NEURODYNAMIC FUSION
Bridging EEG and fMRI through Simulation-Based Integration

Project report submitted in partial fulfillment of the requirement for the degree of

Bachelor of Technology

Submitted by

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(December 2023)

Candidate Declaration

I/We hereby declare that the thesis entitled "NEURODYNAMIC FUSION Bridging EEG and fMRI through Simulation-Based Integration" submitted for the B. Tech. degree program. This thesis has been written in my/our own words. I/We have adequately cited and referenced the original sources.

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CERTIFICATE

It is certified that the work contained in the project report titled "NEURODYNAMIC FUSION Bridging EEG and fMRI through Simulation-Based Integration," by "**Sai Sri Maddirala**" has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree.

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CERTIFICATE

It is certified that the work contained in the project report titled "NEURODYNAMIC FUSION Bridging EEG and fMRI through Simulation-Based Integration," by "**Siddamsetty Srinitha**" has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree.

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Date: 27/11/2023

ABSTRACT

This project will begin with an introduction to the measurement principles involved in EEG and fMRI and the advantages of combining these methods. The challenges faced when combining the two techniques will then be considered. EEG-fMRI integration captures brain activity fluctuations by simultaneously measuring electrical (EEG) and blood flow (fMRI) signals. This approach enhances understanding of responses to stimuli and state changes, vital for deciphering brain function. In diagnosing neurodegenerative and psychiatric diseases, EEG and MRI data offer objective insights for clinical management. The hybrid EEG-fMRI technology establishes labs to study cognitive and pathological functions, such as epileptic brain activity, by bridging electrophysiological and hemodynamic data. Overall, this integration provides a robust tool to unravel brain dynamics and advance neurological disease diagnosis and treatment

Table of Contents

List of Figures

List of Tables

Chapter 1

INTRODUCTION

In recent years, the field of neurofeedback (NF) has witnessed transformative advancements, particularly with the emergence of bimodal approaches integrating EEG (Electroencephalography) and fMRI (Functional Magnetic Resonance Imaging) data. Our study contributes to the burgeoning understanding of the specific mechanisms and the added value of bimodal EEG-fMRI-neurofeedback in comparison to traditional unimodal approaches.

The integration of EEG and fMRI data represents a landmark achievement in neurofeedback research, providing a unique amalgamation of fine spatial and accurate temporal resolution. This combined modality offers unprecedented insights into the intricate dynamics of neural activity, allowing for a more comprehensive understanding of brain function and connectivity. By harnessing the strengths of both EEG and fMRI, researchers gain the ability to capture subtle neurophysiological nuances, paving the way for a nuanced exploration of brain rehabilitation and peak performance training.

One of the primary advantages of bimodal neurofeedback lies in its enhanced spatial localization. While EEG provides high temporal resolution, allowing the observation of rapid neural changes, fMRI offers exquisite spatial specificity, pinpointing the exact regions involved in a given cognitive or motor task. The synergy of these modalities enables a more precise identification of neural signatures associated with specific mental states or tasks.

Moreover, the integration of EEG and fMRI data facilitates a more comprehensive understanding of the brain's functional connectivity patterns. By examining both global and local network dynamics, researchers can unravel the complexities of information transfer and integration across different brain regions. This holistic approach is crucial for deciphering the underlying neural mechanisms implicated in various cognitive processes.

Despite the promises and potential benefits, the implementation of bimodal EEG-fMRI-neurofeedback in real-time applications introduces a set of challenges. Establishing a continuous neurofeedback loop demands seamless integration of data streams, sophisticated algorithms for feature extraction, and real-time processing capabilities. Overcoming these challenges is pivotal for translating the theoretical advantages of bimodal neurofeedback into practical applications for brain rehabilitation and peak performance enhancement.

1.1 MOTIVATION:

The integration of EEG and fMRI, known as neurodynamic fusion, holds immense promise in unlocking the mysteries of the human brain. By combining electrical and blood flow signals, this approach enables a deeper understanding of brain function, making it a crucial tool for diagnosing neurodegenerative and psychiatric diseases. Through simulation-based integration, we aim to harness the power of these two techniques to advance neurological research and improve clinical management, ultimately paving the way for more effective treatments and a better quality of life for those with brain-related disorders.

1.2 PROBLEM STATEMENT:

The challenge lies in optimizing the integration of EEG and fMRI signals for neurofeedback (NF) in a way that enhances regulation of brain activity. This requires addressing issues related to the distinct temporal and spatial characteristics of EEG and fMRI, the potential cognitive load on participants when controlling both modalities simultaneously, and the design of a suitable integrated feedback metaphor. Achieving a balance between engagement and specificity in bimodal NF remains a significant problem to be solved, with implications for the development of more effective therapeutic applications for various cognitive tasks.

1.3 NEUROFEEDBACK

Neurofeedback, often abbreviated as NF, is a technique used in neuroscience and psychology that allows individuals to receive real-time information about their own brain activity and learn to control or regulate it**.**Neurofeedback provides brain wave patterns which can be useful to control your brain actions and control its behaviour.It requires larger part of EEG and fewer parts of FMRI.

1.4 EEG (Electroencephalography):

Principle: EEG measures the electrical activity generated by neurons in the brain. It involves placing electrodes on the scalp to record voltage fluctuations resulting from the electrical currents within the brain. EEG provides excellent temporal resolution i.e it can detect rapid changes in brain activity with millisecond precision. This makes it well-suited for studying real-time brain processes.

1.5 FMRI(Functional Magnetic Resonance imaging)

Principle: fMRI measures changes in blood oxygenation levels in the brain. It relies on the fact that active brain regions require more oxygenated blood. These changes in blood flow and oxygenation are detected using magnetic resonance imaging techniques.

Chapter 2

LITERATURE SURVEY

2.1 WHY EEG+FMRI?

Simultaneous EEG (Electroencephalography) and fMRI (Functional Magnetic Resonance Imaging) integration offers complementary information with high temporal and spatial resolution, improving the understanding of brain function and dynamics. This synergy enhances neurofeedback training, aiding self-regulation and targeting specific brain processes. It facilitates precise source localization and the study of brain networks, with applications in clinical research and cognitive neuroscience. The combination also enables denoising of EEG data, making it a versatile tool for exploring various aspects of brain function and disorders.

2.1.1 BENEFITS OF EEG+FMRI

Enhanced insights into brain function: Combining EEG and fMRI provides a comprehensive view, capturing both high temporal and spatial resolution data.

Advancements in clinical diagnosis and research: The synergy of EEG and fMRI enables better understanding of neurological and psychiatric disorders, aiding in diagnosis and treatment development.

Improved localization in epilepsy: EEG-fMRI integration aids in pinpointing the source of abnormal electrical activity in epilepsy patients, facilitating surgical planning for seizure management.

Enhanced understanding of neuropsychiatric disorders: Combining EEG and fMRI helps uncover the neural mechanisms underlying conditions like schizophrenia and depression, potentially leading to more effective interventions and therapies.

2.2 EXPERIMENTAL PARADIGM

Participants were instructed to perform kinesthetic motor imagery (kMI) of their right hand without physical movement, aiming to control a ball's movement on the screen by maximizing right-hand brain activity and minimizing left-hand activity to reach a specific neurofeedback target.

The experimental protocol consisted of six EEG-fMRI runs employing a block-design alternating 20 s of rest and 20 s of task (see Figure 1):

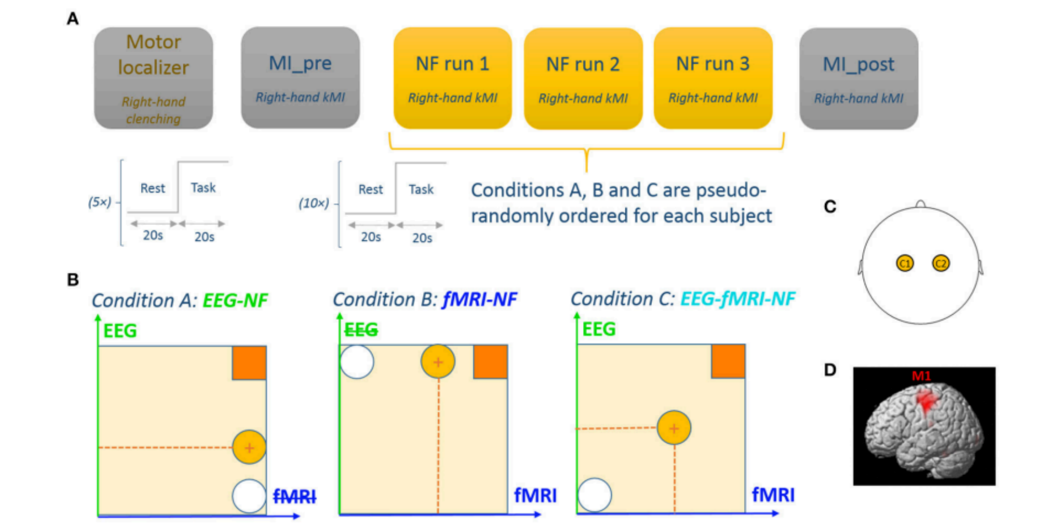
• **A motor localizer run** (MLOC) lasting 5 min 20 s

• **A preliminary motor-imagery run without NF** (MI_pre) lasting 3 min 20 s

• **Three NF runs** (NF1, NF2, NF3) lasting 6 min 40 s each and corresponding to three different feedback modality conditions (A: EEG-NF; B: fMRI-NF; C: EEG-fMRI-NF) whose order was counterbalanced across participants

• And a **final motor-imagery run without NF** (MI_post) lasting 3 min 20 s

FIGURE 1



Motor Localizer (motorloc):
Duration: 5 minutes and 20 seconds (8 blocks)
Task: Clench right hand every second during the task to locate motor-related brain regions.

