Comprehensive Brain Network Analysis Using SAR and LAM Models: Structural and Functional Connectivity Insights

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Abstract

This study investigates the brain's structural and functional connectivity by employing dynamic systems and graph theory, focusing on the Spatial Autoregressive (SAR) and Linear Assignment (LAM) models for analyzing spatial and temporal brain interactions. Using the YANAT library, key normalization techniques and the simple_fit function were used to optimize model parameters, correlating structural connectivity (SC) from MRI data with functional connectivity (FC) from fMRI scans. Data were derived from the Lausanne Consensus Connectome dataset, with structural connectivity measured via tractography and functional connectivity derived from resting-state fMRI scans. The results highlight how different normalization techniques, such as Log Min-Max and Spectral Normalization, influence the models' effectiveness. Through analysis of brain networks across multiple parcellation levels, this project provides insights into the dynamic structure of brain networks and the broader implications for neurological and clinical research.

1. Introduction

Brain network analysis (BNA) aims to understand how different brain regions interact both structurally and functionally. Modern brain research increasingly relies on graph theory to model the brain as a network, with regions represented as nodes and connections between them as edges. This project examines how structural connections, derived from MRI-based tractography, influence functional connections, derived from fMRI data, using advanced models like the Spatial Autoregressive (SAR) and Linear Assignment (LAM) models.

Brain networks are typically analyzed using key metrics such as connectivity, centrality, geodesic distance, and clustering coefficient. These metrics allow researchers to quantify the efficiency, resilience, and organization of brain networks. By modeling the brain's connections over time and space, we can better understand how regions of the brain communicate and how disruptions in these communications might lead to neurological disorders.

This study applies these concepts to a dataset obtained from the Lausanne Consensus Connectome, incorporating both structural and functional brain data. The goal is to analyze the spatial dependencies and dynamic changes in the brain's network over time using the YANAT library, which facilitates the use of graph theory models for brain network analysis.

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2. Materials and Methods

2.1. Dataset

2.1.1. Lausanne Consensus Connectome

The data for this study were partially derived from the Lausanne Consensus Connectome, collected from 70 healthy participants (43 men, 27 women, average age: 29 years) at the Lausanne University Hospital, Switzerland. Structural connectivity (SC) data were acquired using diffusion MRI, employing a 3D modeling technique called tractography to map nerve tracts within the brain. SC matrices were generated for each participant, representing five distinct levels of brain parcellation, with connection strength approximated by fiber density, or "capacity," representing the density of fibers connecting brain regions.

Functional connectivity (FC) data were obtained from resting-state functional MRI (fMRI) scans, which measured the co-activation of brain regions during rest. The initial fMRI data were preprocessed to account for motion artifacts, white matter influence, and other physiological factors. These FC matrices provided insight into how brain regions interact functionally, without direct structural connections.

2.2. Structural and Functional Connectivity Matrices

Structural connectivity (SC) matrices represent the anatomical organization of the brain by showing the direct connections between brain regions. These matrices are typically sparse, as they only capture direct structural links, such as those visualized through tractography. In contrast, functional connectivity (FC) matrices illustrate how brain regions interact during rest or cognitive tasks, even if they are not structurally connected. Comparing SC and FC matrices allows us to explore how the physical structure of the brain underpins its functional behavior.

2.3. Models and Algorithms

This study employed two primary models to analyze the relationships between SC and FC matrices:

- **SAR (Spatial Autoregressive) Model**: The SAR model analyzes spatial dependencies between brain regions, determining how the activity of one region influences others. It uses SC matrices to assess how spatial organization impacts brain function and calculates the covariance between regions based on their structural connections.

- **LAM (Linear Assignment) Model**: The LAM model investigates how connections between brain regions evolve over time, analyzing the dynamic reconfiguration of brain networks during different processes. The LAM model focuses on functional connections, examining how specific regions of the brain form and dissolve functional relationships.

2.4. Normalization Techniques

To allow for more effective comparison between different SC matrices, the following normalization techniques were applied:

- **Log Min-Max Normalization**: This technique logarithmically transforms the data and normalizes it between minimum and maximum values, preserving the relative strength of connections while adjusting for magnitude differences.
- **Min-Max Normalization**: This technique rescales data to fit within a specific range (between minimum and maximum values), making comparisons between matrices easier by standardizing their scale.
- **Binarization**: In this technique, link values are divided into binary categories (0 or 1), indicating whether a connection exists between two brain regions.
- **Spectral Normalization**: This technique normalizes the matrix based on its spectral radius, the largest absolute value of its eigenvalues. This method provides insights into how the connectivity matrix influences dynamic systems, allowing for a more sophisticated understanding of matrix behavior over time.

