Dataset: MOTOR IMAGERY

Related Papers: 10.1073/pnas.0913697107

Helpful Resources:

https://nma-project-planner.vercel.app/

Questions:

1. How do ECoG beta suppression and modulation differ in the brains of epileptic patients compared to non-epileptic patients?
    a. https://pmc.ncbi.nlm.nih.gov/articles/PMC7031656/
2. Can we predict feedback learning from pre-feedback based imagery patterns?
3. How can we classify actual vs imagery data
    a. Using HFB band (using GLMs)
    b. Comparing different electrodes
4. Reading the Brain's Intent: those specific signals . So, when the person *thinks* about taking a step, the BCI "reads" that intention.
    a. Classifying different movements based on imagery data
    b. https://pmc.ncbi.nlm.nih.gov/articles/PMC12209421/
    This paper looks at how EEG can be used to build a BCI model for aiding robotic movements based on motor-imagery. ECog can be used to build a more precise BCI model, given that we have feedback data as well.

5. First try to classify the imagined trials vs. the actual movements.
    a. Investigate which electrodes are better for this classification.
6. Can we develop a real time BCI system that relies solely on ECoG’s HFB signals to achieve faster and more accurate decoding of motor imagery compared to EEG-based systems limited to lower frequencies?
7. Can we find the spatial overlap between movement and imagery - related activity - and remove it ?
    a. https://www.biorxiv.org/content/10.1101/2025.06.13.659445v1

       This paper has decoupled intended and actual movement. We will need to be more specific.

Reference content for project planner:

- Research Question: Analysing neuro-oscillations across different brain regions while performing motor versus imagined tasks using a pre-recorded ECoG data set?

- Significance & Impact:

Personalized BCIs: Reliable single-trial discrimination of real versus imagined movements in High Frequency Band would enable adaptive training and control, benefiting users who cannot generate overt motor commands.

Neurophysiological Insights: Quantifying high-γ amplitude and spatial patterns in motor cortex advances our understanding of how imagined and executed actions are represented and how cortical circuits adapt.

Enhanced Rehabilitation: Tailored neurofeedback based on distinct execution and imagery signals can accelerate recovery and improve neuroplasticity in stroke or paralysis by harnessing patients' intact imagery-driven activity.

Neural Prosthesis Design: Establishing the limits of separability between imagery and movement guides the development of closed-loop prosthetic systems and clarifies how feedback and inhibition shape motor oscillations.

Roadmap:

1. Plot the actual movement trials
2. Convert the signal into the frequency domain (FFT, Wavelet, …)
3. Plot Spectrogram
4. Train a decoder to decode actual vs. imagery movement
    a. Spectrogram => DECODER => Actual/Imagery
5. Compare different decoders (NN, GLM, …)
6. Compare different electrodes

More advanced

7. Try to decode the movement category
8.

Abstract Draft

Background:

High-frequency neural activity captured through electrocorticography (ECoG) has been strongly associated with motor execution. However, distinguishing between real and imagined movements on a single-trial basis remains a significant challenge—one that is critical for the development of reliable brain–computer interfaces (BCIs) and their effective translation into clinical rehabilitation contexts.

Objective:

This project aims to assess whether high gamma power can distinguish real from imagined tongue and hand movements by using human ECoG data collected during both task types.

Methods:

We will preprocess the ECoG dataset by bandpass filtering to isolate high gamma frequencies, then extract and normalize power features from time-locked task epochs. Statistical comparisons

and decoding classifiers will be employed to evaluate differences and discriminate between execution and imagery states on individual trials.

Expected Results:

We anticipate that executed movements will display more pronounced and spatially focused increases in high gamma power within the primary motor cortex, while imagined actions will exhibit subtler, but still detectable, patterns in similar and associated regions. Classification models are expected to reliably separate real from imagined trials.

Implications:

Clear differentiation of neural signals linked to motor execution and imagery would provide valuable insights into cortical representation of action, support development of adaptive BCIs for motor-impaired populations, and inform neurorehabilitation protocols leveraging mental rehearsal and imagery-driven feedback.

ABSTRACT

Study explores how the brain's electrical activity differs between actual movement and imagined movement by analyzing pre-recorded ECoG data. The main research question is: How do neuro-oscillations across different brain regions vary when a person performs real versus imagined motor tasks? Understanding these differences is important for building more effective and personalized brain-computer interfaces (BCIs), especially for people who are unable to make physical movements. It also helps improve rehabilitation techniques for patients with stroke or paralysis and aids in designing smarter neural prosthetics.

We hypothesize that motor execution elicits stronger high-frequency oscillations (70–200 Hz) in the primary motor cortex than motor imagery.

To test this, we converted the ECoG signals into the frequency domain using tools like FFT, and visualized them through spectrograms.We used a pre-recorded ECoG dataset containing multiple trials of both actual and imagined motor movements. For each trial, we extracted the voltage signals recorded from multiple electrodes placed over different brain areas. These signals were converted into spectrograms to analyze how power across frequencies changed over time. We focused on the 1–100 Hz frequency range and used time–frequency data from each electrode as features. We trained several machine learning models ,including Logistic Regression, Support Vector Machine (SVM), Random Forest, and Ridge Classifier, to classify whether each trial represented an actual or imagined movement. We also trained models on data from each electrode individually to identify the brain regions most involved in each task.

Our models achieved over 91% accuracy in distinguishing between actual and imagined tasks. The Random Forest model achieved 100% accuracy on the test set. Some electrodes showed significantly higher accuracy than others, indicating that certain brain regions are more informative for detecting movement intention.

Abstract #3 (submitted!!)

Background: High-frequency neural activity captured through electrocorticography (ECoG), particularly in the high gamma band (70–200 Hz), is closely linked to motor execution. However, distinguishing actual from imagined movement on a single-trial basis remains a major challenge, limiting the development of reliable and personalized brain–computer interfaces (BCIs) and their application in neurorehabilitation for patients with stroke, paralysis, or movement disorders.

Objective: This study aims to assess whether high gamma power can effectively distinguish between executed and imagined tongue and hand movements using human ECoG data.

Methods: We analyzed a publicly available ECoG dataset containing multiple trials of both real and imagined motor tasks (Miller et al., 2010). Signals were bandpass filtered and converted to the frequency domain using fast fourier transform (FFT), and power features were extracted from time–locked epochs. Spectrograms were generated to visualize dynamic changes in power across frequencies. We used machine learning models—including Logistic Regression, Support Vector Machine

(SVM), Random Forest, and Ridge Classifier—to classify trials as executed or imagined. Models were also trained on individual electrodes to localize task-relevant brain regions.

Results: Our models achieved over 91.66% accuracy in distinguishing between executed and imagined tasks. The Random Forest classifier performed best, reaching 100% accuracy on the test set implying that the model is likely overfitting. Spectral analysis revealed that executed movements elicited stronger and more localized high gamma activity in the primary motor cortex, while imagined movements produced weaker but still distinguishable patterns. Certain electrodes consistently contributed more to classification accuracy, highlighting specific cortical regions involved in encoding motor intention.

Future direction: Future work should focus on addressing model overfitting by implementing regularization techniques such as cross-validation, dropout, and feature selection. Additionally, exploring more complex models (Deep Neural Networks, CNNs) and fine-tuning could improve model generalization for test dataset, enhancing the robustness of BCI classifiers in real-world neurorehabilitation applications.

Implications: Accurate separation of motor execution and imagery using ECoG-based high gamma features holds promise for adaptive BCI design, neural prosthetic control, and rehabilitation strategies that utilize motor imagery to drive cortical plasticity and recovery.