Classification of Cognitive States using Task-Specific Connectivity Features

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Received: 6 March 2023 | Revised: 24 March 2023 | Accepted: 29 March 2023

 DOI: https://doi.org/10.48084/etasr.5836

ABSTRACT

Human brain activity maps are produced by functional MRI (fMRI) research that describes the average level of engagement during a specific task of various brain regions. Functional connectivity describes the interrelationship, integrated performance, and organization of these different brain regions. This study investigates functional connectivity to quantify the interactions between different brain regions engaged concurrently in a specific task. The key focus of this study was to introduce and demonstrate task-specific functional connectivity among brain regions using fMRI data and decode cognitive states by proposing a novel classifier using connectivity features. Two connectivity models were considered: a graph-based task-specific functional connectivity and a Granger causality-transfer entropy framework. Connectivity strengths obtained among brain regions were used for cognitive state classification. The parameters of the nodal and global graph analysis from the graph-based connectivity framework were considered, and the transfer entropy values of the causal connectivity model were considered as features for the cognitive state classification. The proposed model achieved an average accuracy of 95% on the StarPlus fMRI dataset and showed an improvement of 5% compared to the existing Tensor-SVD classification algorithm.

Keywords-functional MRI; functional connectivity; nodal analysis; graph analysis; causal connectivity; cognitive state classification

I. INTRODUCTION

Functional connection in neuroscience is the covariation between spatially dispersed brain regions or brain signals. Typically, brain signals are captured using a functional neuroimaging technique, such as electroencephalography (EEG), functional Near Infrared Spectroscopy (fNIRS), functional MRI (fMRI), Magnetoencephalography (MEG), and electrocorticography (ECoG). In general, Functional Connectivity (FC) experiments are conducted under resting state conditions (without any task demands or external stimulation). However, understanding how external stimuli modulate FC has attracted the research interest. During the recent decades, fMRI has been highly successful in establishing functional relations between brain regions. Functional MRI is the most popular method for learning and delineating human brain regions that change their activation level while performing a specific task. The brain imaging modality can reveal information about neural systems that are functionally coupled together for specific stimuli or tasks. Functional neuroimaging can provide deep insight into the neurobiological underpinnings of disabilities. The concept of finding cognitive functions, as referred to by the connectivity networks of brain regions, is crucial in interpreting neuroscientific data [1]. The FC patterns computed over some time comprise enough details to identify the task the individuals are working on [2]. However, whether task-specific or resting-state available connectivity interactions are two manifestations that arise from the same underlying neural phenomenon is still under debate.

Human cognition generally involves dynamic and complex interactions between dispersed cortex and subcortical areas [3]. The brain at rest is usually represented in a small number of networks compared to the number of functions it performs. Revealing the putative correspondence between specific FC features and different aspects of task performance is very important. The studies on distributed patterns of FC are used to classify or decode cognitive states [4]. Task-based connectivity studies produce different FC patterns for different cognitive tasks.

Researchers have been measuring functional relationships among brain areas using neurophysiological data acquired from neural components. Functional and effective connectivity are the two aspects of functional interactivity [5]. When the actions of two brain components are correlated, they are said to be linked. The impact of one neuronal entity on another is referred to as an effective connection that establishes a causal relationship between the brain areas. FC analysis is a model-free approach; on the contrary, effective connectivity is a model-based approach [6]. FC is a simple phenomenon observed from correlations and represented in terms of covariance. The key aspects of the covariance are the patterns of correlated activity delimited by pairwise covariances. Modeling human brain networks is an essential step in determining connectivity patterns. In this work, the human brain is shown as a network through graph-based approaches. The model provides a graphical representation in the form of nodes and edges. The causal connectivity among the brain areas is analyzed using a pipeline framework formed by Granger causality and entropy. Machine learning classifiers have been used for the detection and classification of objects in several scientific applications [7-9].

Resting-state neuroimaging studies soon identified a list of canonical FC patterns that are consistently discovered when at rest and FC patterns and task-evoked activation patterns [10]. The correlations between functional time series are used to assess patterns of brain functional connectivity. Traditional correlation techniques can capture FC and provide a relationship between two Regions of Interest (ROIs) while ignoring the interaction between other ROIs. For instance, the second-ordered relations could give a significant understanding of neurological processes associated with brain regions [11]. As a hypergraph's edges may connect any number of ROIs rather than just two, it has been used to specify the high-order interactions between many ROIs (or vertices) [12]. Instead of simply setting each hyperedge's weight to 1, the hypergraph is used to learn adaptively more flexible hyperedge weights, assuming that all ROIs at each time point are seen as a smooth signal on the hypergraph.

