Analysis of Brain Connectivity Using Graph Theory Metrics in ECoG Data

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1. Introduction

Brain functional connectivity refers to the functional communication between different brain regions, which can be quantified using various methods. Using functional connectivity, networks in the brain can be identified and characterized. One method to quantify functional connectivity is to use coherence between pairs of electrodes, here performed on electroencephalography (ECoG) recordings. This approach provides a measure of synchronization between neural signals or across different brain regions [1]. Studies have shown that coherence can reliably capture functional interactions in the brain [2][3]. This project focuses on analyzing brain connectivity during two distinct states: rest and movie-watching. By applying graph theory metrics to these connectivity networks, we aim to understand how the topological structure of the network changes between different cognitive states.

Graph theoretical analysis, which provides quantitative metrics for quantifying the topology of brain networks, has gained increasing attention in neuroscience in recent years and has been widely used primarily with functional magnetic resonance imaging (fMRI) data [4]. In the context of brain network analysis, the nodes of the graph can represent groups of neurons or larger brain regions, while the edges reflect the connections between these nodes. These connections can be functional, capturing synchronization (i.e., coherent activity patterns) between different regions [5][6]. Metrics in graph theory offer a mathematical framework to study these networks, allowing us to analyze key properties such as node centrality and connectivity between different network regions. [8][9].

The primary aim of this project is to characterize and compare functional connectivity in ECoG using graph theory metrics in rest and movie-watching states across six frequency bands: delta, theta, alpha, beta, gamma, and high gamma.

Understanding how brain connectivity shifts between different cognitive states can reveal how the brain organizes itself to process information efficiently or how to prioritize information flow. By applying graph metrics, we can assess changes in brain network architecture, and provide insights into how different cognitive demands shape connectivity at multiple scales.

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2. Methods

Data Collection

The ECoG data used in this project were obtained from a publicly available dataset from the work published by Berezutskaya et al., (2022)[10] which includes brain activity recordings from 45 human subjects, aged 5 to 55 years, captured during two states: rest and movie-watching. Following preprocessing, the recordings were considered in six frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), gamma (30-100 Hz), and high gamma (100+ Hz). For each subject and state, coherence was calculated between pairs of electrodes, generating a set of coherence matrices. This dataset's electrode count for ECoG grids ranges from 32 to 128 per subject.

Data analysis

All data analysis was conducted using Python, with custom-developed classes. This included constructing brain connectivity networks from ECoG coherence matrices, computing graph theory metrics, statistical testing, and visualization. The code is available in the GitHub repository(https://github.com/guybaruch1/Erez_Lab_Project_Guy.git).

Graph Construction

The connectivity networks were built using the GraphBuild class. This class reads coherence data from CSV files and constructs undirected and weighted graphs for each subject, state, and frequency band. Each graph represents electrodes as nodes and coherence values as the weight of the edges between these nodes. The graphs were thresholded to retain only the top 10% and 20% strongest connections, ensuring that only the most significant connections are analyzed, a commonly employed method in brain network analyses [11][3]. The edges remain weighted after thresholding. An example of these connectivity graphs is shown in Figure 1, which provides a visual representation of the network structure for a subject during the rest state in the gamma frequency band. The graph visualization helps illustrate clustering and network density, which are further analyzed using graph theory metrics. All graphs were saved in GraphML format for further analysis.

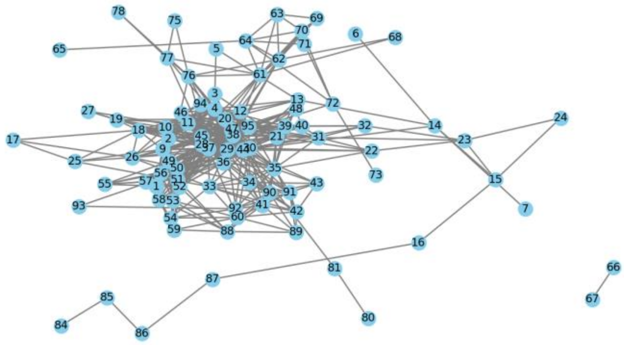

Figure 1: The connectivity network for Subject 03 during the rest state (Gamma band) is visualized using a spring layout. Nodes represent electrodes, while edges represent the strongest coherence-based connections (top 10%). More tightly clustered nodes highlight areas of local connectivity, while distant nodes reflect long-range connections.

