Controllability of Brain Networks

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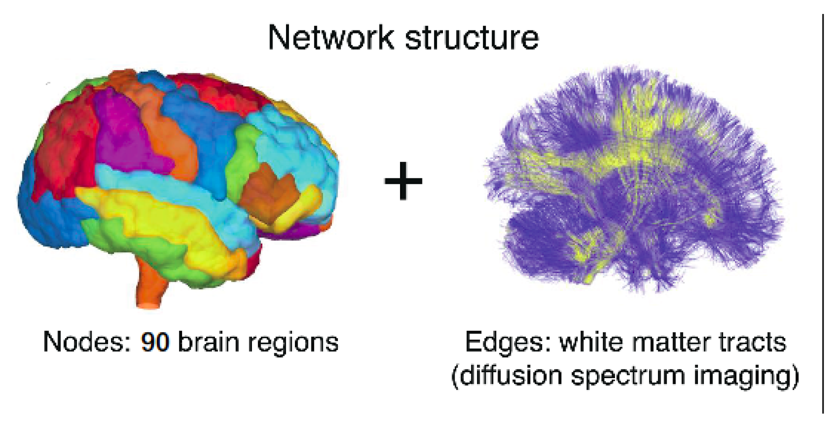
Introduction

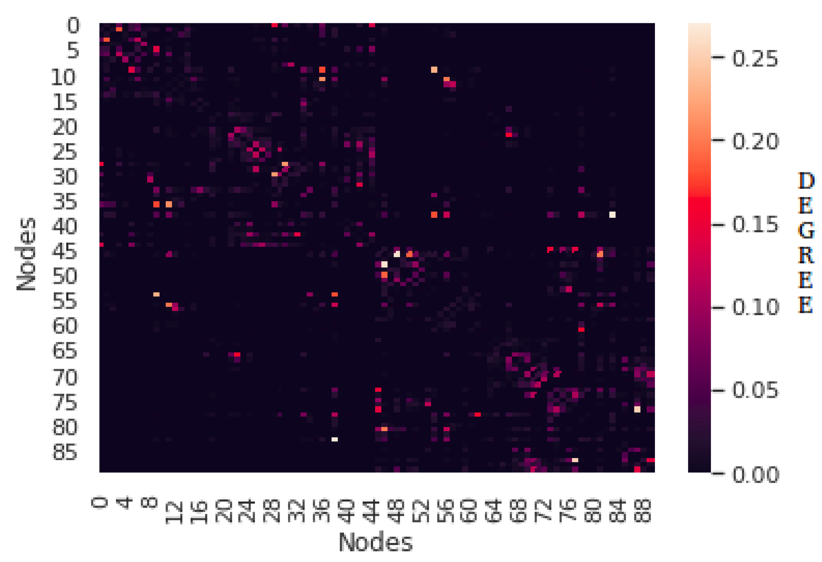
The aim of the project was to study the dynamics of the brain network by selective stimulation of different nodes and the corresponding brain states. For this, a non-linear model of brain dynamics was chosen and the behaviour of local and global stimulation of brain region was observed. Brain regions are clustered together in a set of 90 nodes according to specified Atlas parcellation scheme and an adjacency matrix was obtained. Network control theory(NCT) is deployed to study regional stimulation and to validate the findings with a non-linear model. We conclude that NCT can successfully be used for predictions of regional stimulation and it's effect on other brain regions. The procedure is repeated for 10 different subjects, it was observed that the dynamics and NCT measures vary between subjects.