Preliminary Motor Imagery without Feedback (MIpre):
Duration: 3 minutes and 20 seconds (5 blocks)
Task: Participants practice imagining right-hand movement without feedback.

Neurofeedback Blocks:
Three conditions: EEG-NF (eegNF), fMRI-NF (fmriNF), EEG-fMRI-NF (eeg fmri).
Each condition consists of 10 blocks (6 minutes and 40 seconds each).
Task: Participants control brain activity using EEG, fMRI, or both feedback methods.
Visual feedback: A white ball moves vertically for eegNF, horizontally for fmriNF, or both for eegfmriNF to a target square.

Transfer Block of Motor Imagery without Feedback (MIpost):
Duration: 3 minutes and 20 seconds.
Task: Participants perform motor imagery without feedback to assess the learning effect compared to MIpre

2.3 REAL TIME DATA PROCESSING:

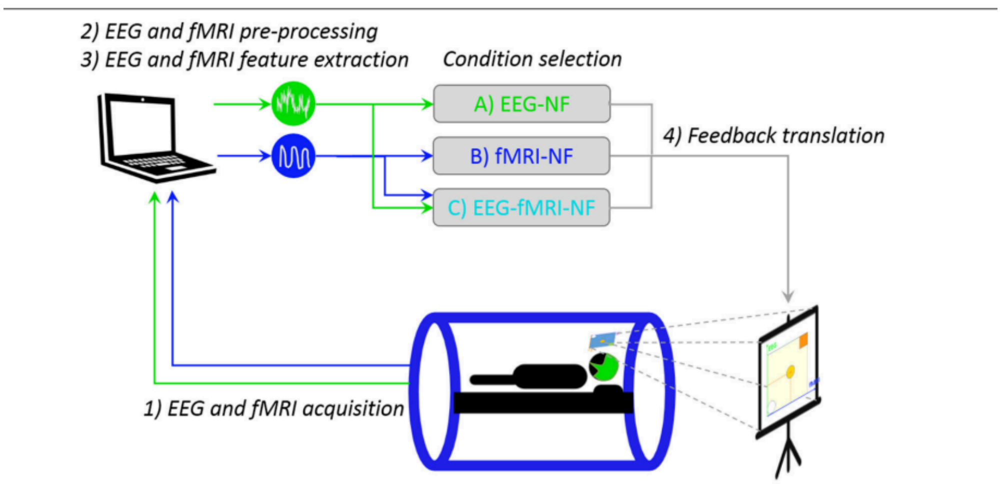


Figure 2: Real-time multimodal EEG/fMRI-NF setup

2.3.1 Analysis of Real time Data processing:

Table 1

ASPECT	**EXPLANATION**
EXPERIMENTAL SETUP	-The participant is inside the MR tube -The Participant wears a 64-channel MR-compatible EEG cap.
DATA COLLECTION	-EEG AND FMRI data are collected Simultaneously
DATA PRE-PROCESSING	-EEG data is pre-processed with BrainVision Review (Brain products GmbH, Gilching, Germany) software
FEEDBACK MECHANISM	-EEG and FMRI laterality features are computed from the integrated data.
FEEDBACK DISPLAY	-The laterality features are used to control the movement of a ball on a stimulation screen. -The Stimulation screen image is projected onto a mirror mounted on the head coil
ROLE OF LATERALITY	-Laterality measures the asymmetry or differences in brain activity between the left and right hemispheres. -It provides feedback to the participant about the balance or imbalance in their brain activity. -Participants aim to self-regulate their brain activity to influence the movement of the feedback ball.

Gradient Artifact Correction (used to remove artifacts from EEG data):

Gradient artifacts occur due to the rapid switching of magnetic field gradients in the MRI scanner. To correct these artifacts, an "average artifact subtraction approach" was used.

Ballistocardiogram Artifact Correction (used to remove artifacts from EEG data):

The data underwent BCG artifact correction, involving pulse detection in the first 15 seconds using a template matching approach with a correlation threshold of 0.7. Subsequent correction around the R-peak was performed using a moving template in a specified time window, and the corrected data was then processed in MATLAB.

2.3.2 FMRI PREPROCESSING:

Table 2

Motion correction	SPM+MATLAB Rigid registration
Slice-time Correction	SPM+MATLAB Performed after motion correction
Spatial smoothing	SPM+MATLAB Smoothing size :3mm
Physiological noise removal	SPM+MATLAB
Temporal averaging	SPM+MATLAB 3 scans moving average window
Real-time data quality	SPM+MATLAB

Chapter 3

WORK DONE

- **We have considered a 31-year MALE as our subject for our study**

3.1 EEG : (EEG-NF, FMRI-NF, EEG-FMRI-NF)

The pre-processed EEG data was acquired online as time series data in real time.

Once we have the EEG-like time series data, we can extract bandpowers within specific frequency ranges corresponding to left and right brain activity. The process involves performing frequency domain analysis and computing the power within the desired frequency bands associated with left and right brain regions.

A simple frequency domain analysis using the Fourier transform is performed which calculates the power within specific frequency bands corresponding to left and right brain activity. In real EEG data, more sophisticated methods might be needed considering noise, signal processing, and individual variability in brain activity patterns.

Data is collected at timeline of 1600 seconds representing all the runs

Table 3: Small code snippet representing the data

```
Columns 1 through 13

  0.1784    0.1161   -0.5067   -0.5105    0.3552    0.1267   -0.2857   -0.5023    0.6612    0.3177    0.4548    0.6407    0.3302

Columns 14 through 26

  0.1379    0.8073   -0.2209   -0.0841    0.2674    0.6571   -0.3057    0.4222   -0.0390   -0.4621   -0.4968   -0.5542   -0.0130

Columns 27 through 39

  0.3015   -0.2941    0.0056    0.9818    0.3242    0.5070    0.1308    0.2010    0.5333    0.9255    0.8382    0.9558    0.6509

Columns 40 through 52

  0.4994   -0.4051   -0.6079   -7.7451   -2.4958    0.5093   -0.7380    0.8132    0.1475   -0.2227   -0.7375    0.4056    0.0783

Columns 53 through 65

  0.6923   -0.1310   -0.1151   -0.2209    0.7282   -0.4699   -0.4905   -0.7729   -0.4056    0.5092   -0.9054   -0.7786    0.9990
```

Now, left and right band powers are extracted from this eeg data using the following code.

```matlab
% Assuming you have synthetic EEG data in a 2x1600 matrix (left and right hemispheres)
% Synthetic EEG data structure: Row 1 - Left hemisphere, Row 2 - Right hemisphere

% Parameters
sampling_rate = 5000;
n_channels = size(combinedEEGData, 1); % Number of channels
duration_seconds = size(combinedEEGData, 2) / sampling_rate; % Duration in seconds
time = linspace(0, duration_seconds, size(combinedEEGData, 2));

% frequency bands for left and right activity
left_band = [8, 12];   %frequency range for left activity
right_band = [8, 30]; %frequency range for right activity

% Initialize matrices to store left and right bandpowers for each channel
left_bandpowers = zeros(n_channels, size(combinedEEGData, 2));
right_bandpowers = zeros(n_channels, size(combinedEEGData, 2));

for i = 1:n_channels
    % Frequency domain analysis for each channel
    left_channel_data = combinedEEGData(1, :); % Extract left hemisphere data for the channel
    right_channel_data = combinedEEGData(2, :); % Extract right hemisphere data for the channel

    % Perform FFT for left and right hemisphere data for the channel
    left_fft_data = fft(left_channel_data);
    right_fft_data = fft(right_channel_data);

    n = length(left_fft_data);
    f = (0:n-1) * (sampling_rate / n); % Frequency axis

    % Find indices for left and right frequency bands
    left_indices = find(f >= left_band(1) & f <= left_band(2));
    right_indices = find(f >= right_band(1) & f <= right_band(2));

    % Compute left and right bandpowers for the channel
    left_bandpowers(i, left_indices) = abs(left_fft_data(left_indices)).^2 / n;
    right_bandpowers(i, right_indices) = abs(right_fft_data(right_indices)).^2 / n;
end

disp('LEFT BAND POWERS');
disp(left_bandpower);

disp('RIGHT BAND POWERS');
disp(right_bandpower);
```

<u>Table 4: Left bandpowers are as: (small snippet)</u>

Columns 1 through 13

0	0	0	0	0	0	0	0	4.6269	10.2617	27.3766	50.5758	57.6052

Columns 14 through 26

39.9439	16.7061	5.6388	3.8892	3.9635	3.7258	2.9565	2.2070	1.9291	1.9605	2.1123	2.1602	2.1882

Columns 27 through 39

2.3373	2.3028	1.8025	1.1294	0.6763	0.4826	0.5704	0.7993	0.9442	0.9608	0.9360	0.8940	0.9659

Columns 40 through 52

1.3745	1.8517	1.9399	1.8520	1.9330	1.9632	1.5686	0.9258	0.4475	0.3178	0.4905	0.9161	1.3829