2.5. simple_fit Function

The simple_fit function plays a key role in optimizing the SAR and LAM models by systematically exploring a range of parameters to maximize the correlation between structural (SC) and functional connectivity (FC) matrices. For the SAR model, it focuses on the alpha parameter, which controls the strength of spatial relationships between brain regions. By testing different alpha values and comparing SC predictions to the target FC matrix using metrics like Pearson correlation, the function identifies the best parameter set.

A major advantage of simple_fit is its use of parallel processing, allowing for the efficient evaluation of many parameter combinations, significantly speeding up the optimization process. Additionally, it supports multi-dimensional optimization, making it flexible enough to tune parameters for both SAR and LAM models, ensuring accurate representation of brain dynamics.

3. Results and Discussion

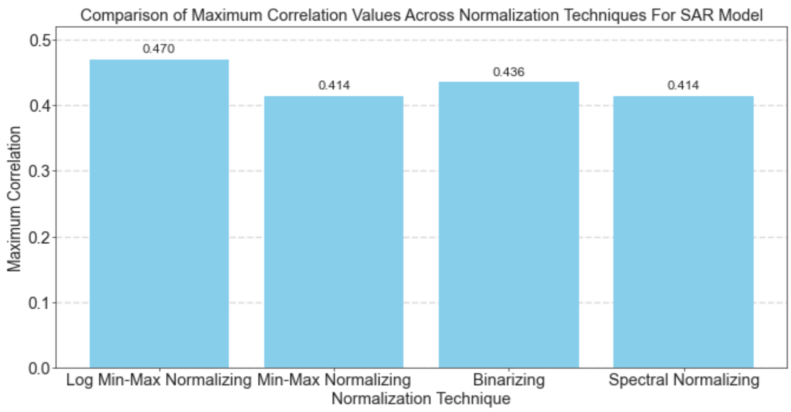
3.1. Model Performance Across Normalization Techniques

The performance of the SAR and LAM models was assessed across all normalization techniques. The models' ability to correlate SC and FC matrices varied depending on the technique used.

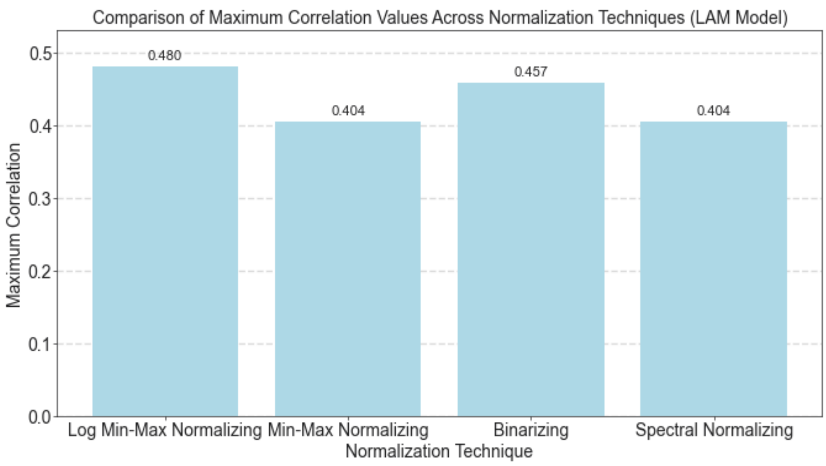
3.1.1. Log Min-Max Normalization Results

Log Min-Max normalization emerged as the most effective technique for both SAR and LAM models. This method transforms the data logarithmically and rescales it, which preserves the relative strength of connections while reducing magnitude differences. By maintaining the essential structure of the SC matrix and enhancing contrast, the Log Min-Max technique allowed for more accurate analysis of the spatial dependencies between brain regions.

For the SAR model, Log Min-Max normalization produced the highest correlation between SC and FC matrices, with a correlation value of **0.4703**. This indicates that the structural brain connections, when normalized using this method, better explain the functional connectivity captured in the fMRI data.