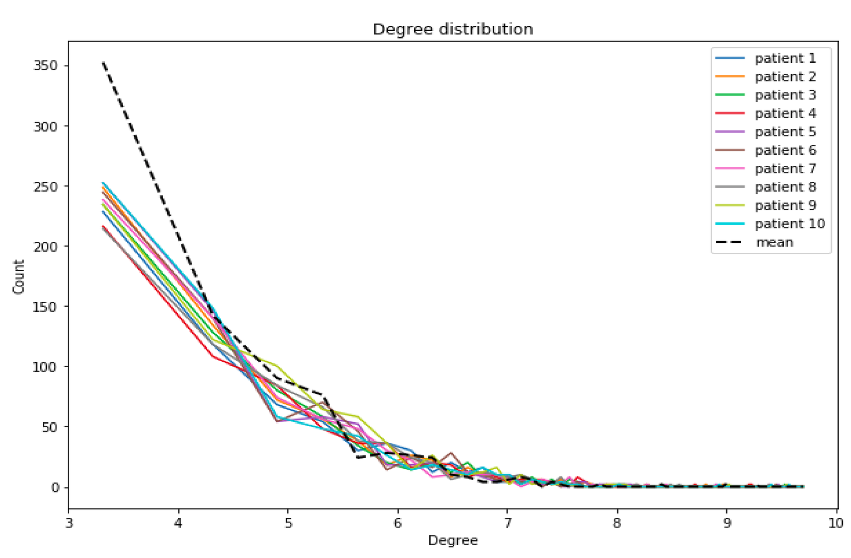
Muldoon et al. 2016 [1]

Structural Connectivity

Structural connectivity is defined as the degree with which a node is connected to other nodes in the network. The degree distribution of the network was obtained using the network adjacency matrix and it was observed that most of the nodes in the network have less degree which corresponds to low structural connectivity.



Structural connectivity matrix: The highlighted areas in the matrix are the nodes with high degree. The upper left quarter represents the left brain hemisphere and the lower right corresponds to the right hemisphere.



Degree distribution of the connectivity matrix Each line corresponds to one subject, with the black line corresponding to the mean

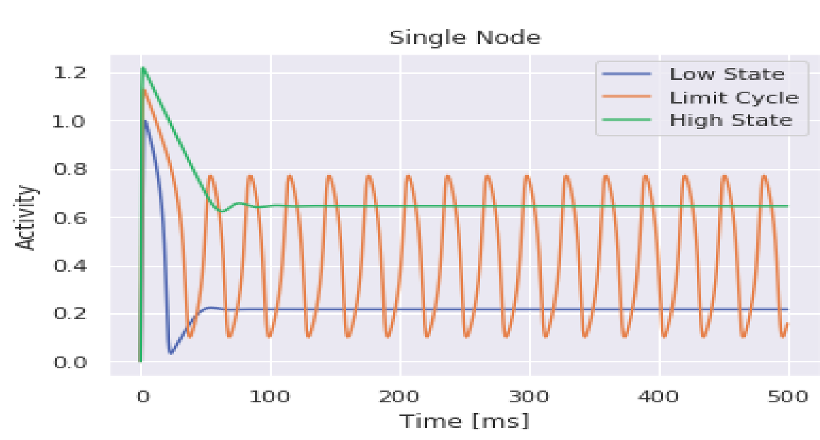
Network Dynamics

Single Node

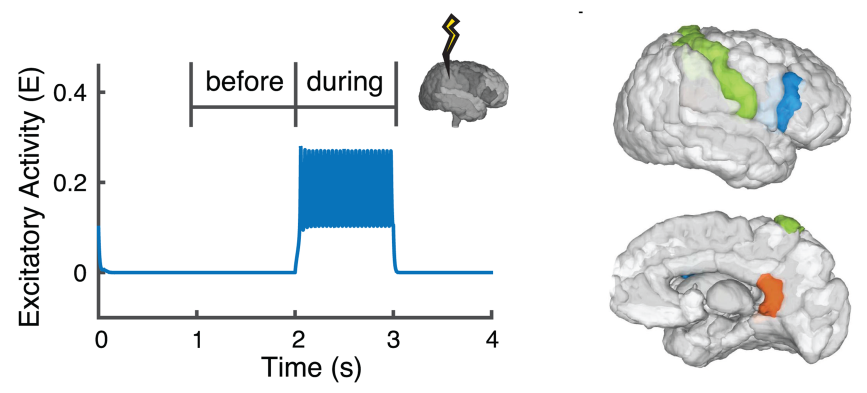
The regional mean-field dynamics of the single node is modelled using FritzHugh Nagumo(FH-N) oscillator.

$$\frac{du}{dt} = \epsilon g(u) - w + I,$$
$$\frac{dw}{dt} = u - aw$$

An important feature of the FH-N oscillators is that it exhibits one of three states, depending upon the amount of external current applied to the system. When no external current is applied (I = 0), the system relaxes to a low fixed point. For moderate amounts of applied current, the oscillator is pushed into an oscillatory limit cycle, and if sufficiently high amounts of current are applied, the system settles at a high fixed point.