Columns 53 through 65

1.4376	1.0161	0.6926	1.0409	1.6097	1.6294	1.1149	0.7637	0.8795	1.3203	1.7711	1.7970	1.3730

Columns 66 through 78

1.0034	0.9785	1.0821	1.1166	1.0222	0.7963	0.5715	0.4631	0.4234	0.3870	0.4411	0.6316	0.8752

<u>Figure 3: Graph representing Left bandpowers</u>

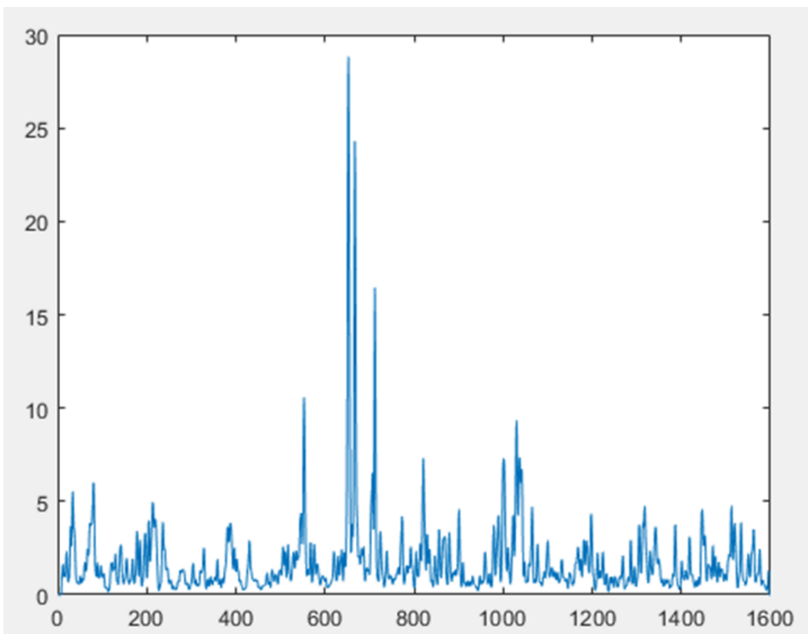
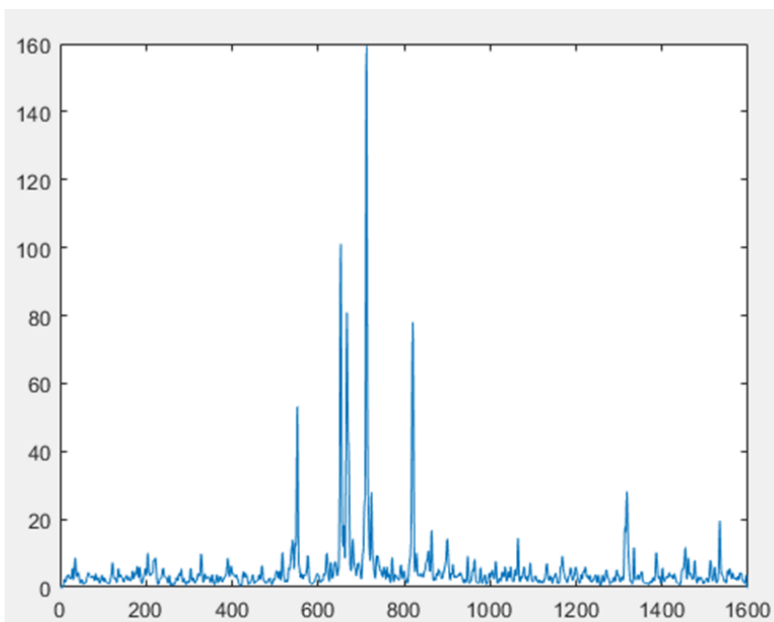


Table 5: Right bandpowers are as: (small snippet)

```
Columns 1 through 13

      0         0         0         0         0         0         0         0    7.5630   13.6124   26.8065   39.2952   38.9795

Columns 14 through 26

 26.3586   13.8365    7.9409    5.8506    6.0680    6.6389    5.7133    3.6628    2.6303    4.1145    6.6434    7.4206    6.0565

Columns 27 through 39

  4.7229    4.1079    3.3589    2.6896    2.3269    2.0352    1.8813    2.1359    2.4697    2.1914    1.4473    1.3271    2.3246

Columns 40 through 52

  3.2656    3.0907    2.4532    2.5358    3.2646    4.1065    4.7694    5.2183    5.5662    5.2550    3.8412    2.1906    1.4203

Columns 53 through 65

  1.4610    1.8484    2.6511    3.5606    3.8607    3.7389    3.9289    4.1404    3.7921    3.9196    4.8053    4.8531    3.5970

Columns 66 through 78

  2.5022    2.1983    1.8290    1.1620    0.6259    0.3407    0.2522    0.3795    0.6205    0.8184    0.9898    1.2967    1.7256
```

Figure 4: Graph representing right bandpowers



Similarly, left bandpowers and right bandpowers are extracted for fmri feedback and eeg-fmri feedback

Bandpower in brain electrodes refers to the power of neural activity within specific frequency bands. The interpretation of less or more bandpower on brain electrodes depends on the frequency band.

Reduced power in certain frequency bands can indicate decreased neural activity within those frequency ranges.

In specific frequency bands, reduced bandpower indicate decreased functional connectivity, cognitive processing, or neural synchronization associated with that band.

Increased power in certain frequency bands suggest heightened neural activity within those frequency ranges.

Higher bandpower indicates stronger synchronization, increased activity, or higher engagement of neural networks associated with that frequency band.

3.2 FMRI : (EEG-NF, FMRI-NF, EEG-FMRI-NF)

The fMRI data acquired from six distinct runs—namely MLOC, MI_pre, NF1, NF2, NF3, and MI_post—underwent comprehensive preprocessing and analysis utilizing AutoMRI, a specialized proprietary software based on SPM8 for fMRI data analysis automation. The preprocessing pipeline encompassed essential steps, including slice-time correction, spatial realignment, co-registration to the 3D T1 anatomical image, followed by spatial smoothing using an 8 mm Gaussian kernel.

Both first-level and second-level analyses were conducted using a General Linear Model (GLM). The first-level GLM incorporated the canonical Hemodynamic Response Function (HRF) for the task, along with its temporal and dispersion derivatives. At the second-level analysis, individual data were normalized to the Montreal Neurological Institute (MNI) template and grouped using a mixed effects linear model.

To identify significant activations, activation maps underwent correction for multiple comparisons utilizing Family-Wise Error (FWE) correction, setting the threshold at $p < 0.05$ with a cluster size exceeding 10 voxels. This rigorous analysis methodology ensured accurate identification and correction of statistically significant activation clusters while minimizing false positives in the fMRI data.

After preprocessing is done, our next step is to compute the laterality indices.

3.2.1 IMPLEMENTATION

- We acquired Region of Interests (ROIs) such that activation levels are higher in those regions on the left and right hemispheres respectively.
- 200 ROIs (Regions of Interest) were considered on both the left and right hemispheres of the brain for taking fMRI readings, it signifies a comprehensive analysis aimed at capturing the activation patterns across multiple brain regions.
- 200 points dataset represents a specific region or set of voxels within the hemisphere that is crucial for the study's objectives.
- Researchers have identified a specific anatomical or functional ROI known to be involved in motor imagery tasks or expected to show laterality differences.

- These activation levels could correspond to BOLD (Blood Oxygen Level Dependent) signals or other metrics indicative of neural activity in the specified left/right hemisphere region.

<u>Matlab Code for loading ROI data</u>

```
data1=load('d_sub-xp104_task-eegNF_NFbold_scores (1).mat','NF_bold');
left_ROI = data1.NF_bold.roimean_right  ;
```

FOR EEG FEEDBACK:

<u>Table 6: Region of Interest Mean_Left Data:(Small snippet of data)</u>

```
Columns 1 through 13

100.0779   99.7654   99.2735  100.0364  100.2920  100.1511   99.4779   99.6475  100.7234  100.8756  100.5656  100.7726  100.4739

Columns 14 through 26

100.5615  101.0626  100.1686  100.6286  100.9534  101.2701  100.4355  100.2307   99.8974   99.7975   99.8786   99.8715  100.3757

Columns 27 through 39

100.7019   99.2685   99.6540  100.1870   99.7037   99.8426  100.2575  100.1728  100.5152  100.4599  100.8165  100.7916  100.5527

Columns 40 through 52

100.5908   99.5819   99.5900   92.8729   99.2580  101.6321  100.0524  100.5428   99.7621   99.6428   99.4514  100.7103  100.0996

Columns 53 through 65

100.7590  100.0956  100.5758  100.5291  101.3498  100.2448  100.6148  100.8915   99.8188  100.5335   98.6446   99.1409  100.7856

Columns 66 through 78
```

<u>Figure 5: Graph represents ROImean_Left data (data points vs activation levels)</u>