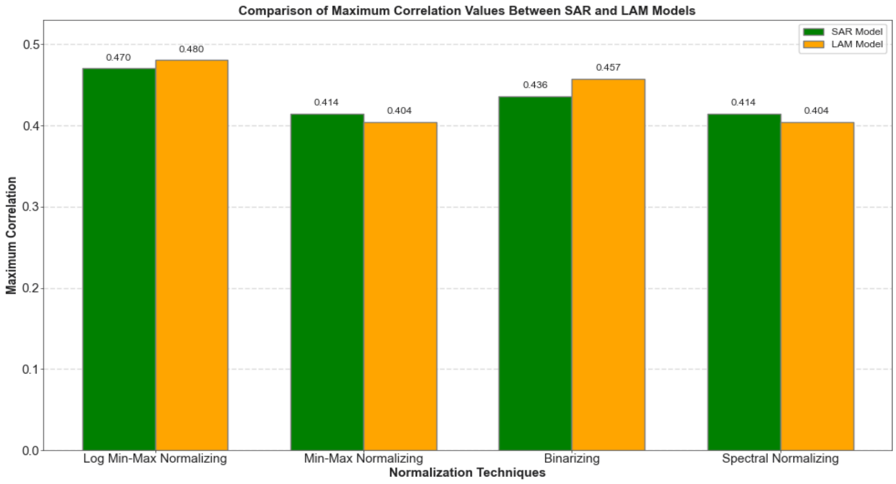


In the LAM model, Log Min-Max normalization yielded an even higher correlation of **0.4804**, making it the most effective normalization technique for this model as well. The LAM model focuses on dynamic changes in functional connectivity, and Log Min-Max normalization's ability to highlight differences in connection strength contributed to its superior performance.



3.2. SAR and LAM Model Comparison

Both models were compared across the different normalization techniques and parcellation levels. The SAR model demonstrated strong performance in capturing spatial dependencies between brain regions, particularly when using Log Min-Max normalization. This model was most effective at coarser brain resolutions (lower res_parcellation values), where broader structural connections exert a more significant influence on overall brain function.



In contrast, the LAM model outperformed the SAR model when analyzing dynamic changes in functional connectivity, especially at finer parcellation levels. The LAM model's focus on the temporal reconfiguration of brain networks allowed it to capture more subtle, time-varying interactions between brain regions. This model benefited most from Log Min-Max and Spectral normalization techniques.

3.3. Correlation Between SC and FC Matrices

One of the primary goals of this study was to assess the correlation between the brain's structural connectivity (SC) and functional connectivity (FC) matrices. Across all tested models and normalization techniques, the correlation values indicated that the structural organization of the brain does, to some extent, predict functional interactions between regions.

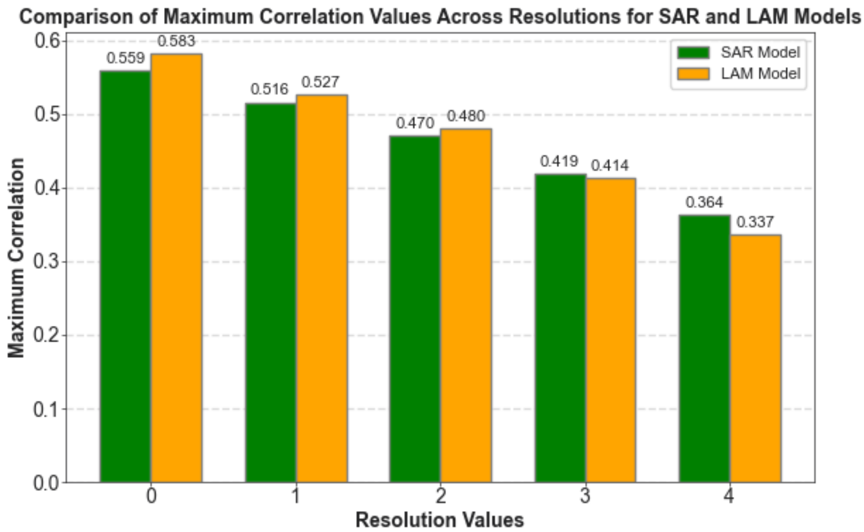
Log Min-Max normalization consistently produced the highest correlation values for both models. This suggests that the logarithmic transformation of the data enhances the relationship between the brain's structural and functional networks. The correlation values were highest for the LAM model at finer parcellation levels, supporting the idea that detailed structural connections are critical in shaping functional dynamics.

