosis, mean, and variance) across all frequency bands

(Delta, Theta, Alpha, Beta, and Gamma). The analysis was conducted for each EEG channel to determine if the features exhibited significant differences between the two conditions. The null hypothesis of the ANOVA test was that there were no significant differences between the two conditions, and the p-value obtained from the test was used to assess the significance [16].

- **Significance Threshold:** A significance threshold of **$p < 0.05$** was used to identify significant results. Features with p-values below this threshold were considered to show significant differences between the "both" and "none" conditions, indicating that they could potentially be useful for differentiating between the two states.

These validation steps ensure that the extracted features are not only informative but also statistically significant, providing a solid foundation for any further analysis or machine learning tasks.

6 RESULTS

To evaluate the statistical significance of differences in EEG features between the "both" and "none" motor imagery conditions, a one-way ANOVA was performed for each feature type, frequency band, and channel. The analysis focused on identifying EEG channels with p-values less than 0.05, indicating significant differences between the two conditions. Below, the results are presented for each feature type and frequency band.

1. **Power Spectral Density (PSD)**

The PSD analysis revealed significant differences in specific EEG channels across all frequency bands:

- **Delta band (0.5–4 Hz):** Significant differences were observed in channels **P3** and **PO3**.
- **Theta band (4–8 Hz):** Significant differences were found in channels **P5** and **TP8**.
- **Alpha band (8–13 Hz):** Significant channels included **FC1**, **FC3**, **P4**, and **T8**.
- **Beta band (13–30 Hz):** Significant differences were detected in channels **C4** and **FC6**.
- **Gamma band (30–100 Hz):** Significant channels were **CP5**, **FC6**, and **Pz**.

2. **Kurtosis**

Kurtosis analysis identified significant channels as follows:

- **Delta band:** Channels **CP2**, **F1**, **Fpz**, and **P3** showed significant differences.
- **Theta band:** Significant differences were found in channels **Fpz** and **P3**.
- **Alpha band:** Channels **F7** and **Oz** exhibited significant differences.
- **Beta band:** Significant channels included **F8** and **POz**.
- **Gamma band:** Significant differences were observed in channels **AF8** and **PO3**.

3. **Skewness**

The skewness analysis yielded the following significant results:

- **Delta band:** Channels **FC6**, **P7**, and **POz** showed significant differences.
- **Gamma band:** Significant channels included **F3** and **FT7**.

4. **Mean**

For the mean feature, the following significant channels were identified:

- **Delta band:** Channels **P7** and **TP8** exhibited significant differences.
- **Theta band:** Significant differences were observed in channel **F1**.
- **Alpha band:** Channels **C6**, **CP5**, and **CP6** showed significant differences.
- **Beta band:** Significant channels included **AFz**, **C3**, **CP1**, **FC5**, and **POz**.
- **Gamma band:** Significant differences were detected in channels **F3**, **FT7**, and **TP7**.

5. **Variance**

The variance analysis highlighted the following significant differences:

- **Delta band:** Channel **CP2** was significant.
- **Theta band:** Channels **P5** and **TP8** showed significant differences.
- **Alpha band:** Significant channels included **AF7**, **FC1**, **FC3**, **P4**, and **T8**.
- **Beta band:** Channels **C4** and **FC6** exhibited significant differences.
- **Gamma band:** Significant differences were observed in channels **CP5**, **Fz**, and **Pz**.

