Neural Patterns in Motor Execution and Imagery:
A Comparative Analysis of EEG Data

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1 Introduction

Brain-computer interfaces (BCIs) represent a critical technology for restoring communication and motor function to millions of patients with severe motor disabilities, making understanding the neural mechanisms of motor imagery essential for clinical applications (Wolpaw, 2007). The remarkable similarity between real and imagined movement neural patterns provides a foundation for mapping valuable control signals from imagined actions to actual outputs such as controlling a robotic arm for paralyzed individuals.

The neural mechanisms underlying real movement execution and motor imagery have been extensively studied, with evidence suggesting significant overlap in the brain areas activated during both conditions. The functional equivalence hypothesis suggests that a similar cortical network, including primary motor areas, is involved during both mental practice of a movement and its overt execution.

While previous research has established that similar neural circuits are involved in both executed and imagined movements, the precise differences in connectivity patterns and dynamical properties are still not completely understood. Previous studies have been limited by focusing on single analytical approaches (typically activation patterns or spectral power) rather than integrating multiple complementary methods to characterize both the spatial and temporal dynamics of these neural states.

Many researchers use the PhysioNet motor imagery dataset primarily for training machine learning classifiers to distinguish between different movement types, focusing on classification accuracy rather than theoretical questions about neural similarity. This practical focus is understandable, particularly given that more specialized techniques like magnetoencephalography (MEG) might be better suited for fundamental neuroscience questions. Nevertheless, examining this dataset from a theoretical perspective could yield interesting insights about the neural similarity between executed and imagined movements, especially given the statistical power available from 109 subjects.

This project addresses a fundamental question: How similar are the neural patterns, connectivity structures, and dynamical properties of real movement and imagined movement, using resting state as a baseline? I hypothesize that real and imagined movements will show: (1) similar functional connectivity patterns in motor networks, (2) poor discriminability in classification analyses, and (3) comparable scale-free dynamics as measured by detrended fluctuation analysis, while both will differ significantly from resting state along all three dimensions.

This study attempts to overcome the methodological limitations of prior work by integrating three complementary analytical frameworks on a large dataset:

1. Functional connectivity patterns using phase-based measures (PLV, iPLV, wPLI)
2. Neural dynamics and criticality using Detrended Fluctuation Analysis (DFA)
3. Discriminability between conditions using classification techniques (CSP + LDA)

By integrating these diverse metrics, I aim to provide converging evidence on the neural similarity between motor execution and imagery.

2 Methods

2.1 Dataset

This study utilized the EEG Motor Movement/Imagery Dataset from PhysioNet (Schalk et al., 2004), containing EEG recordings from 109 volunteers performing both real and imagined movements. The data was recorded using the BCI2000 system with 64 electrodes sampled at 160 Hz.

Each subject performed 14 experimental runs: two one-minute baseline runs (one with eyes open, one with eyes closed), and three two-minute runs of each of four tasks involving real and imagined movements of hands and feet. For this analysis, I focused specifically on three conditions:

- **Rest (T0):** Periods when the subject remained at rest
- **Real right-hand movement (T2):** Execution runs where the subject performed actual opening and closing of the right hand
- **Imagined right-hand movement (T2):** Imagery runs where the subject imagined opening and closing the right hand

2.2 Preprocessing Pipeline

I developed a comprehensive preprocessing pipeline implemented in Python using the MNE library. The core preprocessing functions include:

1. `process_eeg_automatic`: The main entry point for automatic preprocessing, loading EDF files, applying filters, and extracting condition-specific epochs
2. `process_eeg_manual`: Alternative pathway allowing manual review of ICA components
3. `process_eeg_debug`: Debugging version with diagnostic plots
4. Helper functions like `_apply_ica` and `_fit_ica` for artifact removal

This modular design allowed flexible experimentation with different preprocessing approaches. The automatic approach was selected for computational efficiency and consistency across subjects. After obtaining similar results with and without ICA analysis, I decided to use a streamlined pipeline with just bandpass filtering. The simple bandpass filtering approach (6-30 Hz) naturally removed many common artifacts like eye blinks and slow drifts while preserving the motor-relevant oscillations, particularly the mu (8-12 Hz) and beta (13-30 Hz) rhythms associated with motor activity.

