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Workflow for effective integration of community detection algorithms in brain network analysis

Flujo de trabajo para la integración eficaz de algoritmos de detección de comunidades en el análisis de redes cerebrales

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ABSTRACT

This study presents a workflow utilizing network analysis based on community detection methods and functional magnetic resonance imaging (fMRI) to investigate brain connectomics problems. The objective of the study is to enhance the understanding of brain architecture and its clinical implications, particularly in identifying altered connectivity patterns in neurological and psychiatric conditions. Techniques such as intensity normalization and image smoothing were applied to ensure the quality of fMRI data processing. An autoencoder model was employed to analyze functional connectivity networks, and the Louvain algorithm was used to detect communities within these networks. High modularity values were achieved, and validation tests confirmed the robustness of the algorithm used in the analysis. This study advances our understanding of brain architecture and has significant clinical implications by identifying altered connectivity patterns, which may improve the diagnosis and treatment of neurological and psychiatric conditions.

Keywords: brain networks; network analysis; community detection; functional connectivity.

RESUMEN

Este estudio presenta un flujo de trabajo que utiliza análisis de redes basado en métodos de detección de comunidades e imágenes por resonancia magnética funcional (fMRI) para investigar problemas de conectómica cerebral. El objetivo del estudio es mejorar la comprensión de la arquitectura cerebral y sus implicaciones clínicas, en particular en la identificación de patrones de conectividad alterados en condiciones neurológicas y psiquiátricas. Se aplicaron técnicas como la normalización de intensidad y el suavizado de imágenes para garantizar la calidad del procesamiento de datos fMRI. Se empleó un modelo de autocodificador para analizar redes de conectividad funcional y se utilizó el algoritmo de Louvain para detectar comunidades dentro de estas redes. Se lograron altos valores de modularidad y las pruebas de validación confirmaron la robustez del algoritmo utilizado en el análisis. Este estudio avanza en nuestra comprensión de la arquitectura cerebral y tiene implicaciones clínicas significativas al identificar patrones de conectividad alterados, lo que puede mejorar el diagnóstico y el tratamiento de condiciones neurológicas y psiquiátricas.

Palabras clave: redes cerebrales; análisis de redes; detección de comunidades; conectividad funcional.

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Introduction

In the study of biological, social, and technological systems, networks have emerged as a fundamental tool for understanding the complexity of interactions among their components. These networks, characterized by their nodes and connections, exhibit a structure that reflects the organization and dynamics of the systems they represent (Meunier et al., 2010; Newman, 2003). In particular, the human brain, as a complex system composed of a multitude of interconnected regions, has emerged as an important object of study due to its ability to dynamically adapt to a constantly changing environment (Bassett et al., 2011).

Graph theory provides a valuable mathematical framework for studying the architecture of the nervous system, allowing for the identification of key organizational patterns, such as the concept of "communities" (Nicolini et al., 2017). Communities, defined as groups of nodes more tightly connected to each other than to the rest of the network (Figure 1), reveal the modular organization of the brain and may have significant implications for understanding brain functions, diagnosing neurological and psychiatric disorders, predicting clinical outcomes, and developing therapeutic interventions (Tijms et al., 2013).

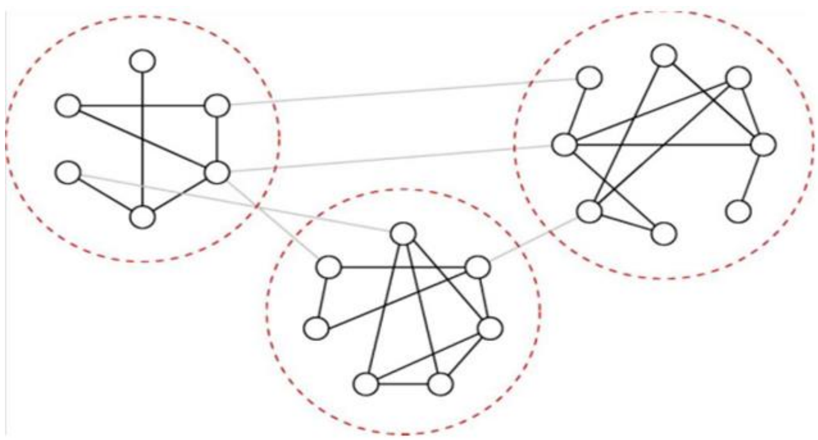

Fig. 1 Communities detected in a network

Source: (Newman & Girvan, 2004).