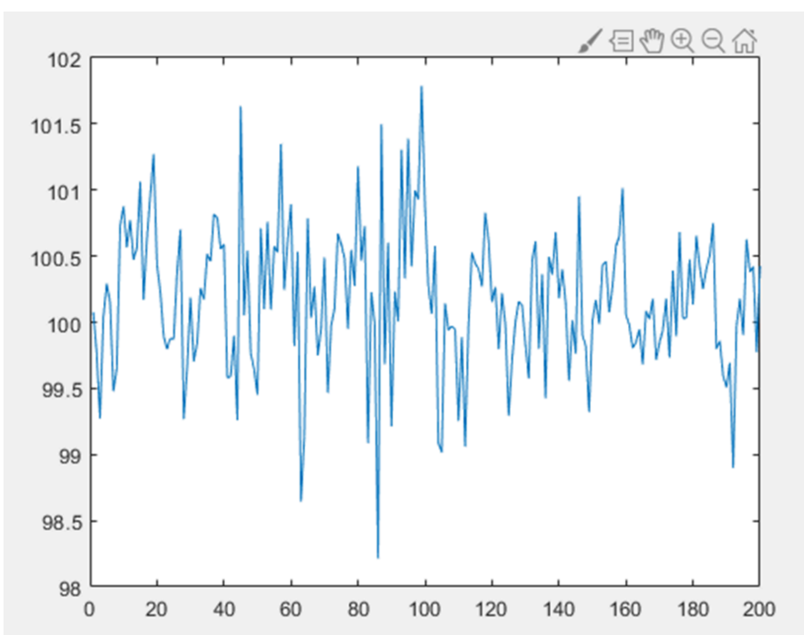
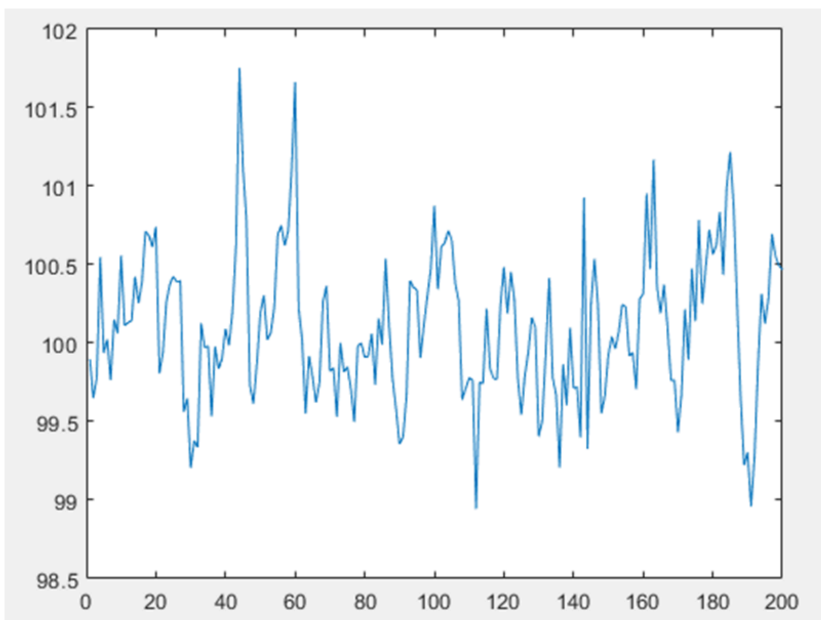


Table 7: Region of Interest Mean_Right Data:(Small snippet of data)

```
Columns 1 through 13

  0.1784    0.1161   -0.5067   -0.5105    0.3552    0.1267   -0.2857   -0.5023    0.6612    0.3177    0.4548    0.6407    0.3302

Columns 14 through 26

  0.1379    0.8073   -0.2209   -0.0841    0.2674    0.6571   -0.3057    0.4222   -0.0390   -0.4621   -0.4968   -0.5542   -0.0130

Columns 27 through 39

  0.3015   -0.2941    0.0056    0.9818    0.3242    0.5070    0.1308    0.2010    0.5333    0.9255    0.8382    0.9558    0.6509

Columns 40 through 52

  0.4994   -0.4051   -0.6079   -7.7451   -2.4958    0.5093   -0.7380    0.8132    0.1475   -0.2227   -0.7375    0.4056    0.0783

Columns 53 through 65

  0.6923   -0.1310   -0.1151   -0.2209    0.7282   -0.4699   -0.4905   -0.7729   -0.4056    0.5092   -0.9054   -0.7786    0.9990

Columns 66 through 78

  0.4128    0.5170   -0.5140   -0.4158    0.6678   -0.3775    0.4436    0.0998    0.8515    0.7407    0.7689    0.4531    0.5636
```

Figure 6: Graph represents ROImean_Right data (data points vs activation levels)



Similarly, ROI mean_left and ROI mean_right for FMRI feedback and EEG-FMRI feedback

These graphs represent mean (average) signal or activity within specific Regions of Interest (ROIs) located in the left and right hemispheres of the brain, respectively. These graphs typically depict the averaged activity levels or BOLD (Blood Oxygen Level Dependent) signals measured across multiple volumes or time points during fMRI (functional Magnetic Resonance Imaging) experiments.

These offer insights into the temporal dynamics and potential hemispheric differences in brain activity during the experimental paradigm under investigation.

3.3 LATERALITY INDEX

Laterality indices are used to assess and quantify changes in hemispheric dominance or activation patterns during tasks or neurofeedback training and can provide insights into how the brain responds to different conditions or interventions.the laterality index assesses the balance or distribution of brain activity between the left and right hemispheres in specific regions of interest.

3.3.1 EEG LATERALITY INDEX

The EEG laterality index measures the relative power of brain activity in the µ (8–12 Hz) band at specific electrodes on the left (C1) and right (C2) motor cortex. A higher laterality index indicates a stronger imbalance in brain activity between the two hemispheres.

$$eeg_{lat}\,(t) = \frac{nLbp\,(t) - nRbp(t)}{nLbp\,(t) + nRbp(t)} \qquad nLbp\,(t) = \overline{Lbp(previous\_rest)}/Lbp(t)$$

$$nRbp\,(t) = \overline{Rbp(previous\_rest)}/Rbp(t)$$

nLbp(t): This represents the normalized band power on the left side of the brain at a specific time t.

nRbp(t): This represents the normalized band power on the right side of the brain at the same time t.

```
%%
%Sai Sri Maddirala & Srinitha Siddamsetty
data1 = load('eeg_NFeegscores.mat');
nLbp1 = data1.NF_eeg.filtpower_left;
nRbp1 = data1.NF_eeg.filtpower_right;
% Calculate laterality index (eeglat)

% Assuming nLbp1 and nRbp1 are already defined or loaded
% Calculate lateralitydata1
lateralitydata1 = (nLbp1 - nRbp1) ./ (nLbp1 + nRbp1);

% Load existing data or create a new structure
if exist('eeg_NFeegScores.mat', 'file')
    data1 = load('eeg_NFeegScores.mat');
else
    data1 = struct();
end

% Assign lateralitydata1 to the specified field
data1.NF_eeg.nf_laterality = lateralitydata1;

% Save the updated structure to the MAT file
save('eeg_NFeegScores.mat', '-struct', 'data1');
```

```
data2 = load('fmri_NFeegscores.mat');
nLbp2 = data2.NF_eeg.filtpower_left;
nRbp2 = data2.NF_eeg.filtpower_right;
% Calculate laterality index (eeglat)

% Assuming nLbp1 and nRbp1 are already defined or loaded
% Calculate lateralitydata1
lateralitydata2 = (nLbp2 - nRbp2) ./ (nLbp2 + nRbp2);

% Load existing data or create a new structure
if exist('fmri_NFeegScores.mat', 'file')
    data2 = load('fmri_NFeegScores.mat');
else
    data2 = struct();
end

% Assign lateralitydata1 to the specified field
data2.NF_eeg.nf_laterality = lateralitydata2;

% Save the updated structure to the MAT file
save('fmri_NFeegScores.mat', '-struct', 'data');
```

```
%%
data3 = load('eegfmri_NFeegscores.mat');
nLbp3 = data3.NF_eeg.filtpower_left;
nRbp3 = data3.NF_eeg.filtpower_right;
% Calculate laterality index (eeglat)

% Assuming nLbp1 and nRbp1 are already defined or loaded
% Calculate lateralitydata3
lateralitydata3 = (nLbp3 - nRbp3) ./ (nLbp3 + nRbp3);


% Load existing data or create a new structure
if exist('eegfmri_NFeegScores.mat', 'file')
    data3 = load('eegfmri_NFeegScores.mat');
else
    data3 = struct();
end

% Assign lateralitydata1 to the specified field
data3.NF_eeg.nf_laterality = lateralitydata3;

% Save the updated structure to the MAT file
save('eegfmri_NFeegScores.mat', '-struct', 'data');
```

Laterality indices are calculated for EEG(EEG-NF),EEG(FMRI-NF) AND EEG(EEG-FMRI NF) as mentioned in the above snippets .

The above code calculates the laterality index for EEG neurofeedback data, representing the relative balance between left and right hemispheric activities. It then updates the existing or creates a new MAT file containing the laterality index information. The laterality index is a common measure used in neuroimaging studies to assess hemispheric imbalances or lateralization of brain activity.

Similarly it has been done for FMRI neurofeedback data and EEG-FMRI neurofeedback data.

3.3.2 fMRI LATERALITY INDEX

The fMRI laterality index is calculated based on the average blood oxygen level-dependent (BOLD) signal in specific regions of interest (ROI) in the left and right primary motor cortex. It reflects the asymmetry in brain activation between these ROIs. An increased fMRI laterality index suggests a more pronounced difference in activity levels between the left and right motor cortex

$$fMRI_{lat}(v) = B_{left}(v) / \overline{B_{left}(previous_{rest})} - B_{right}(v) / \overline{B_{right}(previous_{rest})}$$

$$\frac{B_{left}(v)}{\overline{B_{left}(previous\_rest)}} - \frac{B_{right}(v)}{\overline{B_{right}(previous\_rest)}}$$

Where Bleft (v) is the average of the BOLD signal in the left ROI at volume v.