A typical FC network for different subjects is represented by a graph-based hypergraph derived from the fMRI time series. The obtained connectivity is further used to classify Alzheimer's disease [13]. Inter-individual variations in resting FC patterns have been linked to various phenotypic qualities, as well as clinical problems (e.g., mental and neurological illnesses), and can be used to predict behavioral performance and identity [14]. Beyond what mechanistic insight they may (or may not) provide on interregional brain interactions and their relation to cognition, FC estimates can be useful, according to the results of [15].

The graph-based method provides more information on topological reconfiguration in response to external stimuli or task modification [16-17]. The framework explains how brain functions and structure are related. Both functional and structural networks have been shown to organize intrinsically when information is transferred and related hub regions are formatted [18-19]. Most FC methods used with BOLD fMRI data are constrained in their ability to provide details on the specific topology of the underlying causal graph, but still, they restrict the range of network topologies that may be considered [20]. Even though resting state FC research has contributed to a deeper grasp of how the brain works in various subjects, it has been limited by the application of approaches that cannot resolve critical motivating difficulties concerning task-specific FC in the context of cognitive task categorization and effective connectivity among the brain areas. This study used graph-based FC analysis and entropy-based causal connection for connectivity analysis, and the connectivity parameters obtained were used as features to decode cognitive states.

II. PROPOSED TASK-SPECIFIC CONNECTIVITY ANALYSIS FOR COGNITIVE STATE CLASSIFICATION

The study of FC of the human brain has piqued the interest of the scientific community. Defining and comprehending how various brain regions interact requires identifying functional connectivity networks using fMRI data. FC aims to find statistical connections between two or more ROIs. The utility of connectivity analysis is also applied to the classification of fMRI data. The connection characteristics are used to create a classifier to categorize cognitive states. Figure 1 shows the proposed task-specific connectivity analysis framework.

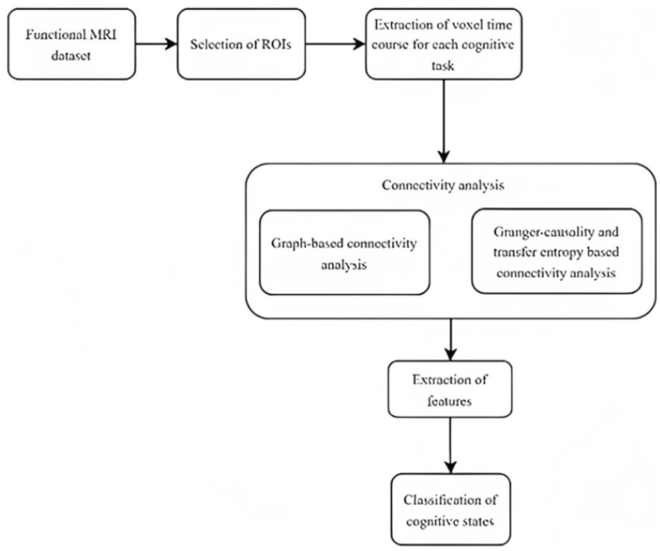


Fig. 1. Proposed connectivity analysis framework for decoding the cognitive states.

The proposed model is a 5 step approach for cognitive state classification. In Step 1, brain regions or ROIS are selected from the fMRI dataset. Since fMRI data comprise a significant number of ROIs, it is often essential to select appropriate ROIs from the pool. Step 2 involves the extraction of the voxel time course. As fMRI data are usually represented in ROIs, each ROI comprises a voxel time course. Since the proposed model operates with time series, the required voxel time course is extracted from each ROI to perform connectivity analysis. Step 3 involves the connectivity analysis over the extracted time series. This step performs the functional and causal connectivity analyses to find the connectivity relation among the ROIs. Connectivity analysis includes the graph-based connectivity analysis and the Granger causality Transfer Entropy (TE) framework. The details of the graph-based and causal connectivity analyses are elaborated below.

A. *Graph-based Connectivity Analysis*

The behavior of networks is described in terms of nodes and their connections in a graph theory study on fMRI data. In the human brain network, brain areas are nodes and connections are edges. Histological, functional, or anatomical parcellation schemes can be used to designate the sections of the brain graph nodes. Interactions among the regions are used to define the edges. After pooling the pairwise connections between nodes in the network, the characteristics of a brain graph are assessed to estimate connections at local and global levels. Relationships that are both temporal and functional with other regions are characterized by these qualities. This study investigates the functional connection strengths among the brain areas for task-specific fMRI data. The interconnectedness between ROIs (nodes) would be quantified once the cohorts for each participant and the brain atlas are built. Using brain network analysis, the connection between the ROIs (nodes) is assessed and the statistical correlation between them is measured using graph analysis. This study utilized Pearson's correlation for both individual and group analyses. A weighted undirected graph was used to create a functional connectivity graph and several global and nodal parameters were computed for the study.