Graph Theory Metrics Calculation

Graph theory metrics were computed using the GraphMetrics class, which calculates both global metrics and node-level metrics. The key metrics analyzed include: (1) *Degree Centrality* - The number of connections each node has, indicating its importance in the network. (2) *Node Clustering Coefficient (NCC)*- A measure of how tightly connected a node's neighbors are, indicating local clustering. (3) *Modularity*- A global measure of how well the network divides into distinct communities. (4) *Global Clustering Coefficient (GCC)*- A global measure of the overall tendency of the network to form clusters. Global metrics were computed for each graph, representing the overall structure and organization of the brain network, while node-level metrics were calculated for each individual node within the graph, capturing the local connectivity and importance of individual brain regions within the network. The analysis follows the framework described in Kaiser (2011)[9] and Centeno (2022)[11], which outlines how to apply graph theory to brain networks. A detailed summary of the relevant metrics and their calculations is provided in the appendix, *Graph Metrics in Neuroscience Network*. The results were then saved to a .pkl file for statistical testing and visualization.

Statistical Analysis

Statistical tests were performed using the SignificanceTester class. Global metrics were analyzed using paired t-tests to compare differences between the rest and movie-watching states for each frequency band. Node-level metrics were analyzed using Kolmogorov-Smirnov (K-S) test to compare the distribution of values between the two states. The significance threshold was set at an alpha level of 0.05. All statistical outputs were saved for subsequent visualization and interpretation.

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3. Results

10% Threshold

Global Metrics

Gamma Band: Global clustering coefficient (**GCC**) was larger during the movie-watching state compared to rest ($t(19) = -2.76$, $p = 0.0098$), indicating a higher level of global integration during cognitive tasks. However, no significant difference in modularity was found ($p > 0.05$).

Figure 2 illustrates the average GCC across the six frequency bands, highlighting the notable increase in GCC in the gamma band during movie-watching, reflecting higher global connectivity.

No significant differences were observed in modularity or GCC between the rest and movie-watching states across the Delta, Theta, Alpha, Beta, and High Gamma bands ($p > 0.05$).

Node-Level Metrics

Gamma Band: A significant increase in the node clustering coefficient (**NCC**) was observed during movie-watching (K-S statistic = 0.0488, p = 0.0071), indicating more pronounced local clustering. Degree centrality showed no significant differences (p > 0.05).

No significant differences were observed in degree centrality or NCC between the rest and movie-watching states across the Delta, Theta, Alpha, Beta, and High Gamma bands (p > 0.05).

20% Threshold

Global Metrics

Alpha Band: GCC was larger during movie-watching compared to rest (t(19) = -3.26, p = 0.0028), suggesting greater global integration in this frequency band. No significant changes in modularity were observed (p > 0.05).

Gamma Band: GCC was larger during the movie-watching state (t(19) = -2.45, p = 0.0203), reinforcing the finding that cognitive engagement enhances global clustering in the gamma band. No significant changes in modularity were found (p > 0.05).

No significant differences were observed in modularity or GCC between the rest and movie-watching states across the Delta, Theta, Beta, and High Gamma bands (p > 0.05).

Node-Level Metrics

Alpha Band: Significant increases were observed in both **degree centrality** (K-S statistic = 0.0482, p = 0.0051) and **NCC** (K-S statistic = 0.0737, p < 0.0001), indicating enhanced local clustering and node importance during movie-watching.

Beta Band: Significant increases were observed in the **NCC** during the movie-watching state (K-S statistic = 0.0439, p = 0.0439), indicating more localized clustering among connected nodes in this frequency band.

Gamma Band: The **NCC** remained significantly higher during the movie-watching state (K-S statistic = 0.0690, p < 0.0001), consistent with the 10% threshold results. No significant differences in degree centrality were observed (p > 0.05).

High gamma: A significant increase in the **NCC** was observed during movie-watching (K-S statistic = 0.0423, p = 0.0284), indicating more pronounced local clustering. Degree centrality showed no significant differences (p > 0.05).

Figure 3 presents the density distributions of NCC values across six frequency bands. The Kernel Density Estimation (KDE) applied here highlights differences in distribution, particularly in the alpha, beta, gamma and high gamma bands, where shifts suggest increased local clustering during movie-watching.

No significant differences were observed in degree centrality or NCC between the rest and movie-watching states across the Delta and Theta bands (p > 0.05).