Where Bright (v) is the average of the BOLD signal in the right ROI at volume v.

```matlab
%% Laterality
%Sai Sri Maddirala & Srinitha Siddamsetty
data1=load('eeg_NFboldscores.mat');
% Extract BOLD signals
Bleft = data1.NF_bold.roimean_left;
Bright = data1.NF_bold.roimean_right;
lateralityData1 = (Bleft - circshift(Bleft, -1)) ./ (Bright - circshift(Bright, -1));
% Load existing data or create a new structure
if exist('eeg_NFboldScores.mat', 'file')
    data1 = load('eeg_NFboldScores.mat');
else
    data1= struct();
end

% Assign lateralitydata1 to the specified field
data1.NF_bold.normnf_laterality  = lateralityData1;

% Save the updated structure to the MAT file
save('eeg_NFboldScores.mat', '-struct', 'data');
```

```matlab
%% LATERALITY
%Sai Sri Maddirala & Srinitha Siddamsetty
data2=load('fmri_NFboldscores.mat');
% Extract BOLD signals
Bleft2 = data2.NF_bold.roimean_left;
Bright2 = data2.NF_bold.roimean_right;

lateralityData2 = (Bleft2 - circshift(Bleft2, -1)) ./ (Bright2 - circshift(Bright2, -1));
% Load existing data or create a new structure
if exist('fmri_NFboldScores.mat', 'file')
    data2 = load('fmri_NFboldScores.mat');
else
    data2 = struct();
end

% Assign lateralitydata1 to the specified field
data2.NF_bold.normnf_laterality  = lateralityData2;

% Save the updated structure to the MAT file
save('eeg_NFboldScores.mat', '-struct', 'data');
```

```
%%
%Sai Sri Maddirala & Srinitha Siddamsetty
data3 = load('eegfmri_NFboldscores.mat');
% Extract BOLD signals
Bleft3 = data3.NF_bold.roimean_left;
Bright3 = data3.NF_bold.roimean_right;
lateralityData3 = (Bleft3 - circshift(Bleft3, -1)) ./ (Bright3 - circshift(Bright3, -1));

% Load existing data or create a new structure
if exist('eegfmri_NFboldScores.mat','file')
    data3 = load('eegfmri_NFboldScores.mat');
else
    data3 = struct();
end

% Assign lateralitydata1 to the specified field
data3.NF_bold.normnf_laterality  = lateralityData3;

% Save the updated structure to the MAT file
save('eegfmri_NFboldScores.mat', '-struct', 'data');
```

The circshift function is used to circularly shift the BOLD signal vectors by one position to the left. This means that the last element of the vector becomes the first, and the rest of the elements are shifted to the next position.

(Bleft - circshift(Bleft, -1)) calculates the difference between the current BOLD signal in the left ROI and the BOLD signal in the left ROI at the previous volume. This represents the change in the left BOLD signal from the previous volume to the current volume.

(Bright - circshift(Bright, -1)) similarly calculates the change in the right BOLD signal from the previous volume to the current volume.

Using Matlab we have calculated laterality indices of FMRI Modality i.e FMRI(EEG-NF),FMRI(FMRI-NF),FMRI(EEG-FMRI NF).

3.4 ACTIVATION ENERGY

The laterality indices obtained from the analysis of neural data provide valuable insights into the relative balance and lateralization of brain activity. By examining the changes in activation levels between different brain regions, we can derive activation energies that serve as indicators of the intensity and direction of neural activity. In this context, higher activation energies signify increased neural engagement and are often associated with more effective cognitive processing or task performance. Therefore, the discovery of elevated activation energies, derived from the laterality indices, suggests a heightened state of neural responsiveness and can be interpreted as indicative of enhanced cognitive functioning.

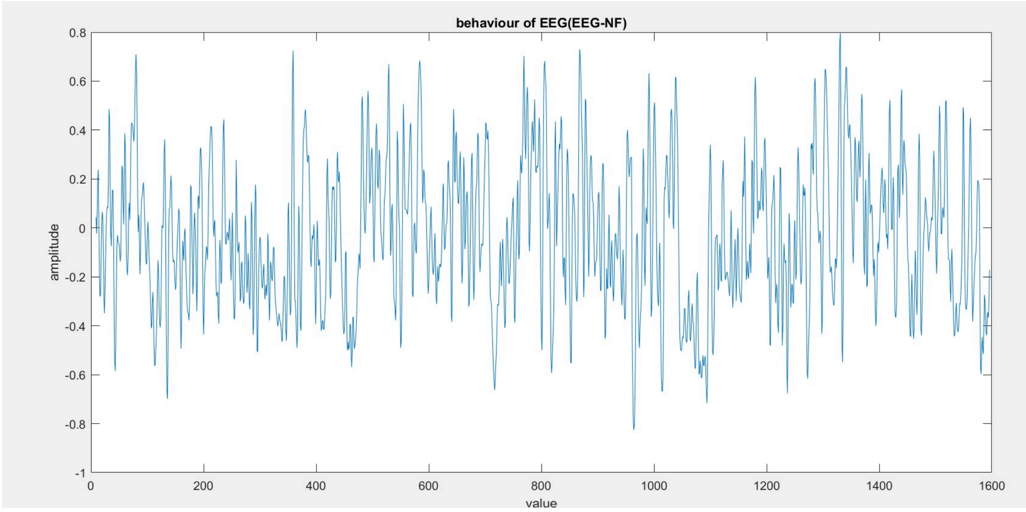
3.4.1 ACTIVATION ENERGY OF EEG(EEG-NF)

```
%% ACTIVATION LEVEL OF EEF(EEG-NF)

% Load data
data1 = load('eeg_NFeegscores.mat');
lateralityData1 = data1.NF_eeg.nf_laterality;
% Assuming lateralityData1 is your dataset
pv1 = lateralityData1(lateralityData1> 0);
%Plot a histogram of positive values for visualization (optional)
figure;
histogram(pv1, 'BinEdges', linspace(0, max(pv1), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of EEG-NF');
% Calculate the energy
energy1 = sum(pv1.^2);
```

Result: EEG(EEG-NF)

data1	*1x1 struct*
energy1	61.0654
lateralityD...	*1x1600 double*

Figure 7: Behavior of EEG(EEG-NF)



3.4.2 ACTIVATION ENERGY OF EEG(FMRI-NF):

```
%% ACTIVATION LEVEL OF EEG(FMRI-NF)
data2 = load('fmri_NFeegscores.mat');
lateralityData2 = data2.NF_eeg.nf_laterality;
% Assuming lateralityData1 is your dataset
pv2 = lateralityData2(lateralityData2> 0);
% Plot a histogram of positive values for visualization (optional)
figure;
histogram(pv2, 'BinEdges', linspace(0, max(pv2), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of FMRI-NF');


% Calculate the energy
energy2 = sum(pv2.^2);
```

Results: EEG(FMRI-NF)

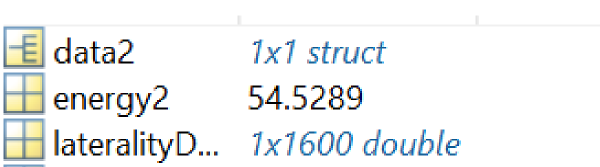
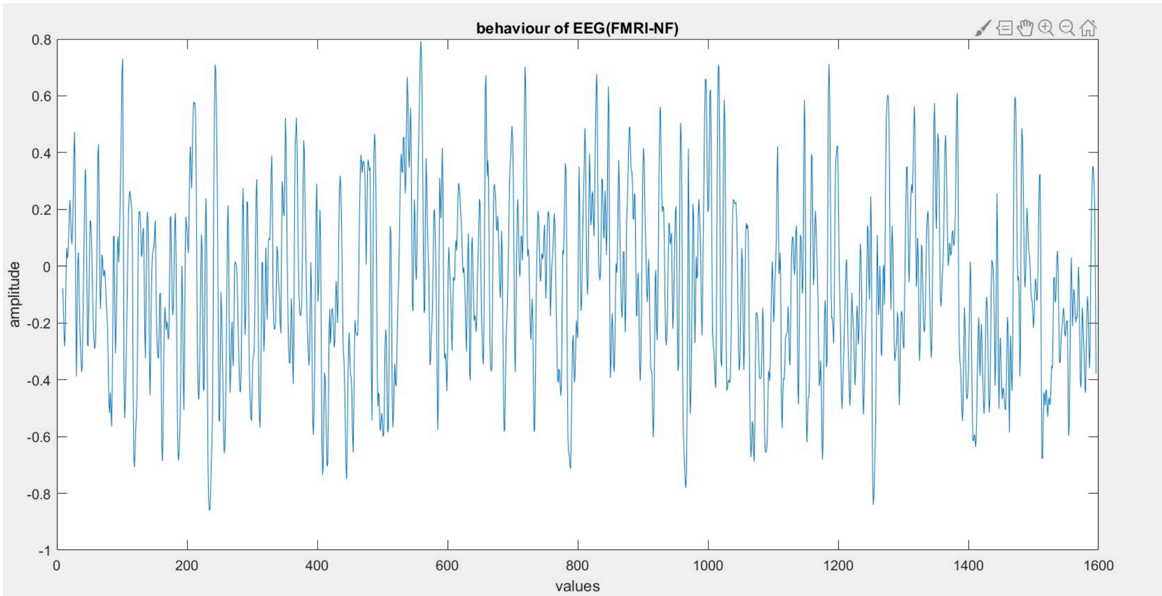