B. *Task-Specific Connectivity Analysis using Granger-Causality and Transfer Entropy Framework.*

Causal connectivity is the comprehension of the causal connection between different brain areas. To conduct task-and disease-specific research, it is assumed that fMRI-based causal connectivity approaches would shed light on these connection differences. The results of a causal connection study show a causal or significant reliance between ROIs. Effective connection explores the causal chain between different brain areas. The co-activation of brain regions is the basis for FC. Understanding the causal connection between various brain areas is referred to as causal connectivity. Effective connection analysis is provided by the Granger Causality (GC) [21] technique using a data-driven methodology. Each ROI is regarded as a variable for the GC analysis when assessing causal connection. A time series T1 impacts T2 if the information from T1's history may be used to anticipate the values of T2's future observations. When this criterion is met, information flows from T1 to T2. A time series-based brain connectivity estimate was carried out to investigate the functional interconnections between the ROIs. In this connection investigation, the primary goal was to estimate the Granger causality-based task-specific causal interactions between the ROIs. TE calculates the causal strength in a given situation. The suggested human brain cognitive connectivity analysis was applied to StarPlus fMRI data and the Granger causality technique was used to assess the influential connections among brain areas.

In Step 4, the feature vectors were formed from the nodal and global parameters of functional connectivity analysis, and TE values were obtained for the Granger causality. The obtained features were treated as attributes for cognitive state classification. In Step 5, a classifier was developed using features extracted in the previous step. Three classifiers, namely Gaussian Naïve Bayes, Support Vector Machine, and KNN classifiers, were built for cognitive state classification. The proposed classification model based on the connectivity features was verified on standard StarPlus fMRI data.

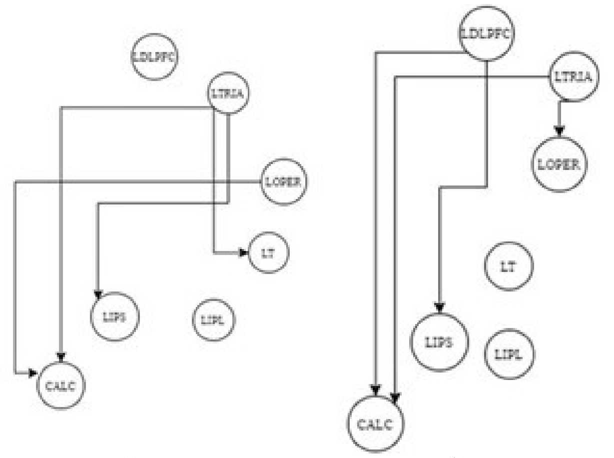
III. STARPLUS FMRI DATA

The suggested approach was confirmed based on the StarPlus fMRI data [22], which provide easily accessible fMRI data for the categorization and study of the human brain's cognitive states. The captured brain volumes are divided into a set of trials in the two-phase experimental design. For each trial, subjects are required to determine if a statement or symbol was followed by a different sentence or symbol and negotiate properly.

The first phase involved displaying one of two sentences to the subject: "The Star is above the Plus" or "The Star is below the Plus." After 4 seconds, this will disappear from the screen and an empty screen will appear. An image stimulus will be shown for 4 seconds following 4 seconds of the screen being blank. The individual is required to touch the button after 4 seconds of visual stimulation to indicate whether or not the statement accurately describes the image. Brain images are captured during the experiment every 0.5 seconds. Throughout the experiment, each participant has a 15-second rest or fixation interval. The experiment is repeated in the second phase, but this time, the picture and phrase stimuli are exchanged. The subjects in the dataset have approximately 5000 voxels marked as 25 ROIs. As reported in the literature, 7 out of 25 ROIs, CALC, LDLPFC, LIPS, LIPL, LOPER, LT, and LTRIA, are used for the classification and analysis of the cognitive behavior of the brain.

