EEG

Talib Siddiqui[1], Himanshu Sarraf[1], and Sajja Patel[1]

[1]IIIT Hyderabad

April 22, 2024

Abstract

Graph Signal Processing (GSP) is a burgeoning field that focuses on analyzing and processing signals within graph structures. In GSP, data is represented as graphs, with nodes denoting entities and edges symbolizing relationships. Graph Learning, a subset of GSP, addresses data generated from graph-based interactions, aiming to enable machines to learn the original graph structure. This methodology finds applications across diverse domains such as protein networks, social networks, anomaly detection, and neurological disease analysis. In the context of neurological disorders, particularly epilepsy, GSP offers promising avenues for detection, pre-detection, prediction, and understanding specific network alterations indicative of epileptic activity.

1 Introduction

Within the realm of neurological disease detection and analysis, epilepsy stands out as a primary area of interest. Several key challenges have been identified, including: Epilepsy Detection, Pre-detection, Prediction, Epilepsy-specific Node Identification, Network Metric Changes, Epilepsy-specific Graph Identification (ATLAS).This project focuses on leveraging GSP methodologies to address the aforementioned challenges, particularly in the context of EEG data analysis for epilepsy detection and understanding epileptic network dynamics. By constructing and analyzing brain networks derived from EEGP6 data, we aim to contribute to the development of effective tools for epilepsy diagnosis, prediction, and understanding.

2 Background

Epilepsy is a neurological disorder characterized by recurrent seizures, which are sudden, brief changes in the brain's electrical activity. These seizures can manifest as convulsions, loss of consciousness, or altered awareness, depending on the affected areas of the brain. **Electroencephalography (EEG)** is a non-invasive technique used to record the electrical activity of the brain. It involves placing electrodes on the scalp to detect the electrical impulses generated by neurons. EEG can capture abnormal brain wave patterns associated with seizures.

Viewing the brain as a graph involves conceptualizing the brain's structural and functional connectivity as a network of nodes (representing brain regions or neurons) and edges (representing connections or interactions between them). This graph-based perspective allows researchers to analyze complex brain networks and investigate how disruptions in connectivity may contribute to neurological disorders such as epilepsy. EEG data can be analyzed within this framework to identify patterns of connectivity and detect abnormalities associated with epilepsy.

3 Problem Statement

Existing Work: The current approach to epilepsy detection primarily relies on band-pass filtering, particularly focusing on the theta band, and time-frequency analysis (TFA). Graph Learning techniques have been applied to TFA data to analyze network metrics of interest. Additionally, accuracy calculation methods utilizing Convolutional Neural Networks (CNN) have been explored.

What we will focus upon: Our objective is to extract time series data that encompasses seizure occurrences, including a buffer of 5000 data points before and after each seizure event. These time series should adequately capture seizure onset and offset points. Clinically identified seizure timing will guide our selection process, which can be further

validated through amplitude analysis. When visualizing the reconstructed time series data, "frequency distribution" refers to frequency domain analysis, typically achieved through Fourier transform techniques. Constructing correlation matrices using mutual information will facilitate comprehensive network analysis.
Also, to compute the threshold to binarize the correlation matrix, we used the method of **Giant Component**.
A threshold was computed to formalize the correlation matrix such that

$$\frac{GCCsize}{Graphsize}$$

4 Overview

The data we analyzed spanned a total duration of 445 seconds, with 395 seconds corresponding to periods of active epilepsy. The remaining time was divided into pre-epileptic and post-epileptic phases, each lasting 25 seconds. This temporal distribution provides a framework for studying the progression of epilepsy, allowing for the examination of pre-epileptic signals, epileptic events, and the recovery period that follows.

4.1 Degree

In order to focus on a specific frequency range, We have filtered the data using the **Alpha Band**, typically defined as frequencies between 8 and 12 Hz, This band is often associated with brain states like relaxation and alertness, making it a key area for analyzing brain activity.

Pearson correlation (PC) measures the linear relationship between two continuous variables, with values from -1 to 1 indicating the strength and direction of the correlation.