The preprocessing pipeline consisted of the following steps:

1. **Data loading:** EDF files were read using `mne.io.read_raw_edf`
2. **Channel standardization:** Channel names were standardized using `mne.datasets.eegbci.standardize`
3. **Montage application:** The standard 10-10 montage was applied
4. **Re-referencing:** Data was re-referenced to the average reference
5. **Filtering:** A bandpass filter (6-30 Hz) was applied

6. **Epoching:** Data was segmented into epochs from -1.0 to 3.0 seconds relative to event markers

7. **Baseline correction:** Epochs were baseline-corrected using the pre-stimulus period (-1.0 to 0.0 seconds)

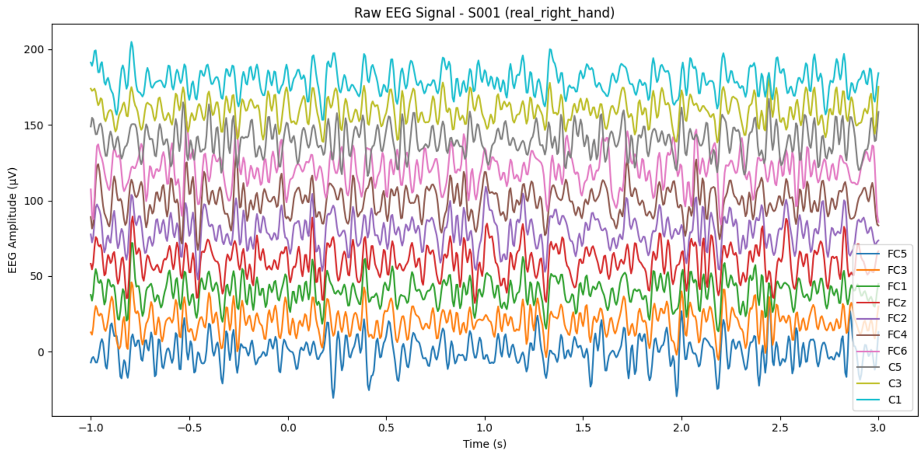


Figure 1: Raw EEG signal for a single trial of real right-hand movement.

2.3 Analytical Approaches

2.3.1 Event-Related Desynchronization (ERD/ERS)

To validate the preprocessing pipeline, I examined the Event-Related Desynchronization/Synchronization (ERD/ERS) patterns using the `compute_erd_ers` function. When no sensory inputs or motor outputs are being processed, the mu (8-12 Hz) and beta (13-30 Hz) rhythms are synchronized. During movement preparation or execution, a desynchronization occurs (ERD), which can be detected 1-2 seconds before movement onset. Subsequently, these rhythms synchronize again (ERS) within 1-2 seconds after movement. The 3-second window after the "go" signal was chosen as a natural interval for the opening and closing hand movement task.

2.3.2 Connectivity Analysis

I implemented a set of connectivity functions to analyze functional relationships between brain regions. Volume conduction can cause signals recorded from one electrode to affect nearby electrodes, creating spurious connectivity measures. To address this issue, I implemented multiple connectivity metrics with varying sensitivity to volume conduction:

1. `compute_plv_matrix`, `compute_plv_pairwise`: Calculate Phase Locking Value (PLV), a standard measure of phase synchronization

2. `compute_iplv_matrix`, `compute_iplv_pairwise`: Calculate imaginary PLV, reducing volume conduction effects by using only the imaginary component of phase differences

3. `compute_wpli_matrix`, `compute_wpli_pairwise`: Calculate weighted Phase Lag Index, highly resistant to volume conduction by weighting phase differences by the magnitude of the imaginary component

4. `analyze_pairwise_connectivity`: Process multiple subjects/channel pairs

5. Statistical testing functions: `paired_ttest_connectivity` for statistical comparison between conditions

These metrics were calculated for all electrode pairs, with special focus on motor-related regions (C3, C4, Cz, FC3, FC4, CP3, CP4) and control regions (occipital and frontal). Occipital regions were included as control areas because participants were viewing visual cues, and frontal regions were included as they relate to top-down movement control.

2.3.3 Classification Analysis

I implemented a classification pipeline using:

1. `perform_csp_lda` and `perform_group_csp_lda`: Functions for Common Spatial Patterns (CSP) and Linear Discriminant Analysis (LDA) classification

2. `classify_condition_pairs`: Main function for running classification on multiple condition pairs

3. `analyze_frequency_bands` and `analyze_time_windows`: Functions examining classification performance across different frequencies and time periods

The pipeline was applied to two binary classification problems by training the classification algorithm on the three classes: Real movement vs. Rest and Real movement vs. Imagined movement. To understand what factors influence classification performance, I examined how accuracy varies across different frequency bands and time windows.