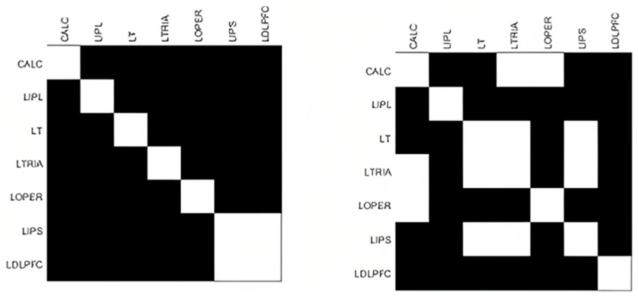
IV. RESULTS AND DISCUSSION

Functional brain networks show how the brain's architecture and behavior are related. Functional networks built using fMRI data tailored to a certain activity aid in gaining insight into how multitasking affects brain structure. In [23], the graph-based connectivity model was used to determine the connectivity strengths among the cognitive tasks. The graph-based connectivity model has not been used to build the classifier for cognitive state classification. In [24], the causal connectivity model was used for cognitive state classification, where the model considered 11 ROIs from a similar StarPlus dataset. This study combined both connectivity model parameters as features for the classification of cognitive states. There are several disciplines in which graph theory and GC analysis are useful. Nevertheless, graph theory and GC are new when applied to cognitive fMRI data. For cognitive data, nodal and global parameters are used to evaluate the interconnectedness between ROIs, and TE is used to assess the causal potency of those connections. The StarPlus fMRI dataset voxels are grouped into 25 ROIs. Of these, the 7 most important ROIs were chosen for further study. The ROI level analysis reveals two distinct functional networks for image and sentence tasks, as shown in Figure 2. The connectivity graphs are defined from nodal measurements for each task. Figure 3 shows the correlation matrix for each task (visual and verbal) for the StarPlus fMRI data.



(a) (b)

Fig. 2. (a) Obtained FC network for a sentence task, (b) obtained connectivity network for a visual task.



(a) (b)

Fig. 3. (a) Acquired binary weighted matrix for the visual task, (b) acquired a binary weighted matrix for the verbal task.

The causal connectivity analysis was conducted using the GC approach, and the corresponding causal strengths were obtained from Transfer Entropy (TE). Although it is used to analyze neuroimage data, the GC-TE framework is unique in the context of task-specific connectivity analysis. Consequently, 6 subjects from the StarPlus fMRI data were subjected to the GC test. An analysis utilizing a Vector Autoregressive Model (VARM) can characterize GC. The model's order was set to 2, meaning the ROI time course will be modeled using the previous two values of the time series data. This study used a classifier based on graph analysis and causal connection characteristics to identify the cognitive states in the StarPlus fMRI data. Voxels selected using a maximum margin criterion based on clustering define the ROI time series. Feature vectors are formed by the concatenation of graph analysis, such as nodal and global parameters, and TE values from causal connectivity analysis. Table I shows the classification accuracy for the SVM, GNB, and KNN classifiers. The classification was carried out in a Leave-One-Out fashion. Table II shows the classification accuracy results for the training-test scheme, where 80% of the data was utilized for training and 20% for testing. The proposed classification framework achieved an average accuracy of 95% for the 6 subjects in the StarPlus fMRI data. These results were compared with those reported in [25] using the tensor Singular Value Decomposition (t-SVD) framework for the classification of cognitive states. The t-SVD framework achieved a classification accuracy of 90%.

TABLE I. LEAVE ONE OUT CLASSIFICATION ACCURACY (%) FOR STARPLUS FMRI DATA ACROSS THE CLASSIFIERS

S. N.	Subject	SVM (%)	KNN (%)	GNB (%)
1	05710	78	95	84
2	05680	78	96	78
3	05675	82	98	95
4	04847	64	94	80
5	04799	74	92	70
6	04847	76	94	75
Average		75.3	94.8	80.3

TABLE II. TRAINING-TEST SCHEME CLASSIFICATION ACCURACY (%) FOR STARPLUS FMRI DATA ACROSS THE CLASSIFIERS

S. N.	Subject	SVM (%)	KNN (%)	GNB (%)
1	05710	60	98	75
2	05680	75	96	78
3	05675	82	95	94
4	04847	60	93	78
5	04799	75	94	72
6	04847	64	94	76
Average		69.3	95	78.8

V. CONCLUSION

The classification of cognitive states is achieved using connectivity features. The functional connectivity models considered in this work included the graph analysis framework and the Granger causal connectivity analysis framework. The analysis was conducted using functional MRI data having a pair of cognitive states. The ROI connectivity analysis provides insight into the ROI connectivity strengths. This work was identified by a graph analysis method. Data from ROIs' voxel time series were fed into the system, a brain atlas was developed, and both global and nodal factors were considered while calculating connection strengths. In the case of causal connectivity analysis, the Granger causality transfer entropy paradigm was applied to assess the strength of causal connections between ROIs. Connectivity analysis was carried out using the StarPlus fMRI data. The connection of each ROI was evaluated and Granger causal connectivity was used to perform causal or influential connectivity. Nodal and global graph analysis parameters of the graph-based connectivity framework were considered, and the transfer entropy values of the causal connectivity model were considered as features for cognitive state classification. The proposed classification model achieved an average classification accuracy of 95%. The results obtained were compared with the existing tensor SVD-based classification which achieved a 90% classification accuracy. This study used graph-based and causal connectivity analysis parameters for the classification of cognitive states. The proposed framework produced a new classifier with connectivity features as input in the context of decoding brain states.

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