Figure 8: Behavoir of EEG(FMRI-NF)



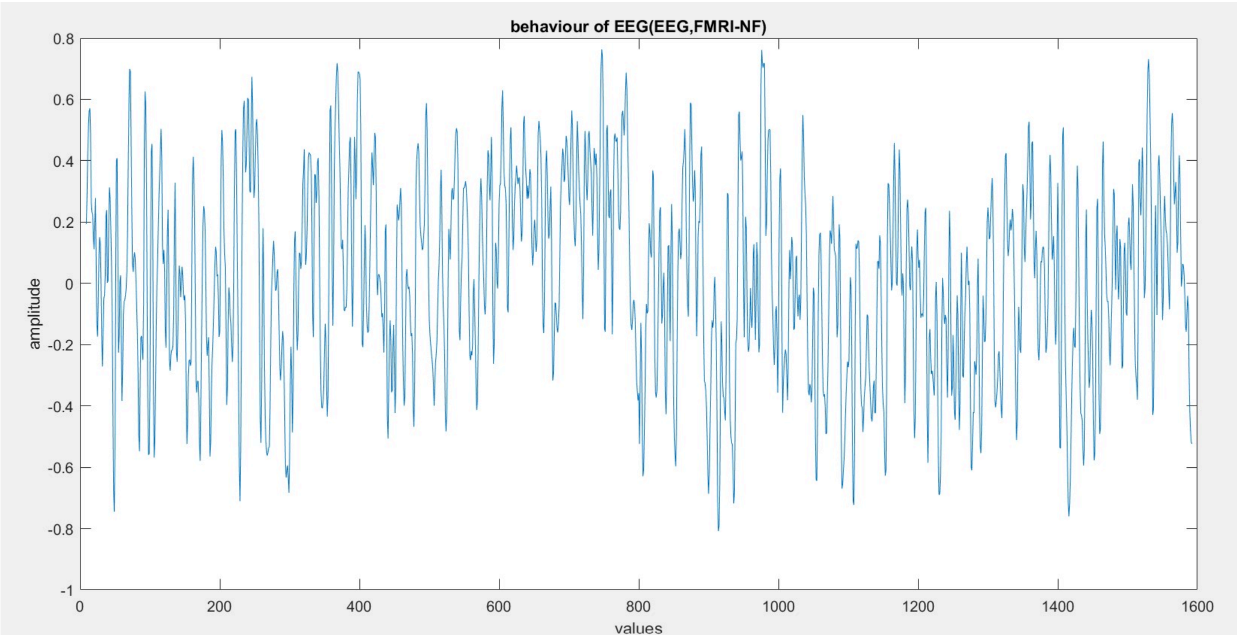
3.4.3 ACTIVATION ENERGY OF EEG(EEG-FMRI-NF):

```
%% ACTIVATION LEVEL OF EEG(EEG-FMRINF)
data3 = load('eegfmri_NFeegscores.mat');
lateralityData3 = data3.NF_eeg.nf_laterality;
% Assuming lateralityData1 is your dataset
pv3 = lateralityData3(lateralityData3> 0);
% Plot a histogram of positive values for visualization (optional)
figure;
histogram(pv3, 'BinEdges', linspace(0, max(pv3), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of eegfmri-NF');
% Assuming positiveValues is your dataset of positive values
% Calculate the energy
energy3 = sum(pv3.^2);
```

Results: EEG(EEG-FMRI-NF)

data3	1x1 struct
energy3	82.5837
lateralityD...	1x1600 double

Figure 9: Behavior of EEG(EEG-FMRI-NF)



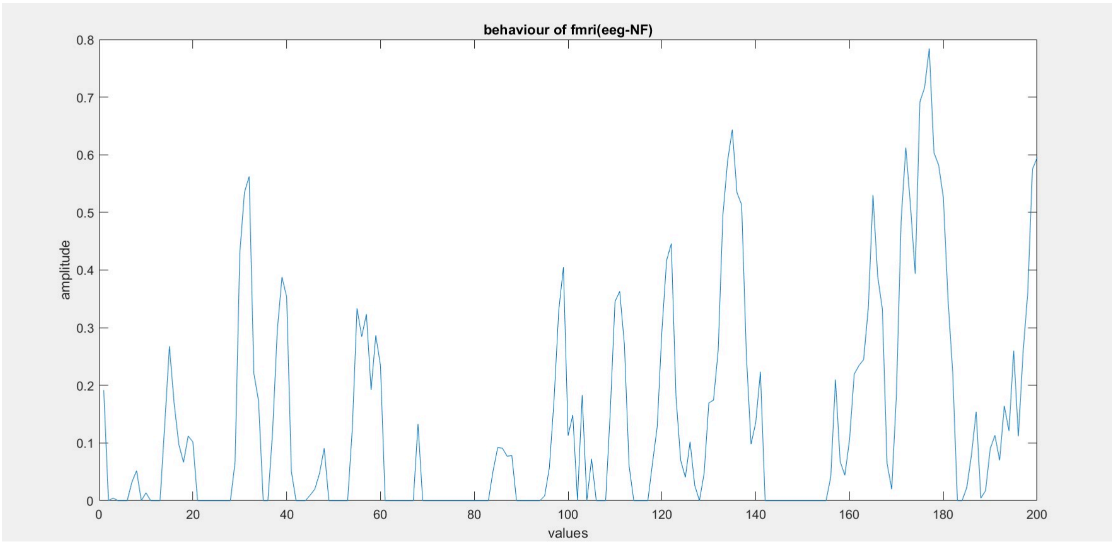
3.4.4 ACTIVATION ENERGY OF FMRI(EEG-NF):

```
%% ACTIVATION OF FMRI(EEG-NF)
data1=load('eeg_NFboldscores.mat');

lateralityData1 = data1.NF_bold.normnf_laterality  ;

% Calculate the energy
energy1 = sum(lateralityData1.^2);
%Plot a histogram of positive values for visualization (optional)
figure;
histogram(energy1, 'BinEdges', linspace(0, max(energy1), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of EEG-NFbold');
```

Results: FMRI(EEG-NF)

data1	1x1 struct
energy1	10.8407
lateralityD...	1x200 double

Figure 10: Behavior of FMRI(EEG-NF)



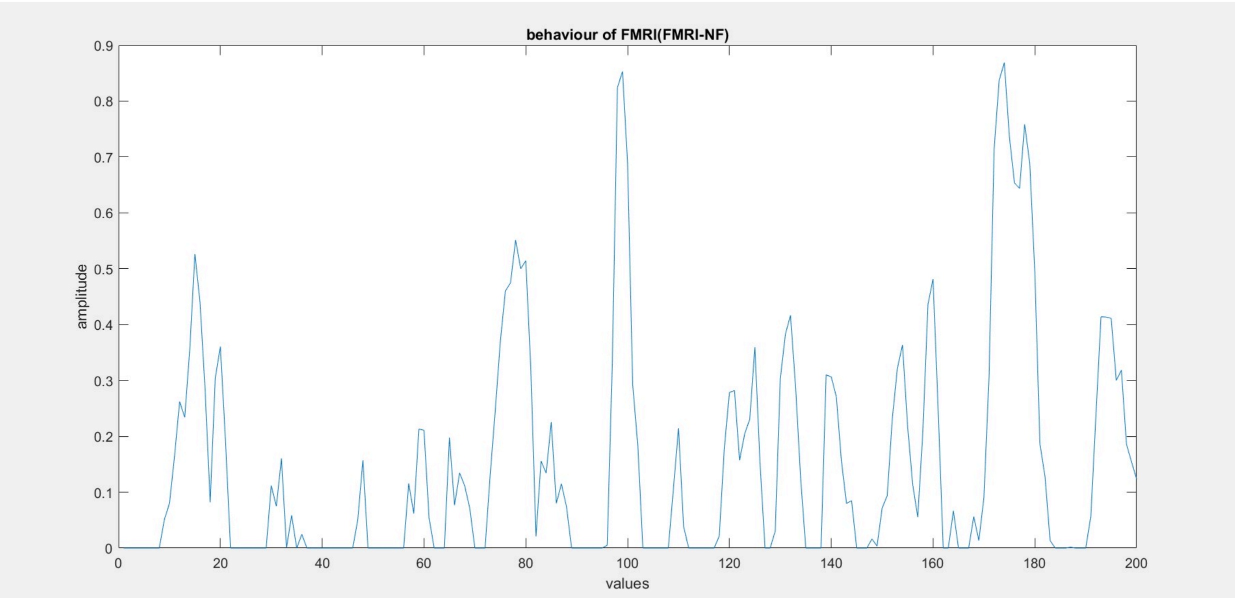
3.4.5 ACTIVATION ENERGY OF FMRI(FMRI-NF):

```
%% ACTIVATION OF FMRI(FMRI-NF)

data2=load('fmri_NFboldscores.mat');

lateralityData2 = data2.NF_bold.normnf_laterality ;
% Calculate the energy
energy2 = sum(lateralityData2.^2);
%Plot a histogram of positive values for visualization (optional)
figure;
histogram(energy2, 'BinEdges', linspace(0, max(energy2), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of FMRI-NFbold');
```