However, despite advances in community detection in brain networks, significant challenges persist that limit their application and replicability. The lack of a universally accepted and standardized method hinders comparison between studies and consistent interpretation of results (Betzel, 2023; Fortunato & Hric, 2016; Newman, 2006). This lack of standardization is further exacerbated by high variability in functional magnetic resonance imaging (fMRI) data, influenced by individual differences in brain anatomy, signal quality, and experimental conditions.

Interpretation of community detection results can vary widely between studies due to differences in algorithm selection, analysis parameters, and underlying theoretical approaches. This variability, coupled with the lack of validation and replicability of results, raises important concerns in neuroscience research (Nicolini et al., 2017).

Therefore, to advance research on brain functional connectivity networks, it is crucial to address the lack of standardization, inconsistent interpretation, and lack of validation in community detection. This requires the development of standardized and robust community detection methods, as well as the implementation of rigorous validation strategies that allow for evaluating the reliability and stability of results across various datasets and populations. By doing so, we can progress towards a deeper understanding of the functional organization of the human brain and its relevance to mental and neurological health.

The relevance of this research is multifaceted and encompasses both scientific and clinical domains. Firstly, within the scientific context, research on the functional organization of the human brain using functional magnetic resonance imaging (fMRI) techniques and network analysis significantly contributes to understanding the complexity of the human mind. By revealing how different brain regions communicate and coordinate during cognitive and emotional tasks, this research advances our knowledge of the fundamental principles of brain function (Dennis & Thompson, 2014).

Moreover, the application of network analysis techniques in studying functional brain connectivity provides valuable insights into how neural networks are organized and structured in the human brain. This can have important implications in areas such as cognitive and computational neuroscience, helping us better understand how cognition emerges from neuronal activity.

From a clinical perspective, research in this field is directly relevant to the diagnosis and treatment of neurological and psychiatric disorders. Identifying altered patterns of functional connectivity in conditions such as Alzheimer's disease, schizophrenia, autism spectrum disorder, and depression can provide useful biomarkers for early diagnosis and monitoring disease progression. Additionally, this research can guide the development of more specific and personalized therapies aimed at restoring altered brain connectivity in these conditions.

The purpose of the research is to delve into the understanding of the functional organization of the human brain using functional magnetic resonance imaging (fMRI) techniques and network analysis. Through this research, the aim is to identify patterns of functional connectivity among different brain regions and understand how these neural networks contribute to human cognition and behavior.

This approach primarily seeks to unravel the fundamental principles underlying the complexity of the human brain by examining how cognitive and emotional functions are integrated and segregated at the level of brain connectivity. Furthermore, the research aims to explore how these functional networks may be altered in neurological and psychiatric conditions, with the goal of improving the diagnosis, treatment, and understanding of these diseases**.**

Considering the problematic situation described above, the following research problem arises: How can an effective workflow be designed to integrate community detection algorithms into the analysis of functional brain connectivity networks to enhance understanding of the functional organization of the human brain?

The main objective of the research is to design a workflow that enables the efficient application of community detection algorithms to functional brain connectivity networks.

The importance of this research lies in its ability to develop an effective workflow that allows for the integration of community detection algorithms into the analysis of functional brain connectivity networks. By overcoming current challenges in implementing these algorithms, the identification of significant functional communities in the human brain is facilitated, thereby improving our understanding of its functional organization. This advancement will directly contribute to the diagnosis and treatment of neurological diseases by providing a solid foundation for identifying biomarkers and formulating more precise and effective therapeutic interventions. Additionally, by establishing a standardized and reproducible workflow, the replicability of findings is promoted, laying the groundwork for future research in the fields of neuroscience and connectomics.

Computational Methodology

In the study, a series of preprocessing and data analysis procedures were carried out to investigate the organization of functional brain connectivity networks using functional magnetic resonance imaging (fMRI) images and community detection techniques. To standardize the procedure, a workflow was designed (Figure 2) that describes the steps to follow to achieve the research objective. This workflow consists of four main stages: preprocessing of fMRI images to ensure proper data quality, construction and training of a learning model capable of extracting latent representations from the preprocessed images, construction of a weighted graph using the representations extracted by the model, and finally, the application of the community detection algorithm to the resulting graph from the previous stage.