2.3.4 Detrended Fluctuation Analysis

To examine the scale-free dynamics and criticality of brain activity, I implemented several DFA functions:

1. `compute_dfa`: Core DFA algorithm calculating the scaling exponent
2. `compute_dfa_from_epochs`: Wrapper for MNE epochs objects
3. `analyze_band_dfa`: DFA analysis across multiple frequency bands
4. `compare_conditions_dfa`: Statistical comparison between conditions

DFA calculates the scaling exponent α which characterizes the long-range temporal correlations in the signal:

$$F(n) \sim n^{\alpha} \tag{1}$$

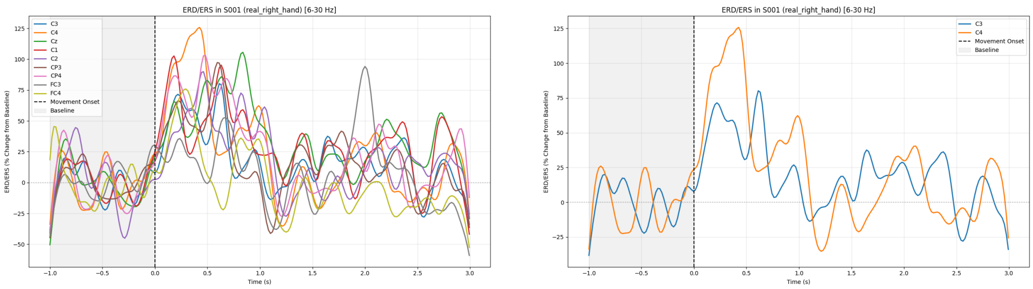
where $F(n)$ is the fluctuation function at scale n.
The analysis was performed on:

- Raw EEG signals
- Amplitude envelopes of alpha band (8-13 Hz)
- Amplitude envelopes of beta band (13-30 Hz)

3 Results

3.1 Event-Related Desynchronization (ERD/ERS)

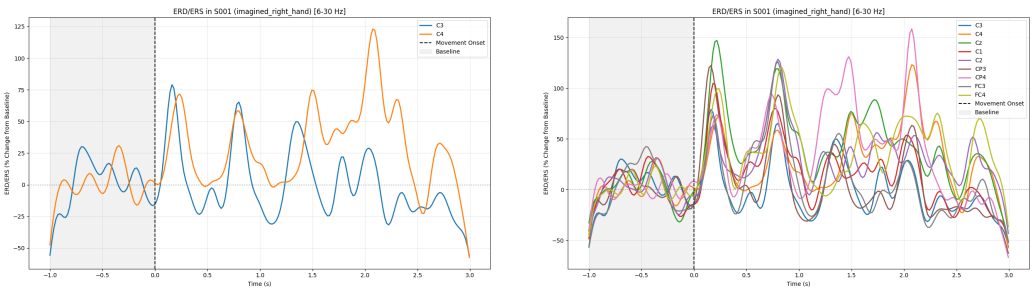
The ERD/ERS analysis revealed characteristic patterns for both real and imagined movements:



(a) Time course of ERD/ERS.

(b) Topographical distribution.

Figure 2: ERD/ERS for real right-hand movement (subject S001). The left panel shows the time course with movement onset at $t = 0$, and the right panel shows ERD/ERS across motor-related channels.



(a) Time course of ERD/ERS.

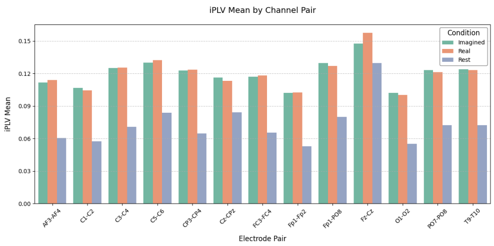
(b) Topographical distribution.

Figure 3: ERD/ERS for imagined right-hand movement (subject S001), resembling real movement but with reduced amplitude.

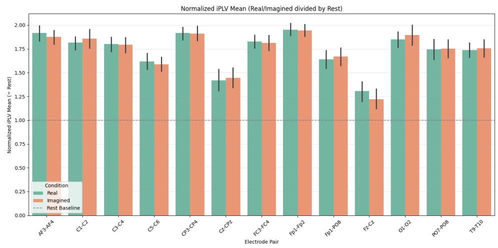
The ERD/ERS analysis confirms that both real and imagined movements elicit similar neurophysiological responses in motor regions. This pattern is consistent with previous findings that demonstrated ERD during both real and imagined movements, supporting the functional equivalence hypothesis.