The results demonstrate that significant differences between the "both" and "none" conditions were distributed across a range of frequency bands and channels. Notably, specific channels, such as **FC6**, **Pz**, and **POz**, appeared significant across multiple feature types and frequency bands, suggesting their potential importance in differentiating motor imagery tasks. These findings highlight the complexity of the neural activity patterns associated with motor imagery and underscore the necessity of examining multiple features and frequency bands to comprehensively understand EEG dynamics in such tasks. The tables below presents the results:

PSD Results (Both)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	100.13	121.32	143.61	434.96	59.88
AF7	112.40	129.27	139.66	420.03	60.75
AF3	96.33	107.62	140.70	486.56	60.32
F1	136.43	110.54	132.36	439.50	60.72
F3	93.36	100.65	124.59	425.05	61.91

Skewness Results (Both)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	-1.17	-0.01	-0.004	0.007	0.002
AF7	-0.41	-0.02	-0.03	-0.04	0.0003
AF3	-0.53	0.01	-0.001	-0.01	0.0003
F1	1.04	0.01	-0.001	-0.004	-0.00001
F3	0.19	-0.01	-0.001	-0.001	0.00008

Kurtosis Results (Both)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	8.22	-0.24	-0.03	-0.03	0.08
AF7	2.38	-0.06	0.14	-0.21	-0.30
AF3	1.92	-0.02	-0.01	0.04	0.42
F1	6.38	0.08	-0.08	-0.02	-0.24
F3	0.32	0.18	-0.05	0.01	0.20

Mean Results (Both)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	-0.003	-0.0005	-0.0002	-0.00006	-6.7e-05
AF7	-0.002	-0.0007	-0.0005	-0.0005	-1.97e-05
AF3	-0.002	-0.0003	-0.0002	-0.00001	-2.60e-05
F1	0.003	0.0005	0.00005	-0.0001	4.85e-07
F3	0.001	0.0004	0.00002	0.0001	-3.52e-06

Variance Results (Both)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	0.026	0.029	0.036	0.109	0.014
AF7	0.024	0.030	0.036	0.105	0.015
AF3	0.024	0.026	0.036	0.121	0.014
F1	0.032	0.027	0.033	0.110	0.014
F3	0.023	0.02	0.031	0.107	0.015

PSD Results (None)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	98.90	115.20	143.84	449.78	62.38
AF7	93.42	130.64	123.99	434.66	64.69
AF3	95.54	115.73	123.11	460.89	58.82
F1	71.72	125.67	146.85	438.11	67.01
F3	167.75	134.87	152.35	472.43	60.19

Skewness Results (None)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	-0.93	-0.03	0.0002	-0.008	-0.0001
AF7	-0.69	-0.02	0.0006	-0.009	0.0003
AF3	0.02	0.008	0.0005	-0.005	-0.0003
F1	0.02	-0.004	0.0003	-0.009	-0.0004
F3	-3.57	-0.76	0.05	-0.01	-0.0002

Kurtosis Results (None)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	3.75	-0.20	-0.12	0.008	0.08
AF7	2.89	-0.03	0.53	-0.14	-0.03
AF3	0.52	-0.09	-0.13	-0.06	0.05
F1	-0.08	0.07	0.12	-0.08	-0.02
F3	33.07	10.18	0.96	0.21	0.19

Mean Results (None)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	-0.003	-0.0006	-0.00001	-0.00001	0.000009
AF7	-0.002	-0.0006	-0.0001	-0.0002	0.00001
AF3	0.001	0.0005	-0.0001	0.0001	0.00001
F1	0.0001	0.00009	-0.00003	-0.0001	0.00002
F3	-0.007	-0.001	-0.0005	-0.00008	-0.00004

Variance Results (None)

Pilot Channel	Delta	Theta	Alpha	Beta	Gamma
FP1	0.025	0.029	0.034	0.114	0.014
AF7	0.024	0.032	0.030	0.109	0.015
AF3	0.022	0.029	0.031	0.116	0.015
F1	0.017	0.031	0.037	0.110	0.016
F3	0.046	0.032	0.037	0.118	0.014

7 DISCUSSION

The statistical analysis performed in this study provides significant insights into the neural dynamics of motor imagery (MI) tasks involving leg movements. By analysing EEG features across frequency bands, we identified specific channels that exhibited significant differences between the "both" and "none" conditions. This section interprets these findings in the context of existing research and discusses their implications for motor imagery-based brain-computer interfaces (BCIs).