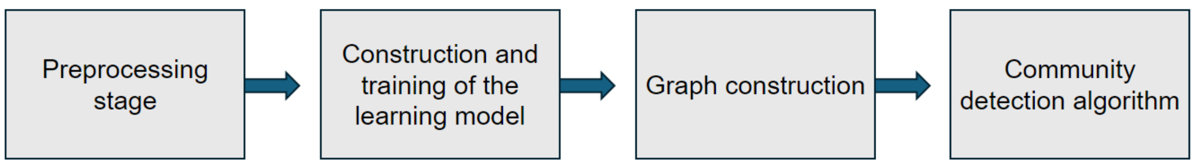

Fig. 2 Proposed workflow.

1 Intensity Normalization

Intensity normalization is essential to ensure comparability between fMRI images acquired from different subjects or scanning sessions (Mohan et al., 2014). Z-score normalization was chosen due to its effectiveness in this type of analysis. By centering the data around zero and scaling it according to the standard deviation, it ensures that all fMRI images have a comparable intensity distribution. This is crucial for accurately detecting patterns of brain activation between subjects or experimental conditions. Additionally, Z-score normalization helps reduce bias in the statistical analysis of fMRI data, facilitating a more precise interpretation of the results (Margulies et al., 2010; Monti, 2011).

2 Image Smoothing

fMRI image smoothing was applied to improve data quality is shown in (Figure 3), reduce noise (Wald, 2019), and ensure reliable detection of areas of brain activation. This technique, commonly used in image processing, involves applying a filter that averages the intensities of neighboring pixels. By doing so, abrupt fluctuations in signal intensity are attenuated, resulting in a smoother and more homogeneous representation of brain activity. In addition to improving the signal-to-noise ratio, smoothing facilitates the identification of areas of brain activation, significantly contributing to statistical analysis.

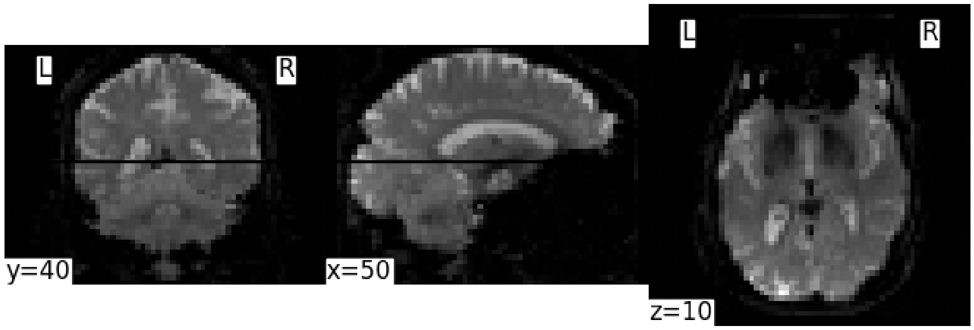

Fig. 3 fMRI image treated with Gaussian smoothing.

3 Autoencoder Model Construction

To capture the latent features of fMRI images, an autoencoder was implemented. This model, widely used in unsupervised learning, consists of an input layer, a hidden layer, and an output layer. The input layer flattened the input data, while the hidden layer provided a latent representation of the images (Peña-Torres et al., 2019). In this study, a dense layer was used for the latent representation and an output layer to reconstruct the original images. The ReLU activation function was employed in the hidden layer to introduce nonlinearities into the model, enhancing its ability to learn complex data representations.

4 Autoencoder Training

The autoencoder was trained using the stochastic gradient descent method to minimize the loss function. An appropriate number of epochs and batch size were specified to ensure model convergence. During training, the performance of the autoencoder on a validation dataset was evaluated to control for overfitting. Optimization of model hyperparameters was conducted rigorously to ensure stability and generalization of the model.

5 Obtaining Latent Representations

After training the autoencoder, the prediction method was used to obtain the latent representations of fMRI images. These representations, compressed encodings of the original images, were used as a basis for network analysis and community detection.