3.2 Connectivity Analysis

The connectivity analysis revealed clear differences between rest and both movement conditions, but minimal differences between real and imagined movement:

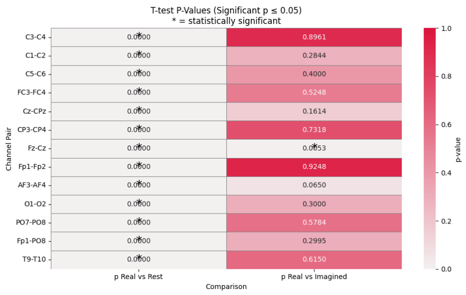


(a) Mean iPLV values across electrode pairs.

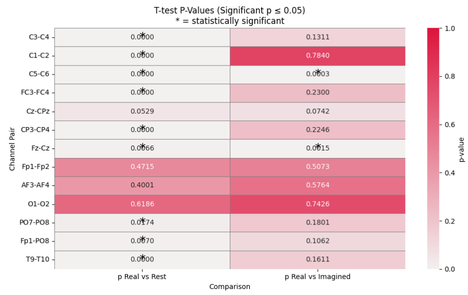


(b) Normalized iPLV values (Rest = 1.0).

Figure 4: iPLV metrics across conditions. Left: Mean iPLV values by condition across motor and control electrode pairs. Both real and imagined movement show increased connectivity compared to rest. Right: Normalized iPLV (Real/Imagined divided by Rest) shows comparable increases in functional connectivity for both task conditions.

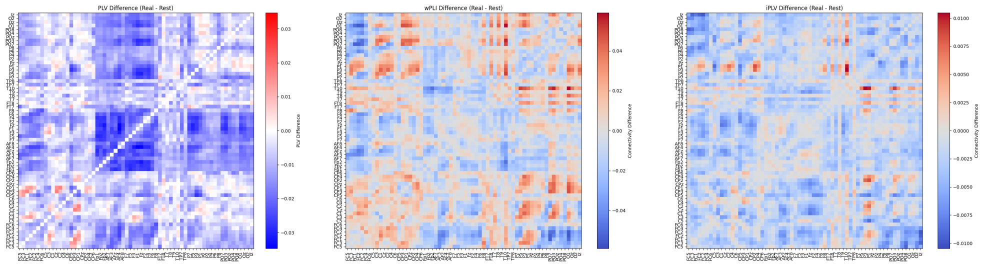


(a) iPLV t-test showing statistical significance for all channels in Real vs Rest, but for only one channel in Real vs Imagined



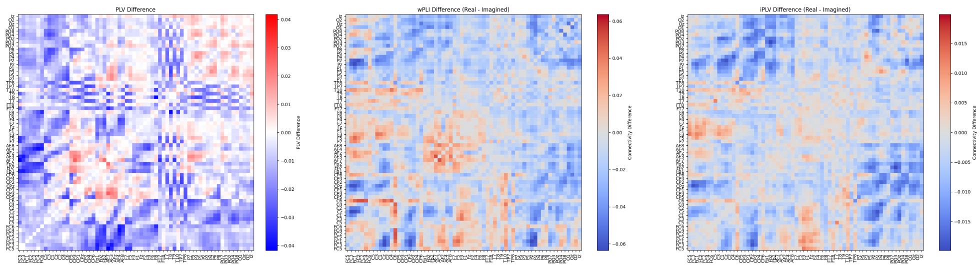
(b) T-test for PLV values showing statistically significant differences in Real vs Rest for most channels, but for only a few channels in Real vs Imagined.

Figure 5: T-test results from 30 subjects comparing connectivity metrics between conditions.



(a) PLV: Real vs. Rest (b) iPLV: Real vs. Rest (c) wPLI: Real vs. Rest

Figure 6: Connectivity difference matrices comparing Real movement vs. Rest across three metrics. The spatial patterns show consistent differences, with wPLI and iPLV reducing the number of connections as they more effectively control for volume conduction.



(a) PLV: Real vs. Imagined (b) iPLV: Real vs. Imagined (c) wPLI: Real vs. Imagined

Figure 7: Connectivity difference matrices comparing Real vs. Imagined movement. The differences are notably smaller than those between Real and Rest (Figure 6), suggesting greater similarity between the active conditions.