Network

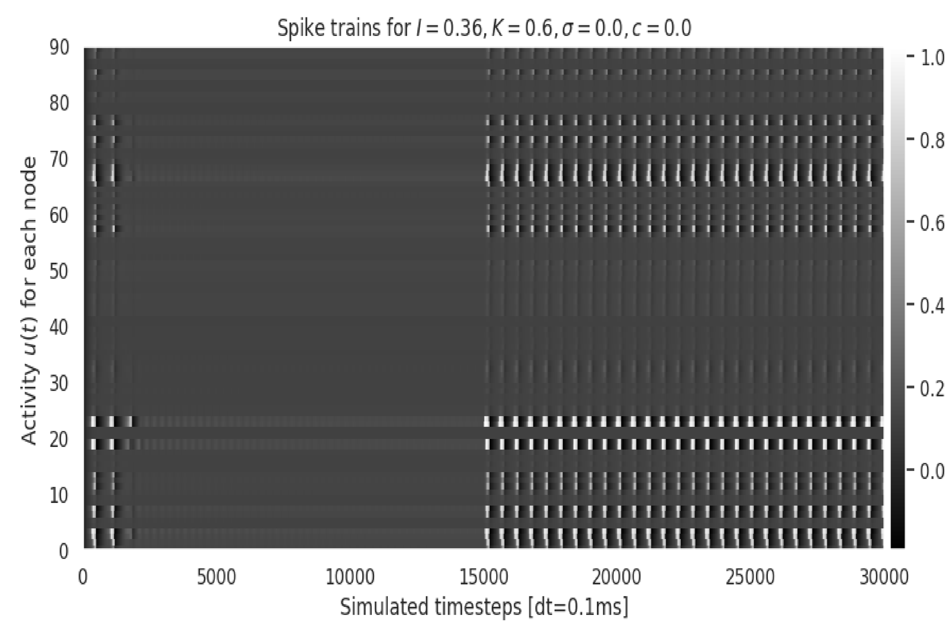


Muldoon et al. 2016 [1]

The bifurcation point at which the system jumps into the limit cycle was obtained for each subject, by keeping the current constant and varying the coupling coefficient. The system was adjusted very close to the bifurcation point and the behaviour of the system is observed when control is applied to single node with two measures. Namely, Energy and Functional effect.

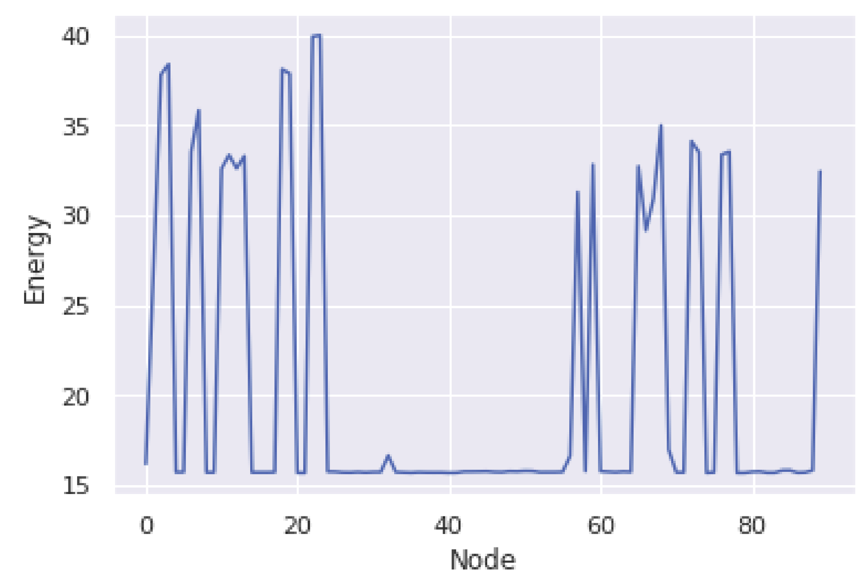
Functional Effect

We assess the pairwise change in brain states by subtracting the correlation values obtained in with-stimulation and without-stimulation windows. We then measure the average change in functional brain states, termed as functional effect, as the absolute value of this difference averaged over all region pairs. Greater effect means greater effect of stimulation on brain states.