6 Graph Construction and Community Detection

Based on the latent representations, a weighted graph was constructed using correlation metrics. This graphical representation allowed visualization of relationships between different data samples.

Subsequently, the Louvain community detection algorithm was applied to identify underlying structures and organization patterns within the data (Figure 4). This algorithm, based on modularity maximization, is widely used in community detection due to its effectiveness and scalability

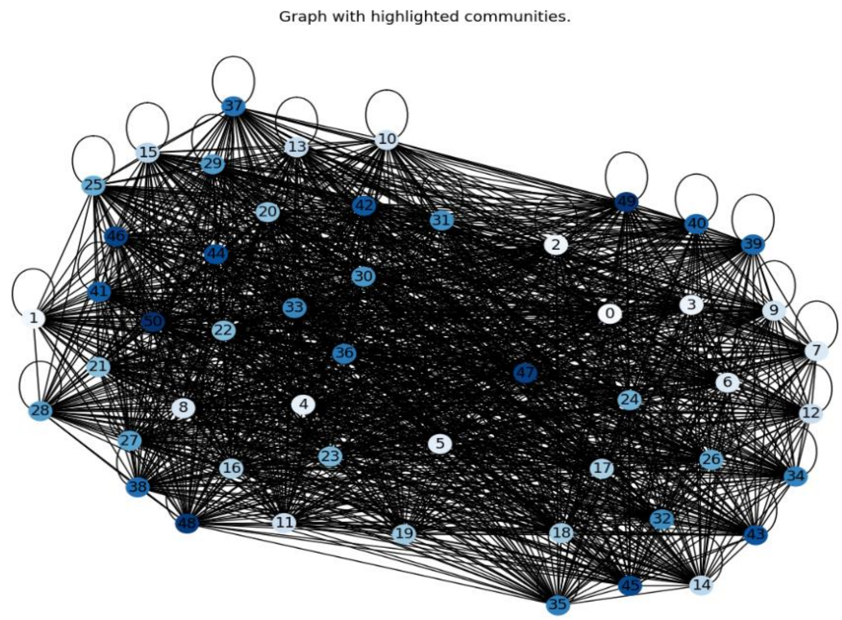

Fig. 4 Graph with highlighted communities.

The combination of these preprocessing and analysis methods provides a comprehensive strategy for investigating the organization of functional brain connectivity networks. The procedures detailed here are designed to be replicable and enable reproducibility of results in future studies. The meticulous selection and application of advanced techniques ensure the robustness and validity of the conclusions drawn in this study.

Results and Discussion

In this study, a collection of analyses was conducted to explore the organization of functional brain connectivity networks using community detection techniques in networks constructed by the data of functional magnetic resonance imaging (fMRI) and. One of the key aspects evaluated was the effectiveness of the Louvain community detection algorithm in identifying underlying structures in the data.

In Figure 5, we present a graph showing the distribution of the community detection results using the Louvain algorithm. Based on the fact that 46 of the 50 fMRI images in the sample yielded satisfactory results in community detection, it reinforces the idea that the Louvain community detection algorithm has a high capacity to identify underlying structures in the studied brain networks. This high success rate supports the reliability and robustness of the algorithm, suggesting that it can be an effective tool for analyzing the organization of functional brain connectivity networks.

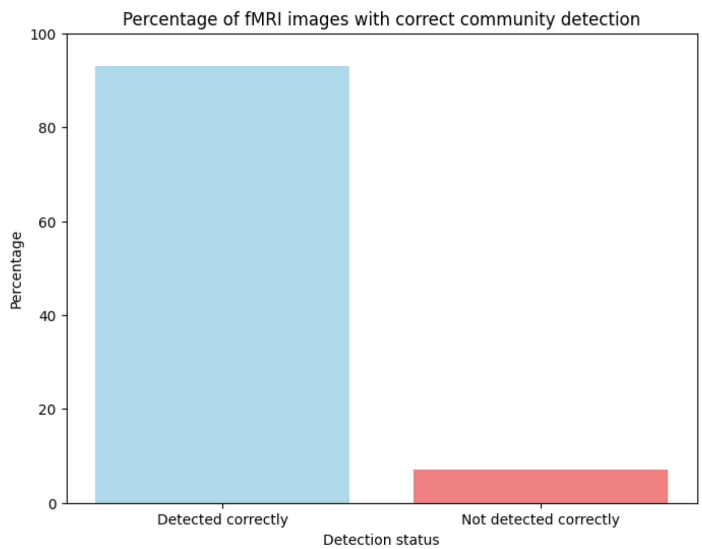

Fig. 5 Percentage of fMRI images with correct community detection.