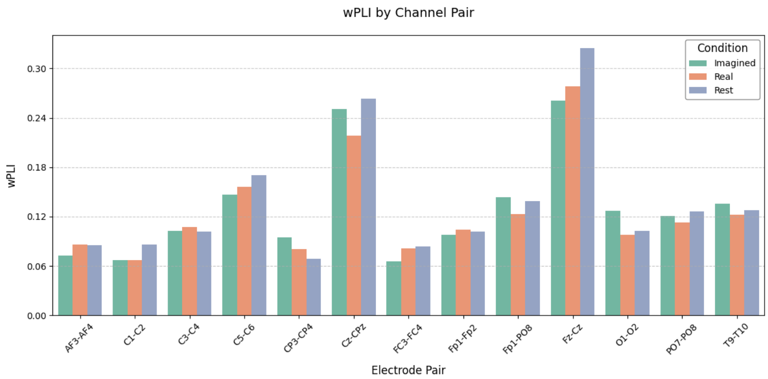


Figure 8: wPLI mean values by condition across electrode pairs. Here the result is less clear.

Key findings from the connectivity analysis include:

- Both PLV and iPLV showed significantly higher values for real and imagined movement compared to rest across multiple electrode pairs (all $p < 0.001$)
- When normalized to rest, both real and imagined movement displayed comparable increases in connectivity for motor-related electrode pairs
- Statistical comparison between real and imagined movement showed no significant differences in connectivity for most electrode pairs ($p > 0.05$)
- Motor area connections displayed the largest increases in connectivity during both real and imagined movement

3.3 Classification Analysis

The classification results provided quantitative evidence for the relative similarity between real and imagined movement compared to rest:

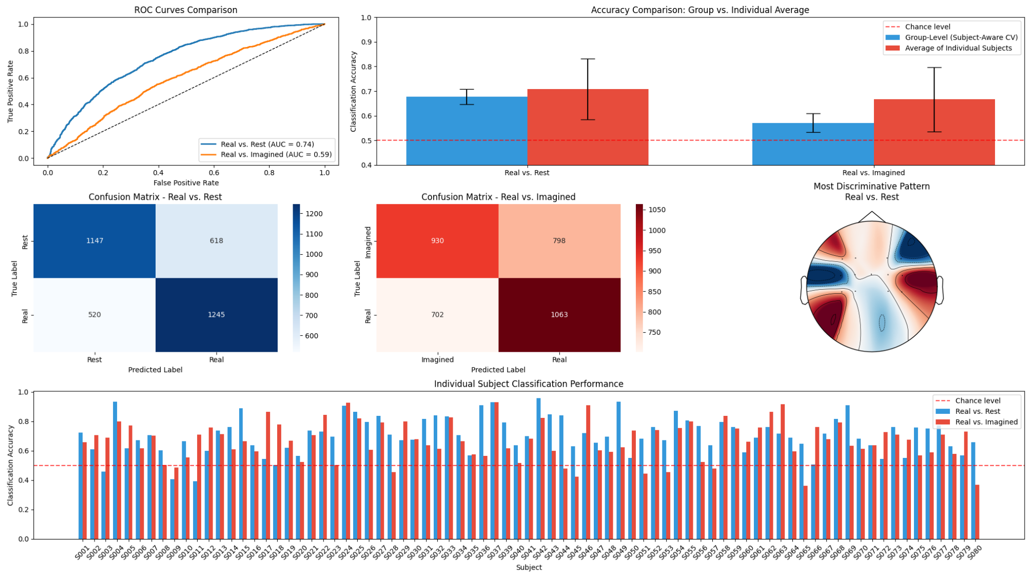


Figure 9: Classification performance overview across 80 subjects. Top-left: ROC curves show better performance for Real vs. Rest (AUC = 0.74) than Real vs. Imagined (AUC = 0.59). Top-center: Group-level accuracies (68.5% vs. 57.8%) reinforce this pattern. Middle: Confusion matrices show more misclassifications between Real and Imagined conditions. Bottom: Subject-wise accuracy bars demonstrate consistent patterns across individuals.