Results: FMRI(FMRI_NF)

data2	*1x1 struct*
energy2	13.0372
lateralityD...	*1x200 double*

Figure 11: Behavior of FMRI(FMRI-NF)



3.4.6 ACTIVATION ENERGY OF FMRI(EEG-FMRI-NF):

```
%% ACTIVATION OF FMRI(EEG-FMRINF)
data3 = load('eegfmri_NFboldscores.mat');
lateralityData3 = data3.NF_bold.normnf_laterality  ;
energy3 = sum(lateralityData3.^2);
%Plot a histogram of positive values for visualization (optional)
figure;
histogram(energy3, 'BinEdges', linspace(0, max(energy3), 20));
xlabel('Value');
ylabel('amplitude');
title('activation level of EEGFMRI-NFbold');
```

Results: FMRI(EEG_FMRI_NF)

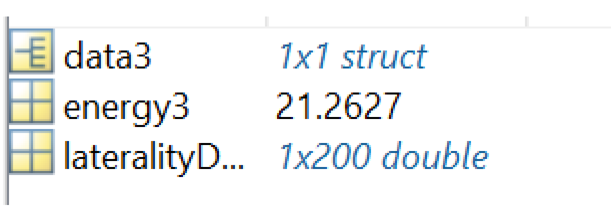
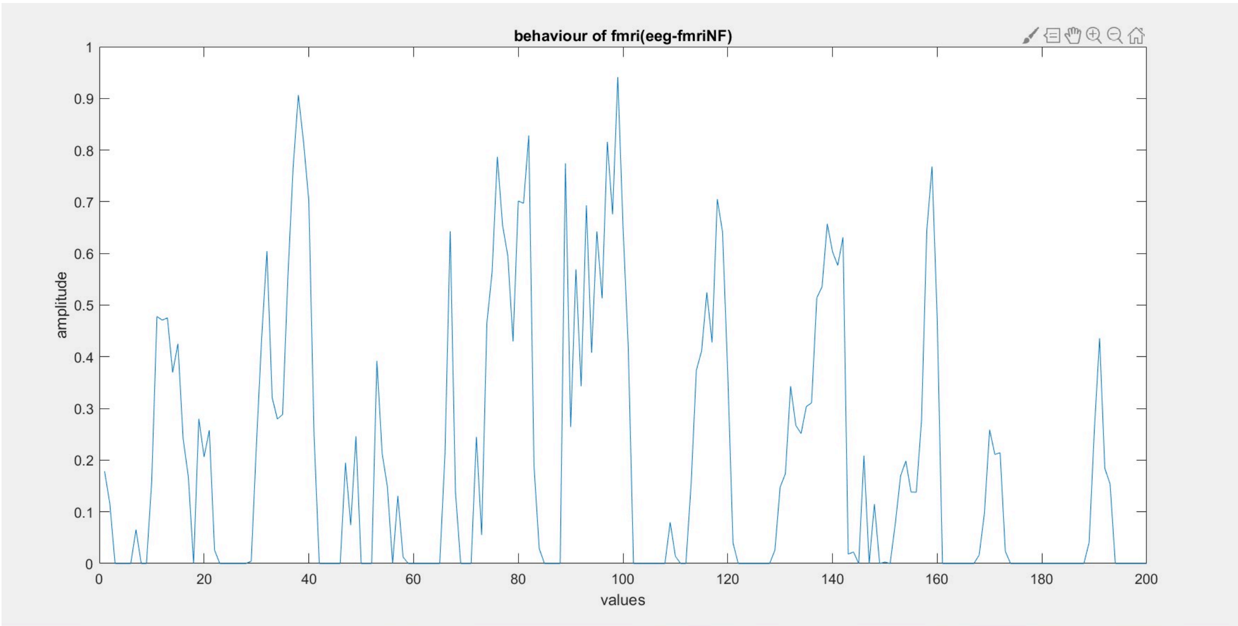


Figure 12: Behavior of FMRI(EEG-FMRI-NF)



3.5 ANALYSIS OF ACTIVATION ENERGY:

Table 8

EEG(EEG-NF)	EEG(FMRI-NF)	EEG(EEG-FMRI-NF)
61.0654	54.5289	82.5837

Increased neural engagement is indicated by a larger activation energy, which can be obtained via neural laterality indices and is thought to be helpful in comprehending brain function. EEG measurement during simultaneous EEG-fMRI neurofeedback (EEG-fMRI) shows a significantly higher activation energy in the context of our investigation than EEG alone (EEG) and EEG during fMRI neurofeedback (fMRI). This shows that a more robust and dynamic brain response is elicited by the combined EEG-fMRI modality, which may reflect increased cognitive processing or control capacities. These results emphasize the potential benefits of using multimodal methods, particularly EEG-fMRI, for a more thorough evaluation of brain activity and show the complex interactions between various modalities in neurofeedback paradigms.

The notably higher activation energy observed in EEG during simultaneous EEG-fMRI neurofeedback suggests enhanced neural engagement, implying potential advantages of the bimodal approach.

Table 9

FMRI(EEG-NF)	FMRI(FMRI-NF)	FMRI(EEG-FMRI-NF)
10.8407	13.0372	21.2627

The bimodal neurofeedback approach appears to offer richer and more dynamic information regarding brain activity, as evidenced by the much higher activation energy in FMRI (EEG-FMRI-NF). The higher cognitive processing and regulatory capacities implied by the greater activation energy highlight the potential superiority of the combined EEG-fMRI neurofeedback in recording a more complete picture of neural responses during the feedback

3.6 EEG MODALITY BASED ON STATISTICAL APPROACH:

The use of ANOVA (Analysis of Variance) and t-tests in our analysis serves the crucial purpose of statistically assessing the differences in laterality indices among multiple conditions. ANOVA is employed to determine if there are overall significant differences in means across all conditions (EEG-NF, fMRI-NF, and EEG-fMRI-NF). Subsequently, t-tests are conducted to pinpoint specific pairwise differences between conditions, providing detailed insights into which combinations exhibit significant variations. By employing these statistical tests, we can rigorously examine and validate the significance of observed differences, thereby enhancing the robustness and reliability of our conclusions regarding the impact of neurofeedback modalities on laterality indices in the study.

```matlab
%% ANOVA AND T STATS
data1 = load('eeg_NFeegscores.mat');
data2 = load('fmri_NFeegscores.mat');
data3 = load('eegfmri_NFeegscores.mat');
lateralityData1 = data1.NF_eeg.nf_laterality;
lateralityData2 = data2.NF_eeg.nf_laterality;
lateralityData3 = data3.NF_eeg.nf_laterality;

% Combine the laterality data
combinedData = [lateralityData1; lateralityData2; lateralityData3];

% Perform one-way ANOVA
[p_value_anova, ~, stats] = anova1(combinedData, [], 'off');

% Display results
disp(['p-value for one-way ANOVA: ' num2str(p_value_anova)]);
% Remove NaN or Inf from each dataset
lateralityData1 = lateralityData1(~isnan(lateralityData1));
lateralityData2 = lateralityData2(~isnan(lateralityData2));
lateralityData3 = lateralityData3(~isnan(lateralityData3));
```

```matlab
% Perform t-tests
[~, p_value_t1] = ttest2(lateralityData1,lateralityData2);  % Compare EEG-NF and fMRI-NF
[~, p_value_t2] = ttest2(lateralityData1,lateralityData3);  % Compare EEG-NF and EEG-fMRI-NF
[~, p_value_t3] = ttest2(lateralityData2, lateralityData3);  % Compare fMRI-NF and EEG-fMRI-NF

% Display results
disp(['p-value for t-test (EEG-NF vs. fMRI-NF): ' num2str(p_value_t1)]);
disp(['p-value for t-test (EEG-NF vs. EEG-fMRI-NF): ' num2str(p_value_t2)]);
disp(['p-value for t-test (fMRI-NF vs. EEG-fMRI-NF): ' num2str(p_value_t3)])

% Find means for each condition
mean_EEG_NF = mean(lateralityData1);
mean_fMRI_NF = mean(lateralityData2);
mean_EEG_fMRI_NF = mean(lateralityData3);

disp(['Mean laterality index for EEG-NF: ' num2str(mean_EEG_NF)]);
disp(['Mean laterality index for fMRI-NF: ' num2str(mean_fMRI_NF)]);
disp(['Mean laterality index for EEG-fMRI-NF: ' num2str(mean_EEG_fMRI_NF)]);

% Create a bar graph to visualize laterality indices
figure;
bar(1:3, [mean(lateralityData1), mean(lateralityData2), mean(lateralityData3)], 'FaceColor', [0.5 0.9 0.5], 'EdgeColor', 'k', 'LineWidth'
hold on;
```

```matlab
% Add error bars (standard deviation)
errorbar(1:3, [mean(lateralityData1), mean(lateralityData2), mean(lateralityData3)], ...
    [std(lateralityData1), std(lateralityData2), std(lateralityData3)], 'k', 'LineStyle', 'none', 'LineWidth', 1.5);

% Customize the plot
xlabel('Conditions');
ylabel('Laterality Index');
title('Laterality Index for Different Conditions');
xticks(1:3);
xticklabels({'EEG-NF', 'fMRI-NF', 'EEG-fMRI-NF'});
grid on;

hold off;
```

3.6.1 RESULTS OF EEG MODALITY :

```
p-value for one-way ANOVA: 3.2e-07
p-value for t-test (EEG-NF vs. fMRI-NF): 8.0745e-05
p-value for t-test (EEG-NF vs. EEG-fMRI-NF): 1.1871e-05
p-value for t-test (fMRI-NF vs. EEG-fMRI-NF): 1.0116e-15
```

One-way ANOVA:

This extremely small p-value suggests that there are significant differences in laterality indices among the three conditions. In other words, the laterality indices are not equal across all groups.