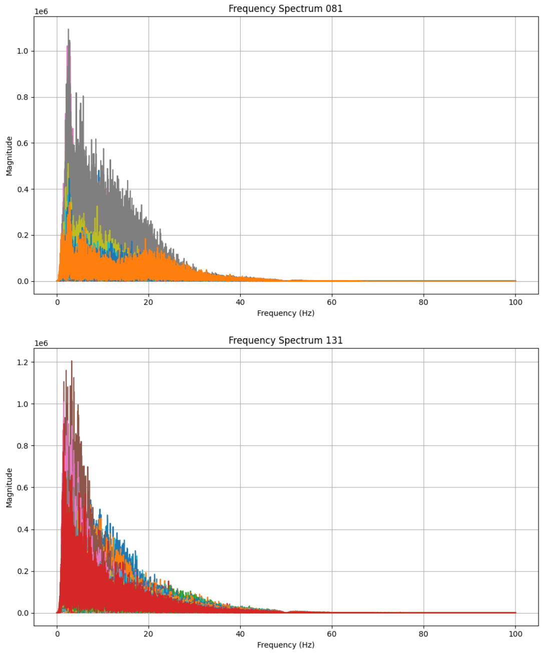


Figure 1: Before Band Filtering

It's great for detecting linear trends but fails to capture nonlinear associations.

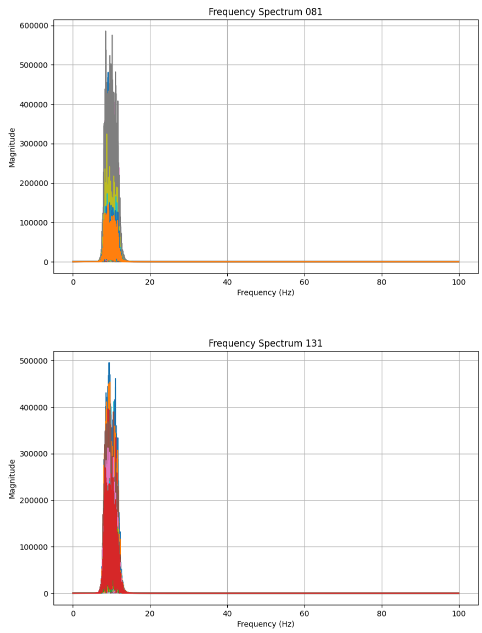


Figure 2: After Band Filtering

Mutual information (MI), however, assesses the total shared information between two variables, capturing both linear and nonlinear relationships. MI is calculated from joint and marginal probability distributions, offering greater flexibility in identifying complex connections. For example, consider rolling a standard six-sided die and another die indicating whether the outcome is odd or even. Mutual information would capture how the specific number rolled on the first die relates to whether the outcome is odd or even, revealing underlying patterns. MI is often better than PC in complex systems, as it can detect more intricate relationships without the linearity constraint.

Mutual information is more flexible than Pearson correlation because it can capture both linear and nonlinear relationships. It provides a more comprehensive measure of association and doesn't assume a specific distribution or relationship structure. This flexibility makes MI particularly useful in complex systems where relationships might be intricate or not well-defined by linear trends. As a result, MI is often a better choice for exploring complex data sets and finding deeper patterns and connections.
Both datasets indicated seizure onsets from the left mesial temporal lobe. This consistent finding suggests a specific region for seizure origination across both datasets.

5 Solution

5.1 Correlation Matrix

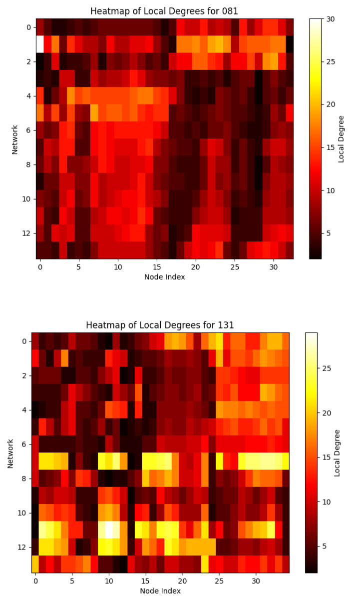
In this analysis, we generated a correlation matrix using mutual information to understand the relationships between various data points.
This matrix was then divided into 14 distinct segments:

- 2 parts → The Pre-epileptic phase
- 10 parts → The Epileptic phase
- 2 parts → The Post-epileptic phase

Each segment is designed to highlight the correlation structure at different stages of epilepsy, offering insights into the changing patterns of information exchange throughout the epileptic process.
This segmentation approach facilitates a more granular analysis and aids in identifying key trends and shifts across the phases.

5.2 Degree

The local degree represents the number of connections or edges a node has with its immediate neighbors, providing a measure of its connectivity within the graph. By analyzing the local degree, I aimed to identify patterns and clusters that might indicate epileptic activity. This approach allows for pinpointing nodes with unusually high or low connectivity, which can be crucial indicators of abnormal brain activity related to epilepsy.
In the **first patient**, we observe



5.3 Assortativity

In this analysis, we computed the Assortativity for all nodes in a graph to assist in epilepsy detection. Assortativity measures the tendency of nodes in a graph to connect with similar or dissimilar nodes based on a certain attribute, such as degree or node type.