Further analysis of performance across frequency bands and time windows revealed:

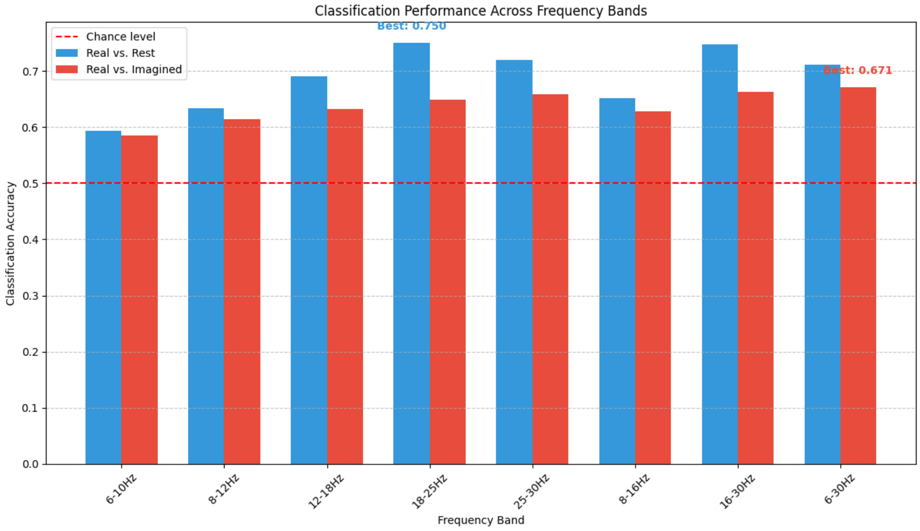


Figure 10: Classification accuracy across different frequency bands. The 18–25 Hz (upper beta) and 16–30 Hz bands yielded the best performance for both classification tasks, indicating that beta oscillations contain the most discriminative information for motor activity.

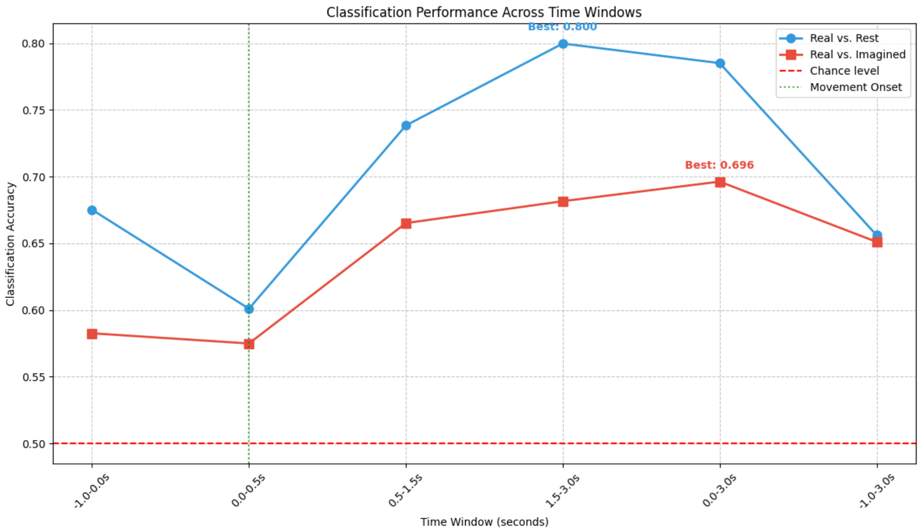


Figure 11: Classification accuracy across different temporal windows. Peak performance for both classification problems occurs in the 0.5-3s window after movement onset, corresponding to the period of active movement execution or imagination.

Key classification findings include:

- Real vs. Rest classification achieved moderate performance (AUC = 0.74, accuracy = 68.5%)
- Real vs. Imagined classification performed substantially worse (AUC = 0.59, accuracy = 57.8%), only marginally above chance level
- Individual subject analysis consistently showed better Real vs. Rest than Real vs. Imagined discrimination
- Beta band (18-25 Hz) provided the most discriminative information for both classification tasks
- Peak classification performance occurred during the 0.5-1.3s post-cue interval

The classification analysis provides objective evidence that while both conditions can be distinguished from rest with moderate accuracy, real and imagined movements have substantially more similar neural patterns, making their discrimination more challenging. This quantitatively confirms the neural similarity suggested by the connectivity analysis.

3.4 Detrended Fluctuation Analysis

The DFA analysis revealed similar scaling properties across conditions:

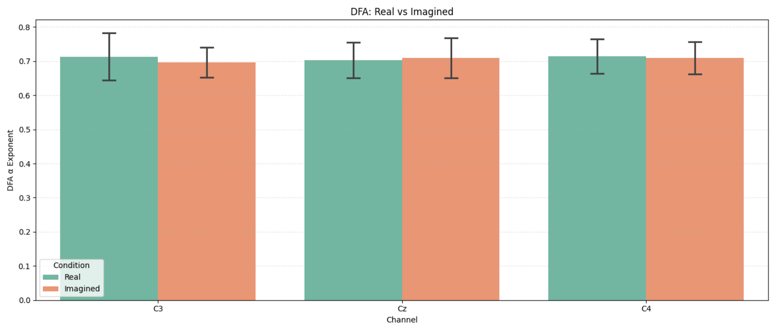


Figure 12: DFA α exponent comparison between Real and Imagined movement across motor channels (C3, Cz, C4). The exponents are remarkably similar, indicating nearly identical dynamical properties in both conditions.