7.1 INTERPRETATION OF RESULTS

The results indicate that significant differences between the two MI conditions were primarily localized in parietal (e.g., **P3**, **P5**, **Pz**), frontal (e.g., **FC1**, **FC6**, **F1**), and occipital (e.g., **Oz**, **PO3**, **POz**) regions, depending on the feature type and frequency band. These regions align with areas implicated in MI-related neural activity in prior studies. The parietal cortex plays a critical role in motor planning and sensorimotor integration, while the frontal cortex is associated with motor preparation and higher-order cognitive functions [1, 2].

- **Power Spectral Density (PSD):**
  Significant differences were observed in parietal channels (e.g., **P3**, **P5**) and frontal channels (e.g., **FC1**, **FC3**, **FC6**) across the **alpha** (8–13 Hz) and **beta** (13–30 Hz) bands. These findings are consistent with established evidence that alpha and beta rhythms exhibit event-related desynchronization (ERD) during MI tasks [3]. Additionally, the identification of significant differences in the **gamma** band (30–100 Hz) in channels such as **CP5** and **Pz** provides novel insights, as gamma activity is less frequently analyzed in MI tasks but has been linked to higher-order motor functions and cortical excitability [4].
- **Statistical Features:**
  Features such as kurtosis, skewness, mean, and variance identified significant differences in both traditional motor-related regions and additional areas such as frontal (**F7**, **F8**) and occipital (**Oz**) regions. For example, significant differences in the **alpha** and **gamma** bands highlight the involvement of these regions in visuospatial and cognitive processing during MI tasks [5].

The widespread distribution of significant channels across multiple frequency bands and feature types underscores the complexity of neural responses during MI tasks. These findings support the hypothesis that MI is a multimodal process engaging diverse cognitive and sensorimotor networks [6].

7.2 COMPARISON TO EXISTING STUDIES

Our findings corroborate prior studies, such as those by Pfurtscheller and Lopes da Silva [4], which emphasize the role of **alpha** and **beta** rhythms in motor planning and execution. The involvement of occipital regions (e.g., **Oz**, **POz**) aligns with research highlighting the importance of visual processing and mental imagery, particularly in studies using visual stimuli as cues [7].

The significant differences observed in the **gamma** band and their association with PSD and variance contribute new insights to the MI literature. While gamma band activity has been less frequently studied, emerging evidence suggests its role in motor learning and cortical synchronization [8]. This highlights the potential of the gamma band in distinguishing MI states and adds a new dimension to feature extraction in MI-based BCIs.

A notable finding is the prominent role of frontal channels (e.g., **F1**, **F7**, **F8**, **AFz**) across multiple features. This suggests that cognitive processes such as attention and working memory, which are modulated by frontal lobe activity, are crucial in distinguishing the "both" and "none" conditions. These findings are consistent with studies, such as those by Blankertz et al. [9], that emphasize the role of frontal activity in tasks requiring sustained attention or effortful imagery.

7.3 IMPLICATION FOR BCIs

The results of this study have significant implications for the design and optimization of MI-based BCIs. The identification of key channels (e.g., **P3**, **Pz**, **FC6**) and frequency bands provides valuable insights for feature selection, a critical factor for improving classification accuracy and reducing computational complexity. These channels, which consistently exhibited significant differences across multiple features, could serve as reliable inputs for BCI systems.

Additionally, the inclusion of statistical features such as kurtosis and skewness, alongside traditional spectral features like PSD, highlights the importance of multimodal feature sets. Combining these features in machine learning models could enhance the discrimination of MI states, particularly under conditions with low signal-to-noise ratios [10]. The integration of diverse feature types can improve the robustness and adaptability of MI-based BCIs.

7.4 LIMITATIONS AND FUTURE WORKS

Despite these promising findings, this study has several limitations. The variability in significant channels across features and frequency bands underscores the heterogeneity of neural responses during MI. This variability may stem from individual differences in brain anatomy, task execution, or cognitive strategies, which were not accounted for in this study. Future research should focus on developing personalized models that adapt to individual neural patterns.