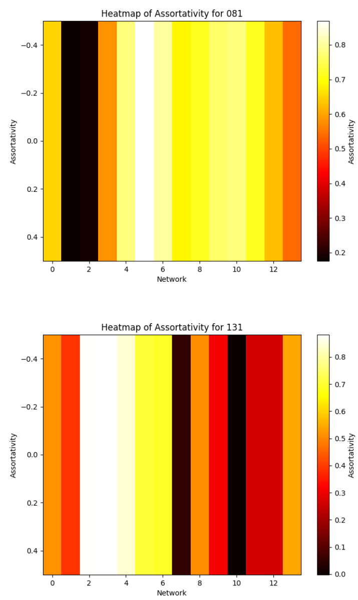


Figure 3: Assortavity of the Nodes

By evaluating assortativity, We aimed to identify whether nodes with similar characteristics were more likely to form connections, which could reveal underlying patterns of epileptic activity. High assortativity could indicate a tendency for nodes with similar connectivity to group together, while low assortativity might suggest a more random or varied pattern.

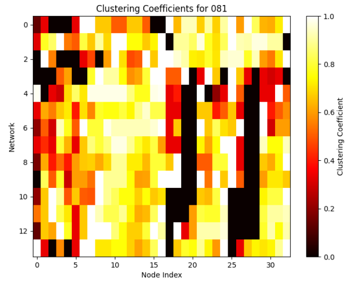
As we observe for the **first patient** that, before the epilepsy the graph seems to be slightly assorted but as soon as the episode starts, there is almost no assortivity at all, implies the disconnection of nodes, and then soon after, within the episode itself we observe a strong assortivity and connectedness in the graph.
This is, although different to the **second patient** where we observe a really assorted graph as the epilepsy starts which slowly reduces into low assortivity and connectedness.

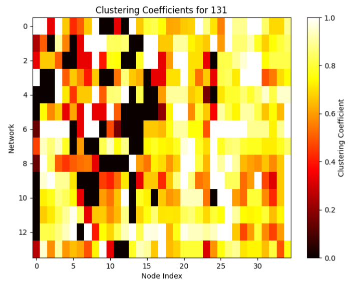
5.4 Clustering Coefficient

In this analysis, we computed the clustering coefficient for all nodes in a graph as part of an epilepsy detection strategy. The clustering coefficient measures the likelihood that two neighbors of a given node are also connected to each other, indicating the level of local interconnectedness or clustering in the graph. By evaluating this metric, We aimed to understand the density of connections in localized areas of the network, which can be indicative of patterns related to epileptic activity. Higher clustering coefficients suggest more interconnected nodes, while lower coefficients point to a more dispersed network structure.

6 Conclusion

- Studied EEGP6 signals to understand epilepsy perception and response in the left mesial brain region.
- Investigated Alpha band to explore specific frequency range associated with epilepsy activity.
- Discovered patterns and correlations in EEGP6 data, revealing dynamics of epileptic episodes.
- Potential implications for epilepsy diagnosis and treatment improvement.
- Future directions include exploring additional EEG signals and advanced analytical techniques.





7 References

1. Behrens E, Zentner J, van Roost D, Hufnagel A, Elger CE, Schramm J. Subdural and depth electrodes in the presurgical evaluation of epilepsy. Acta Neurochir (Wien). 1994;128(1-4):84-7. doi: 10.1007/BF01400656. PMID: 7847148.

2. Brockhaus A, Lehnertz K, Wienbruch C, Kowalik A, Burr W, Elbert T, Hoke M, Elger CE. Possibilities and limitations of magnetic source imaging of methohexital-induced epileptiform patterns in temporal lobe epilepsy patients. Electroencephalogr Clin Neurophysiol. 1997 May;102(5):423-36. doi: 10.1016/s0921-884x(97)96625-x. PMID: 9191586.

3. Šverko, Z.; Vrankić, M.; Vlahinić, S.; Rogelj, P. Complex Pearson Correlation Coefficient for EEG Connectivity Analysis. Sensors 2022, 22, 1477. https://doi.org/10.3390/s22041477

4. Entropy and Mutual Information by Erik G. Learned-Miller, Department of Computer Science, University of Massachusetts, Amherst, Amherst, MA 01003, September 16, 2013