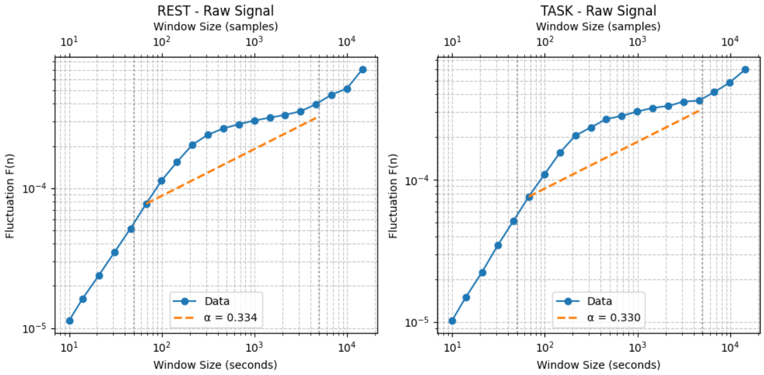
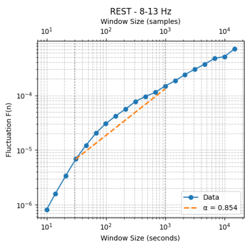
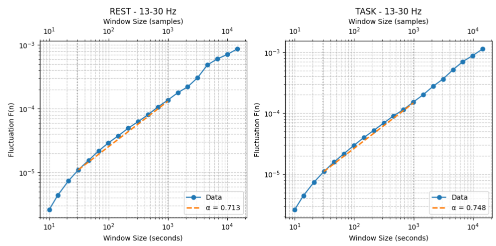


Figure 13: DFA for the data not filtered in any frequency band, and for the channel C3, where we obtain a very low alpha

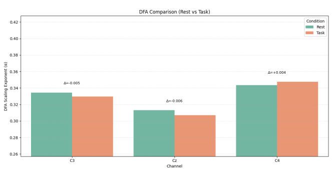


(a) Alpha band (8–13 Hz)

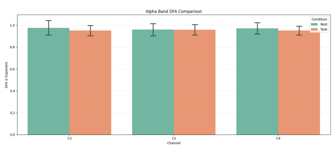


(b) Beta band (13–30 Hz)

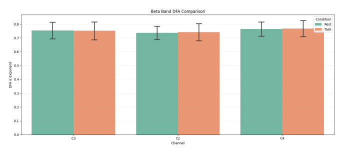
Figure 14: DFA log-log plots comparing Task and Rest conditions. Both alpha and beta bands show consistent scaling behavior across states, with parallel slopes indicating preserved long-range temporal correlations.



(a) Overall DFA comparison



(b) Alpha band



(c) Beta band

Figure 15: Comparison of DFA α values across Rest, Real, and Imagined movement. Left: Overall DFA shows minimal differences, indicating stable criticality. Middle and Right: Alpha and Beta band analyses across C3, Cz, and C4 reveal very similar task-related patterns with slight deviations from rest.

Key DFA findings include:

- Raw signal DFA exponents were nearly identical between real and imagined movement (real: $\alpha = 0.330$, imagined: $\alpha = 0.334$, $p = 0.625$)
- Alpha band envelope DFA showed no significant differences between real and imagined movement (real: $\alpha = 0.973$, imagined: $\alpha = 0.962$, $p = 0.744$)
- Beta band envelope DFA also showed similar scaling between real and imagined conditions (real: $\alpha = 0.748$, imagined: $\alpha = 0.735$, $p = 0.638$)
- Motor-related channels (C3, C4, Cz) displayed consistent scaling properties across conditions

The DFA analysis reveals that the brain maintains similar dynamical properties and criticality levels during both real and imagined movement. The lack of substantial differences in scaling exponents across conditions suggests similar underlying neural processes, providing deeper evidence for the functional equivalence hypothesis beyond mere activation patterns.