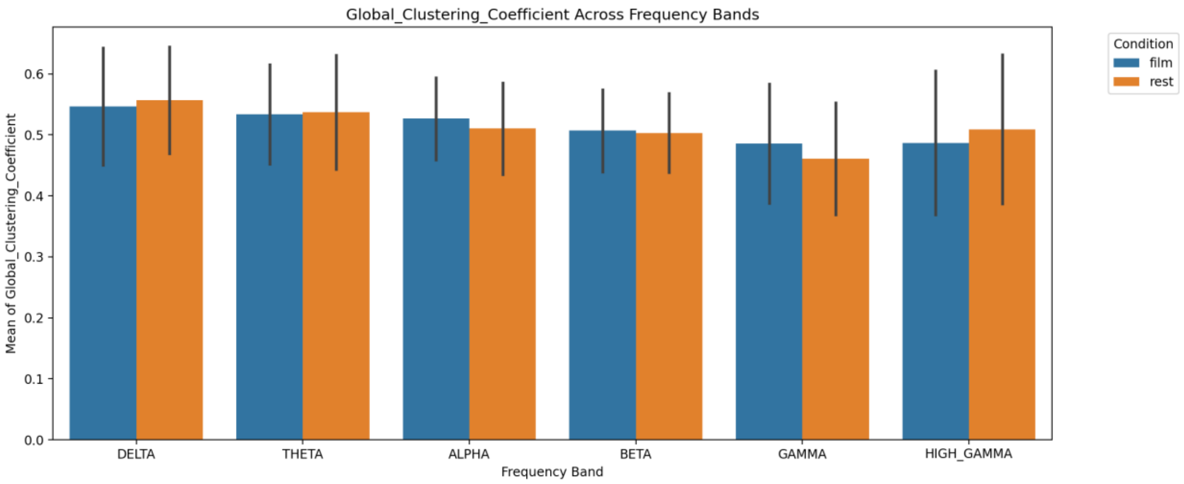

Figure 2. Average Global Clustering Coefficient (GCC) across the six frequency bands for rest and movie-watching conditions at the 10% threshold. Error bars represent the standard deviation within each condition. The increased GCC in the gamma band during movie-watching indicates higher global connectivity during cognitive engagement.

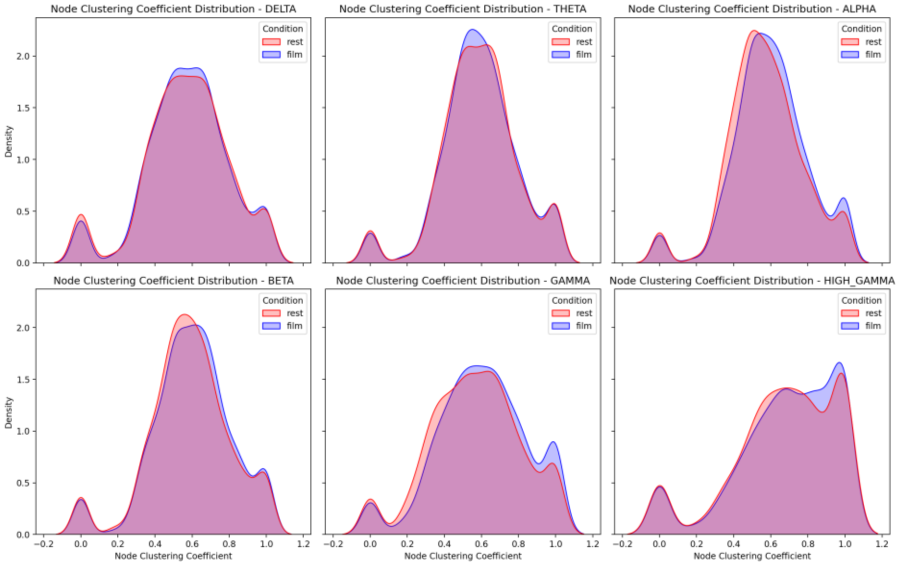

Figure 3. Density distributions of Node Clustering Coefficient (NCC) across six frequency bands for rest and movie-watching conditions at the 20% threshold. Kernel Density Estimation (KDE) was applied to visualize the distribution of NCC values, with each frequency band represented individually. Changes in density distribution, particularly in the alpha, beta gamma and high gamma bands, suggest increased local clustering during the movie-watching condition.