Furthermore, while this study employed ANOVA for statistical validation, more advanced classification approaches could be explored. The application of machine learning techniques, including deep learning models such as convolutional neural networks (CNNs), could provide more robust feature extraction and classification capabilities [8]. Future studies should also investigate the integration of functional connectivity measures to capture network-level interactions during MI tasks.

8 CONCLUSIONS

In conclusion, this study highlights the neural complexity of motor imagery tasks involving leg movements, with significant differences observed across multiple channels, frequency bands, and features. These findings contribute to the growing body of research on motor imagery and provide valuable insights for the development of more accurate and reliable MI-based BCIs. By refining feature extraction and selection methods, future studies can further enhance the potential of BCIs as assistive technologies for individuals with motor impairments.

REFERENCES

1. Simanto S., Darvishi S., Baumert M., Raqibul M., Khawza A., Khondaker A., Ganesh R., Ahsan H. (2021). Progress in Brain Computer Interface: Challenges and Opportunities. *Frontiers in Neuroscience.*
2. Han-Jeong H., Kiwoon K., Chang-Hwang I. (2009). Neurofeedback-based motor imagery training for brain-computer interface (BCI). *Pubmed.*
3. Li Y., Kambara H., Koike Y., Sugiyama M. (2010). Application of covariate shift adaptation techniques in brain-computer interfaces. *IEEE Transactions on Biomedical Engineering*.
4. Pfurtscheller G., Lopes da Silva F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology*.
5. Niedermeyer, E., & da Silva, F. L. (2005). Electroencephalography: Basic principles, clinical applications, and related fields. *Lippincott Williams & Wilkins*.
6. Satya P., Sachin M., Sukrit G., Parasuraman P. (2023). Functional Mapping of the Brain for Brain–Computer Interfacing: A Review. *Research Gate*.
7. Bashivan P., Rish I., Yeasin M., Codella N. (2016). Learning representations from EEG with deep recurrent-convolutional neural networks. *arXiv*.
8. Schirrmeister R. T., Springenberg J. T., Fiederer L. D., Glasstetter M., Eggensperger K., Tangermann M., Ball T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. *Pubmed Central.*
9. Samek W., Meinecke F. C., Müller K. R. (2013). Transferring subspaces between subjects in brain-computer interfacing. *IEEE Transactions on Biomedical Engineering*.
10. Haolong S., Gege Z., Yifang L., Lu W., Jie J., Lihua Z., Zhongxue G., Xiaoyang K. (2024). Analysis of brain network differences in the active, motor imagery, and passive stoke rehabilitation paradigms based on the task-state EEG. *Pubmed*.
11. Sangin P., Jihyeon H., Da-Hye K., Laehyun K. (2021). Improving Motor Imagery-Based Brain-Computer Interface Performance Based on Sensory Stimulation Training: An Approach Focused on Poorly Performing Users. *Frontiers in Neuroscience.*
12. Sanei S., Chambers J. A. (2013). EEG Signal Processing. *Wiley.*
13. Neuper C.,Müller-Putz G., Scherer R., Pfurtscheller G. (2006). Motor imagery and EEG-based control of spelling devices and neuroprostheses. *Pubmed*.
14. Biradar S., Shastri R. K.(2019). Review paper on Feature Extraction Methods for EEG Signal Analysis. *Research Gate*.
15. Stancin I., Cifrek M., Jovic A. (2021). A Review of EEG Signal Features and Their Application in Driver Drowsiness Detection Systems. *Pubmed Central*.
16. Fisher, R. A. (1990). Statistical Methods, Experimental Design and Scientific Inference. *Oxford Science Publication,13th Edition*.
17. Martin J. C., Liley D. T. J., Harvey A. S., Kuhlmann L., Sleigh J. W., Davidson A. J. (2014). *Alterations in the Functional Connectivity of Frontal Lobe Networks Preceding Emergence Delirium in Children.Pubmed*