4 Discussion

4.1 Summary of Findings

The results of this comprehensive analysis strongly support the hypothesis that real and imagined movements engage similar neural circuits and exhibit comparable dynamical properties. The converging evidence from connectivity analysis, classification performance, and DFA indicates that the brain processes motor execution and imagery in fundamentally similar ways, both distinct from the resting state.

The most compelling evidence for neural similarity between real and imagined movement comes from:

1. **Connectivity Analysis:** Both conditions induced nearly identical increases in functional connectivity compared to rest, particularly in motor-related regions. This was consistent across all connectivity metrics, including those designed to minimize volume conduction effects.
2. **Classification Performance:** Machine learning algorithms struggled to distinguish between real and imagined movement (AUC = 0.59) while more easily separating either from rest (AUC = 0.74). These findings align with previous research and provide quantitative confirmation of the neural similarity between the movement conditions.

3. **DFA Scaling Exponents:** The nearly identical scaling exponents observed across conditions suggest that the brain maintains similar dynamical properties and criticality levels during both execution and imagery, providing a deeper level of similarity beyond just activation patterns.

These findings collectively provide strong support for the functional equivalence hypothesis, which proposes that similar neural circuits are engaged during both motor execution and imagery. The results are particularly compelling because they emerge from three complementary analytical approaches, each capturing different aspects of neural activity.

4.2 Limitations

Several limitations should be acknowledged:

1. **EEG Spatial Resolution:** EEG's limited spatial resolution restricts our ability to identify precise neural sources. While EEG provides excellent temporal resolution, its spatial resolution is constrained by volume conduction and reference effects. Future studies could benefit from combining EEG with neuroimaging techniques like fMRI or MEG.

2. **Volume Conduction:** Despite using metrics designed to minimize volume conduction effects (iPLV, wPLI), this confound cannot be completely eliminated in EEG recordings. Brain activity recorded at one electrode can influence nearby electrodes due to volume conduction, potentially inflating estimates of functional connectivity.

3. **Preprocessing Decisions:** The preprocessing pipeline inevitably involves trade-offs between artifact removal and signal preservation. While I implemented multiple approaches, the automatic method was selected for computational efficiency, which may have influenced the results.

4. **Individual Variability:** The discrimination of motor imagery of different movements is a challenging task since those movements have close spatial representations on the motor cortex area. There is considerable inter-subject variability in motor imagery ability, which may influence the observed patterns. Future work could stratify participants based on imagery ability.

5. **Task Complexity:** The simple hand movement task used in this dataset may not capture the full complexity of motor control. More complex sequential movements might reveal more subtle differences between execution and imagery.

4.3 Implications and Future Directions

These findings have several important implications:

1. **Brain-Computer Interfaces:** The neural similarity between real and imagined movement supports the use of motor imagery as a control signal in BCIs. The high discrimination between rest and imagery conditions suggests that detection of imagery vs. rest is a more reliable approach than distinguishing between different imagery types.

2. **Neurorehabilitation:** The engagement of similar neural circuits during imagery and execution supports the use of motor imagery training in rehabilitation protocols for patients with motor impairments. This is particularly relevant for conditions where physical movement is limited or impossible, such as stroke recovery, where mental practice can help maintain neural circuits.

Future research could extend these findings by:

- Examining more complex motor tasks to potentially reveal more subtle differences between execution and imagery
- Investigating individual differences in motor imagery ability and their impact on neural patterns
- Combining EEG with other neuroimaging modalities for better spatial localization
- Exploring the temporal evolution of neural patterns during different phases of movement preparation and execution, building on the temporal analysis findings in this study

5 Conclusion

This study provides comprehensive evidence that real and imagined movements engage highly similar neural circuits and exhibit comparable dynamical properties. Through multiple analytical approaches—connectivity analysis, classification performance, and detrended fluctuation analysis—I tried to demonstrate in this dataset that motor execution and imagery share fundamental neural characteristics that distinguish them both from the resting state.

The findings strongly support the functional equivalence hypothesis, reinforcing the theoretical basis for applications in brain-computer interfaces and neurorehabilitation protocols. The consistent results across different analytical dimensions—functional connectivity patterns, discriminability, and scale-free dynamics—provide particularly compelling evidence for the neural similarity of these processes.

Future research should focus on investigating more complex motor tasks, individual differences in motor imagery ability, and combining EEG with other neuroimaging modalities to better characterize the subtle differences that may exist between motor execution and imagery. Such research will be essential for optimizing BCI systems and rehabilitation protocols that rely on motor imagery.

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