# Graph Theoretical Analysis of Functional Connectivity In The Brain During Visual and Auditory Tasks

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## 1 Introduction

In recent years, there has been explosive growth in the number of neuroimaging studies performed using functional Magnetic Resonance Imaging (fMRI). Functional MRI is a non-invasive technique for studying brain activity. It relies on the fact that cerebral blood flow and neuronal activation are coupled. When an area of the brain is in use, blood flow to that region also increases. Deoxygenated blood is paramagnetic while oxygenated blood is diamagnetic. We use this property to detect activated brain regions in Blood Oxygen Level Dependent (BOLD) fMRI. During the course of an fMRI experiment, a series of brain images are acquired while the subject performs a set of tasks. Each image consists of a number of uniformly spaced volume elements, or voxels, that partition the brain into equally sized boxes. The image intensity from each voxel represents the spatial distribution of the nuclear spin density in that area. Changes in the measured signal between individual images are used to make inferences regarding task-related activations in the brain. A fMRI study thus generates massive amounts of noisy data with a complex spatio-temporal correlation structure. Statistical analysis plays a key role in extracting useful information such as locations of enhanced brain activity during cognitive tasks, functional brain connectivity etc.

Studies relating to the extraction of functional connectivity from fMRI data have rapidly translated to studies of brain network organization. The brains functional systems have been reported to exhibit features of complex networks such as small world topology, highly connected hubs and modularity.

In this work, we use two freely available fMRI datasets- the auditory fMRI dataset and the face fMRI dataset to obtain functional brain connectivity during the performance of simple auditory and visual tasks. We use this functional connectivity information to model the brain as a network of co-activated regions and analyze the graph theoretic properties of this network.

# 2 Methods

## 2.1 fMRI Datasets

The auditory dataset is from the experiment conducted by Geraint Rees at the FIL methods group. This data set comprises of whole brain BOLD/EPI images. 96 acquisitions were made ($TR = 7s$) from a single subject, in blocks of 6, giving sixteen 42 second blocks. Each acquisition consisted of 64 contiguous slices ($64X64X64, 3X3X3mm^3 voxels$). The condition for successive blocks alternated between rest and auditory stimulation, starting with rest.
The face dataset is from the work of Dolan et al. This is a $2X2$ factorial study with factors "fame" and "repetition". Famous and non-famous faces were presented twice against a checkerboard baseline. The subject was asked to make fame judgements by making key presses. There are thus four event-types of interest: first and second presentations of famous and non-famous faces, which we denote as N1, N2, F1 and F2. We include only two event types in our study: N1 and F1. Images were acquired using continuous Echo-Planar Imaging (EPI) with $TE = 40ms$, $TR = 2s$ and 24 descending slices ($64X64, 3X3mm^2$), 3 mm thick with a 1.5 mm gap. A total of 351 images were acquired.

## 2.2 Statistical Analysis of fMRI Data

We used the Statistical Parametric Mapping (SPM8) Matlab toolbox for the analysis of fMRI data from the two datasets. The data was preprocessed using the standard procedure: Realignment, Slice time correction, Co-registration, Segmentation, Normalization and Smoothing. A categorical model was then specified and the parameters of the model were estimated. A bug was detected in the SPM toolbox at this stage and was reported to the creators.

## 2.3 Extraction of Functional Connectivity from fMRI data

Having estimated the model parameters, we used the CONN Matlab toolbox to obtain brain functional connectivity. CONN can only provide the functional connectivity between

Regions of Interest (ROIs) and not between individual voxels. To obtain a network with a large number of nodes, we use a ROI parcellation where each ROI is a $10mm^3$ box.

### 2.4 Graph Theoretical Properties of the Functional Brain Network

After getting the data of the network, we explicitly constructed the graph, taking the voxel regions as vertices and functional connectivity between them as edges. Once we had the graph, we used the NetworkX, MatPlot and Community libraries in Python to analyze the various properties of this graph and compared it with a randomly generated graph of the same size.
The specific properties that we analyzed were :

1. Small world properties Low characteristic path length but high clustering coefficient
2. Modularity
3. Transitivity
4. Community Structure
5. Efficiency of 3D spatial arrangement of voxels in the brain.

## 3 Results

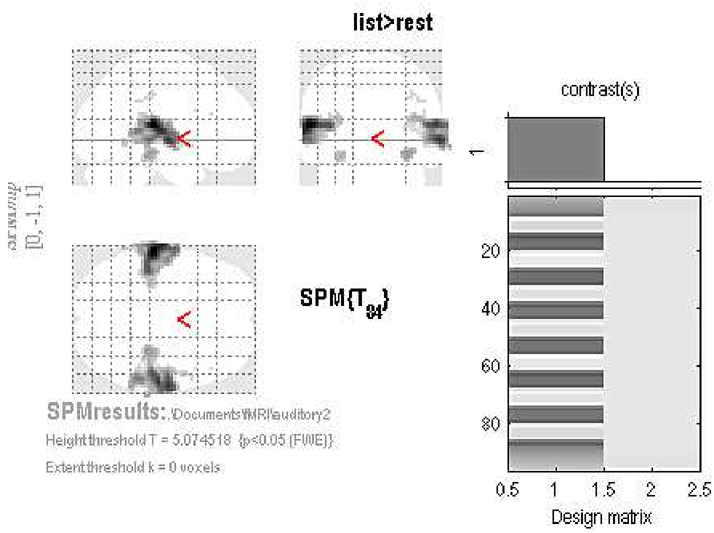


Figure 1: Localization of brain activation during the auditory task.