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4. Discussion

Interpretation of Results

The findings demonstrate that graph theory metrics may be a useful tool to characterize brain connectivity and reveal differences between rest and movie-watching states. One of the primary observations is the significant increase in the GCC during movie-watching in the gamma band at both thresholds, as well as in the alpha band at the 20% threshold. The increase in global clustering within the gamma band, which is known to support high-order cognitive functions such as attention and sensory processing, suggests that cognitive engagement enhances long-range coordination across brain regions [2]. This elevated clustering during movie-watching may reflect the brain's shift toward a more integrated network state, which could facilitate the efficient communication required for complex cognitive processing.

The analysis shows that local clustering increases significantly in the gamma band at both thresholds during movie-watching and in the alpha, beta, and high gamma bands at the 20% threshold. This increase suggests that movie-watching strengthens tightly connected groups within these frequency bands. The alpha band, specifically, shows a higher degree centrality and clustering at the 20% threshold, meaning that local network density and node importance are increased during task engagement. These changes align with findings in network neuroscience that highlight the role of the clustering coefficient in supporting the brain's small-world architecture, where high clustering enhances local processing efficiency [7][12]. Since the alpha band is linked to sensory processing and attention, this increase may help the brain handle sensory information during movie-watching.

Threshold Comparisons

When comparing the two thresholds, similar patterns are evident, with the 10% threshold highlighting changes in the gamma band, while the 20% threshold extending the focus to include the alpha, beta, and high gamma bands. The consistent increase in both global and local clustering within the gamma band at both thresholds highlights the importance of this frequency band in cognitive processing. The addition of significant findings in the alpha, beta, and high gamma bands at the 20% threshold, which retains more edges in the network, suggests that retaining more edges helps reveal smaller changes in these frequency bands.

Implications

These findings suggest that during cognitive engagement like movie-watching, the brain’s functional connectivity network becomes more globally and locally clustered, particularly in the gamma, alpha, beta, and high gamma bands. The increased global clustering, especially in the gamma band, points to a shift toward a more integrated network architecture, enabling effective long-range communication across distant brain regions. The increase in local clustering, seen across multiple frequency bands, suggests that cognitive tasks may promote more localized processing within tightly connected areas, supporting rapid information flow in specific network modules. This clustering pattern aligns with the small-world properties of brain networks, where local clusters of connectivity facilitate efficient local processing while maintaining global connectivity [7].

The lack of significant differences in modularity and degree centrality across most bands and thresholds implies that the brain's community structure and the overall importance of individual nodes remain stable between rest and cognitive task states.

Limitations

A primary limitation of this project is the focus on coherence as the sole measure of connectivity. While coherence provides valuable insights into phase synchronization between brain regions, additional measures, such as phase-locking value or Granger causality, could further elucidate connectivity directionality and dynamics. Furthermore, the choice of two specific thresholds (10% and 20%) offers a limited view of the network's edge structure. Future studies could explore a broader range of thresholds to capture more detailed network behaviors.

Another limitation is that electrode placement differs between subjects, causing variability in network structures that can make it challenging to compare brain connectivity patterns across individuals accurately and reliably. Standardizing electrode placement could improve consistency across subjects. Lastly, this project relies on static connectivity networks. Applying time-varying analyses could offer insights into the dynamic shifts in connectivity over time.

Future Research

This project suggests several directions for future research. Using time-based network analysis could show how connectivity patterns change over time, giving a clearer view of network dynamics during different tasks. Exploring additional graph theory metrics and testing various tasks, such as memory or language activities, might reveal how brain networks adapt to different types of challenges.

Future studies could also look at individual differences in brain connectivity by focusing on factors like age, cognitive abilities, or health status. This may help identify unique patterns within specific groups. Lastly, combining network analysis with machine learning could help find predictive patterns, leading to more personalized insights into brain function.

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5. Conclusion

This project shows that using graph theory metrics helps uncover differences in brain connectivity between rest and movie-watching states with ECoG data. Specifically, increases in both global and local clustering coefficients, particularly within the gamma and alpha bands, highlight how cognitive tasks influence brain network structure. These clustering patterns suggest that movie-watching promotes a more integrated and efficient network state.

While this research focused on certain connectivity metrics and conditions, future studies could build on these findings by exploring additional tasks, metrics, and connectivity measures. Overall, this project enhances our understanding of how brain networks reorganize in response to cognitive demands, offering a valuable framework for analyzing brain connectivity through graph theory.

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Declaration

This project involved at least 60 hours of work, and no financial compensation was received to me.