T-Tests:

The t-tests compare the means of laterality indices between pairs of conditions.

EEG-NF vs. fMRI-NF:indicating a significant difference between the EEG-NF and fMRI-NF conditions. This suggests that the laterality indices in these two conditions are not equal.

EEG-NF vs. EEG-fMRI-NF:signifying a significant difference between the EEG-NF and EEG-fMRI-NF conditions. This implies that the laterality indices differ between EEG-NF and EEG-fMRI-NF.

fMRI-NF vs. EEG-fMRI-NF:indicating a highly significant difference between the fMRI-NF and EEG-fMRI-NF conditions. This suggests that the laterality indices are significantly different when comparing fMRI-NF and EEG-fMRI-NF.

3.7 FMRI MODALITY BASED ON STATISTICAL APPROACH:

```
%%
% Load the data from the three files
data1 = load('eeg_NFboldscores.mat');
data2 = load('fmri_NFboldscores.mat');
data3 = load('eegfmri_NFboldscores.mat');

% Extract the laterality data
lateralityData1 = data1.NF_bold.normnf_laterality;
lateralityData2 = data2.NF_bold.normnf_laterality;
lateralityData3 = data3.NF_bold.normnf_laterality;

% Combine the laterality data
combinedData = [lateralityData1; lateralityData2; lateralityData3];

% Perform one-way ANOVA
[p_value_anova, ~, stats] = anova1(combinedData, [], 'off');

% Display results
disp(['p-value for one-way ANOVA: ' num2str(p_value_anova)]);
```

```
% Remove NaN or Inf from each dataset
lateralityData1 = lateralityData1(~isnan(lateralityData1));
lateralityData2 = lateralityData2(~isnan(lateralityData2));
lateralityData3 = lateralityData3(~isnan(lateralityData3));

% Perform t-tests
[~, p_value_t1] = ttest2(lateralityData1, lateralityData2);  % Compare EEG-NF and fMRI-NF
[~, p_value_t2] = ttest2(lateralityData1, lateralityData3);  % Compare EEG-NF and EEG-fMRI-NF
[~, p_value_t3] = ttest2(lateralityData2, lateralityData3);  % Compare fMRI-NF and EEG-fMRI-NF

% Display results
disp(['p-value for t-test (EEG-NF vs. fMRI-NF): ' num2str(p_value_t1)]);
disp(['p-value for t-test (EEG-NF vs. EEG-fMRI-NF): ' num2str(p_value_t2)]);
disp(['p-value for t-test (fMRI-NF vs. EEG-fMRI-NF): ' num2str(p_value_t3)]);

% Create a bar graph
figure;
bar(1:3, [mean(lateralityData1), mean(lateralityData2), mean(lateralityData3)], ...
    'FaceColor', [0.5 0.9 0.5], 'EdgeColor', 'k', 'LineWidth', 1.5);

hold on;

% Add error bars (standard deviation)
errorbar(1:3, [mean(lateralityData1), mean(lateralityData2), mean(lateralityData3)], ...
    [std(lateralityData1), std(lateralityData2), std(lateralityData3)], ...
    'k', 'LineStyle', 'none', 'LineWidth', 1.5);

% Customize the plot
xlabel('Conditions');
ylabel('fMRI Laterality Group Mean');
title('fMRI Laterality Group Mean with Standard Deviation');
xticks(1:3);
xticklabels({'EEG-NF', 'fMRI-NF', 'EEG-fMRI-NF'});
grid on;

hold off;

% Display p-values in a table
pValuesTable = table(p_value_anova, p_value_t1, p_value_t2, p_value_t3, ...
    'VariableNames', {'ANOVA', 'T_Test_EEG_vs_fMRI', 'T_Test_EEG_vs_EEG_fMRI', 'T_Test_fMRI_vs_EEG_fMRI'});
disp('P-Values Table:');
disp(pValuesTable);
```

3.7.1 RESULTS OF FMRI MODALITY:

```
p-value for one-way ANOVA: 2.5159e-05
p-value for t-test (EEG-NF vs. fMRI-NF): 0.52463
p-value for t-test (EEG-NF vs. EEG-fMRI-NF): 0.0049155
p-value for t-test (fMRI-NF vs. EEG-fMRI-NF): 0.029036
```

The obtained p-values from the statistical tests (ANOVA and t-tests) provide insights into the differences in laterality indices among the three conditions: EEG-NF, fMRI-NF, and EEG-fMRI-NF.

One-way ANOVA:

This small p-value indicates that there are significant differences in the means of laterality indices among the three conditions. In other words, the laterality indices are not equal across all groups.

T-Tests:

The t-tests compare the means of laterality indices between pairs of conditions.

EEG-NF vs. fMRI-NF: The p-value is 0.52463, suggesting that there is no significant difference in laterality indices between EEG-NF and fMRI-NF. The null hypothesis, in this case, is not rejected.

EEG-NF vs. EEG-fMRI-NF: The p-value is 0.0049155, indicating a significant difference between EEG-NF and EEG-fMRI-NF. The null hypothesis is rejected, signifying that the laterality indices differ between these two conditions.

fMRI-NF vs. EEG-fMRI-NF: The p-value is 0.029036, suggesting a significant difference between fMRI-NF and EEG-fMRI-NF. The null hypothesis is rejected, indicating that the laterality indices are significantly different when comparing these two conditions.

In summary, the **ANOVA** results validate that there are overall differences in laterality indices among the three conditions. The subsequent **T-Tests** help identify specific pairs of conditions where these differences are significant. Notably, there is no significant difference between EEG-NF and fMRI-NF, while both EEG-NF vs. EEG-fMRI-NF and fMRI-NF vs. EEG-fMRI-NF exhibit statistically significant differences in laterality indices. These findings contribute valuable information for understanding the impact of different neurofeedback modalities on brain laterality.

CHAPTER 4

CONCLUSION

In the initiation of our experiment, we engaged participants in kinesthetic motor imagery, conducting six EEG-fMRI runs structured with a block-design comprising alternating 20-second intervals of rest and task, as depicted in Figure 1. The runs encompassed a motor localizer run (MLOC) lasting 5 minutes and 20 seconds, a preliminary motor-imagery run without neurofeedback (MI_pre) lasting 3 minutes and 20 seconds, three neurofeedback runs (NF1, NF2, NF3) each lasting 6 minutes and 40 seconds, corresponding to different feedback modalities (A: EEG-NF; B: fMRI-NF; C: EEG-fMRI-NF), with the order counterbalanced across participants. The final motor-imagery run without neurofeedback (MI_post) spanned 3 minutes and 20 seconds.

We meticulously preprocessed EEG and fMRI data to enhance the reliability of our findings. EEG data underwent artifact removal using BrainVision Analyzer II Software, involving automatic gradient artifact correction, low-pass FIR filtering at 50Hz, downsampling (200Hz), and BCG artifact correction. Similarly, fMRI data were processed using SPM8, involving slice-time correction, spatial realignment, coregistration with the anatomical scan, spatial smoothing, and normalization to the Montreal Neurological Institute (MNI) template.

Upon obtaining preprocessed data, we computed bandpowers for EEG, facilitating the calculation of laterality indices and subsequent determination of activation energies for EEG-based modalities. Concurrently, regions of interest (ROIs) for left and right brain regions aided in the calculation of fMRI laterality indices, elucidating activation levels for the fMRI modality. **Our comprehensive analysis revealed a compelling conclusion favoring bimodal over unimodal neurofeedback modalities.**

Furthermore, we conducted statistical analyses, employing ANOVA and t-tests to scrutinize variations in laterality indices. The results underscored significant differences among the conditions, providing robust statistical support for our overarching conclusion. In essence, our meticulous experimental design, preprocessing techniques, and statistical analyses collectively contribute to a nuanced understanding of the superior efficacy of bimodal neurofeedback in modulating brain activity compared to unimodal approaches.

CHAPTER 5

FUTURE WORKS

- We want to use a special way of looking at brain data called "graph signal processing" to understand how the brain works. This method helps us see detailed patterns in how different parts of the brain talk to each other over time. By treating the brain like a signal on a graph, we can get a better picture of how the brain changes and works. This approach also helps us combine different types of brain data, making it easier to understand how the whole brain functions. Using this method, we hope to learn more about how the brain works together, which is important for neuroscience research.

  We would like to use the below 2 approaches :
  1)Models based on signal smoothness
  2)Models based on spectral filtering of graph signals

- In the future, we want to make our data better before studying it. We'll create special templates that fit our data perfectly and use other helpful software tools. This will help us fix any unique details in the brain signals we're studying, making our results more accurate. By combining our templates with other advanced tools, we aim to have a strong and personalized foundation for our future studies.

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