At coarser parcellation levels, the SAR model performed better in capturing broader spatial dependencies, with significant correlations between SC and FC matrices. These results highlight the importance of considering different spatial scales when analyzing brain connectivity.

3.4. Resolution and Parcellation Analysis

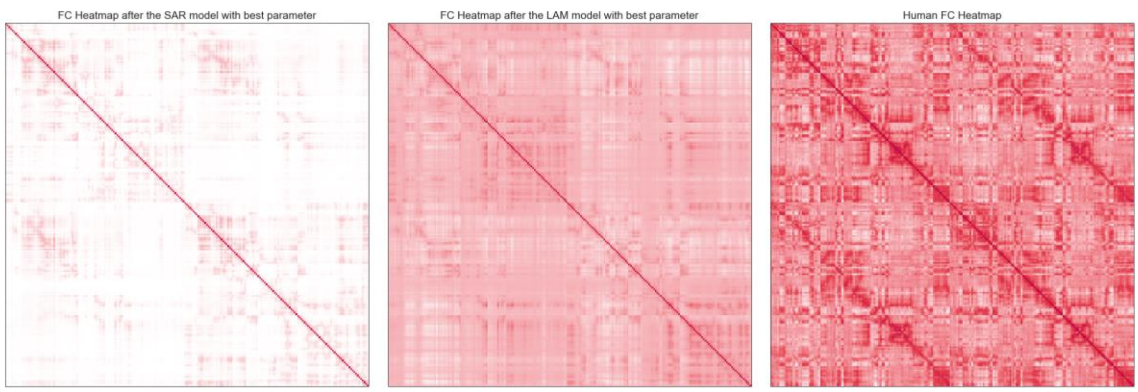
The study highlighted the importance of brain resolution, as represented by the res_parcellation parameter. The SAR model performed best at lower resolutions (res_parcellation = 0), where broader structural patterns are more dominant. This suggests that coarser spatial scales allow structural connectivity to have a stronger influence on overall brain function, with large-scale connections driving functional dynamics.

In contrast, the LAM model excelled at higher resolutions (res_parcellation = 4), where finer interactions between smaller brain regions become more prominent. This allowed the LAM model to capture more detailed, time-varying functional connectivity. However, as resolution increased, the correlation values slightly decreased, possibly due to the added complexity of brain networks at finer spatial scales.



3.5. Visualization and Comparison of Model Correlations

A bar plot was used to compare the correlation values of the SAR and LAM models across all normalization techniques and parcellation levels. The Log Min-Max normalized LAM model achieved the highest correlation between SC and FC matrices, especially at resolution level 0. Additionally, heatmaps were used to visually compare the modeled and actual FC matrices, showing that the Log Min-Max normalized LAM model closely matched the true functional connectivity, confirming its effectiveness.



3.6. Summary of Results

- Log Min-Max normalization was the most effective technique for both SAR and LAM models, producing the highest correlation values between SC and FC matrices.
- The SAR model performed best at capturing broad, spatial dependencies at coarser parcellation levels, while the **LAM model** excelled in analyzing dynamic functional connectivity at finer parcellation levels.
- Lower parcellation levels (res_parcellation = 0) produced the strongest correlations, suggesting that broader brain connections have a more significant influence on functional connectivity.

These findings provide valuable insights into the relationship between brain structure and function, highlighting the importance of selecting appropriate normalization techniques and spatial scales when modeling brain networks.

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4. Conclusion

This study provides valuable insights into how structural and functional brain networks interact. The SAR and LAM models, applied through the YANAT library, enabled a comprehensive analysis of the spatial and dynamic properties of brain networks. By comparing different normalization techniques, we found that Log Min-Max and Spectral normalization techniques were particularly effective in improving model performance and the correlation between SC and FC matrices. Lower parcellation levels provided the most meaningful correlations, highlighting the importance of considering spatial resolution in brain network analysis. Future studies should explore the application of these models to clinical datasets, particularly those involving neurological disorders. Expanding this research to task-based fMRI data could further illuminate how brain networks reconfigure during cognitive tasks, potentially leading to new approaches in understanding brain functionality and disease.