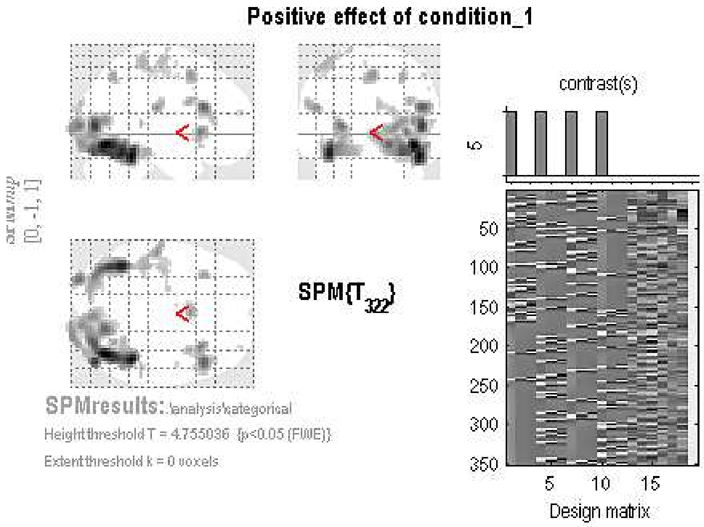


Figure 2: Localization of brain activation during the visual task.

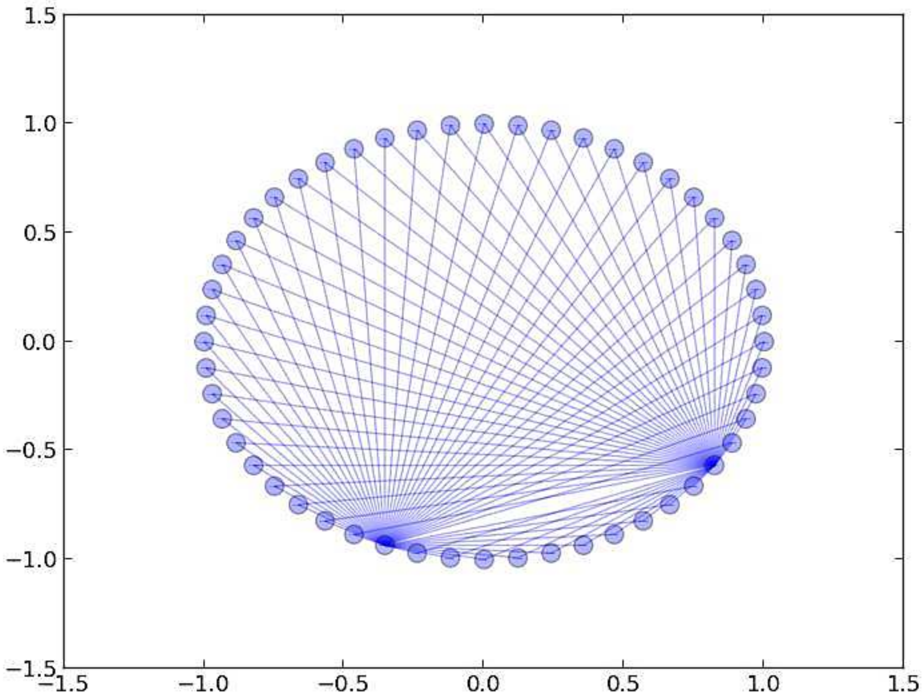

Figure 3: A scaled representation of the graph obtained.

- There were 2287 vertices [voxel regions] and 4520 edges [functional connections between voxels] in the graph.
- In case of the visual input fMRI data, BA-17 [Broadmann Area 17] was the central hub, with 1124 neighbors. This has also been verified numerous times in other studies, which place BA-17 in the visual cortex.
- Similarly, in case of the audio input fMRI data, BA-1 [Broadmann Area 1] was the central hub, with 570 neighbors.
- The graph exhibited small world topology, when compared with random sparse networks. The random graph had high characteristic path length, while our graph had low characteristic path length due to presence of central hubs.
- Also the clustering coefficient in the generated graph was higher than a random graph.
- In a random network, the diameter of the graph is higher [9] compared to the diameter of our brain network.
- Compared to random networks, the modularity is high.
- Compared to random networks, the transitivity is also high.
- The high values of modularity and transitivity also confirm the existence of community structure in the brain network.
- We were also able to verify that economises 3D anatomical placement of voxel regions to increase wiring efficiency. Since the fMRI data gave us the relative co-ordinates of many voxel regions of the brain, we used this data to calculate the average space distance between voxels that are functionally connected and between those which are not functionally connected.

  The results we got showed that the average distance between the connected voxels is less than the average distance between voxels that are not connected.
  Thus, we may infer that in the brain, the 3D spatial arrangement of the connected voxel regions is efficient.

## 4 Conclusion

As our results showed, and as we expected, the brain network exhibits a lot of properties which would lead to an efficient information transfer across the various regions of the brain, and at the same time, it also optimizes the spatial distance between connected regions of the brain to minimize the wiring cost of the brain. The confirmation of these properties of the brain will further encourage research into the evolution of the brain to its current complex form. The methods and techniques used in this project can further be extended to compare different brain networks.

Further research could be done on how the functional connections in the brain evolve with age, by comparing the brain networks of people of different age groups. Another frontier in this direction could be to compare brain networks of humans with other species, to study the process of evolution of the brain. Clearly, there is much scope of exciting research in the field of extracting functional connectivity from fMRI data and studying functional brain networks and a lot remains to be discovered about the network properties of the brain.