One of the fundamental criteria for evaluating the effectiveness of the community detection algorithm was the measure of modularity. Modularity is a metric that assesses the strength of the division of a graph into communities (Meunier et al., 2010), where higher values indicate a more modular and organized network structure (Good et al., 2010). In this study, modularity values were calculated for each community detection performed by the Louvain algorithm. The obtained results are reported in (Figure 6).

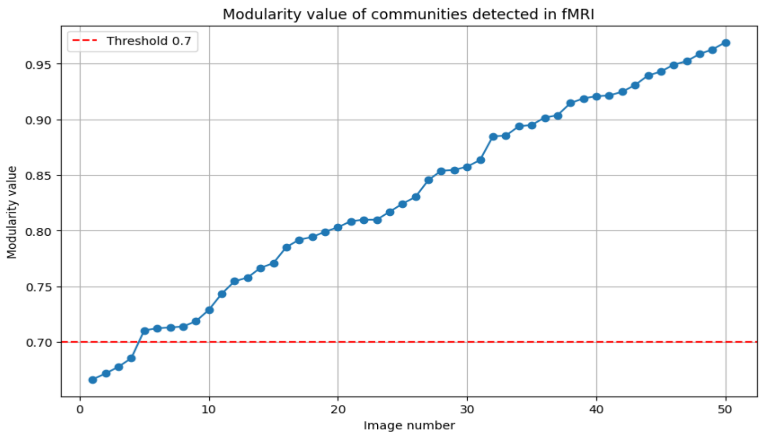

Fig. 6 Modularity value of communities detected in fMRI.

The results revealed that 92% of the modularity values were above 0.7, indicating exceptional quality in identifying communities in the studied functional brain connectivity networks.

These results are highly favorable and support the efficacy of the Louvain algorithm in community detection in complex brain networks. A modularity higher than 0.7 suggests a highly organized and cohesive network structure, reflecting the algorithm's ability to identify groupings of brain regions exhibiting similar functional connectivity patterns, due to its modularity maximization approach, making it ideal for graphs associated with cognition-related neuronal function and age-influenced diseases . This ability is crucial for understanding the functional architecture of the brain and may have important implications in areas such as cognitive neuroscience, clinical neurology, and psychiatry.

Furthermore, these preliminary results underscore the robustness of the methodological approach used in this study. The combination of advanced data analysis techniques, such as community detection and modularity calculation, with high-quality imaging acquisition methods, such as functional magnetic resonance imaging, provides a solid platform for investigating the functional organization of the human brain. The validity of these results is supported by the scientific rigor applied in experimental design, data preprocessing, and statistical analysis.

Conclusions

The research presents a workflow designed to effectively integrate community detection algorithms into brain connectivity networks. The results obtained in the study validate this effectiveness by demonstrating the Louvain algorithm's ability to identify underlying structures in the studied brain networks. The high success rate in community detection, with 92% of the fMRI images in the sample yielding satisfactory results, supports the reliability and robustness of the algorithm. These findings suggest that the proposed approach provides an effective tool for analyzing the organization of functional brain connectivity networks. Furthermore, the results reveal a clear modular structure in the analyzed brain networks, with modularity values exceeding 0.7 in most cases. This high modularity suggests a cohesive organization of brain regions, underscoring the algorithm's ability to identify similar functional connectivity patterns among brain regions.Taken together, these findings support the efficacy of the proposed workflow for investigating the functional organization of the human brain. The combination of advanced data analysis techniques and high-quality imaging acquisition provides a solid foundation for understanding the brain's functional architecture. The results obtained in this study support the validity and effectiveness of the methodological approach used, suggesting its relevance for future research in cognitive and computational neuroscience.

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Conflicto de interés

Los autores autorizan la distribución y uso de su artículo.

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