Energy

The energy of the system is calculated when input is applied to a single node iteratively and the values are squared and summed over time. It was observed that nodes with high degree exhibit a high energy.

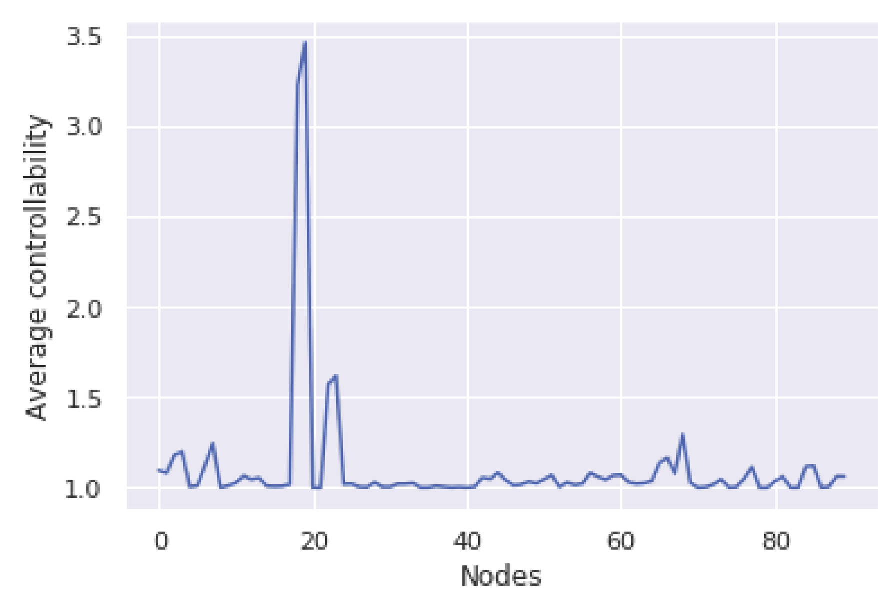


Linear Control Measures

For simplification of the non-linear dynamics of the structural network, we deploy linear network control theory and obtained controllabitily measures based on the structrual connectivity using the network adjacency matrix. Here, we assess two different types of regional controllability measures derived from our structural brain networks: average controllability and modal controllability.

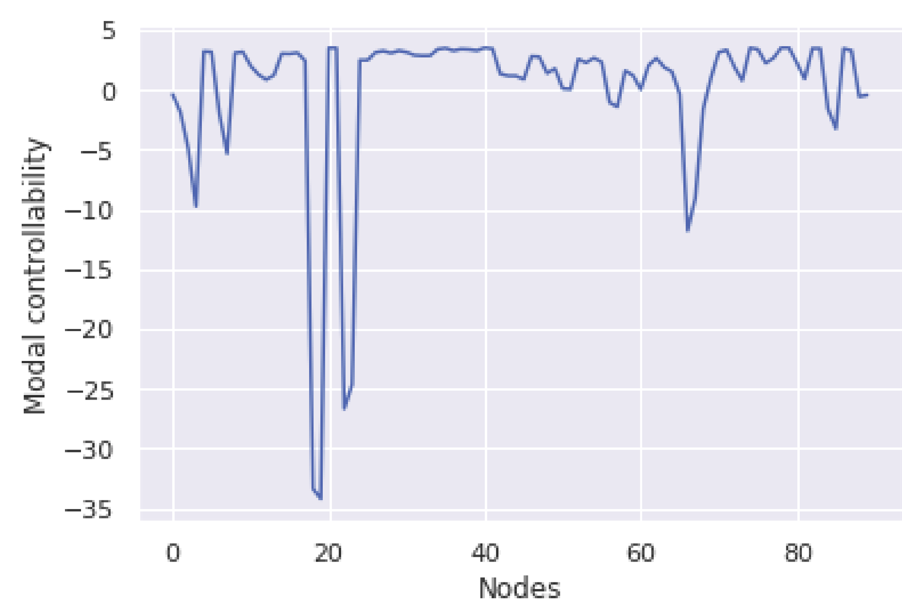
Average Controllability

Average controllability of a network equals the average input energy from a set of control nodes and over all possible target states. Regions with high average controllability are, on average, most influential in the control of network dynamics over all nearby target states with least energy.



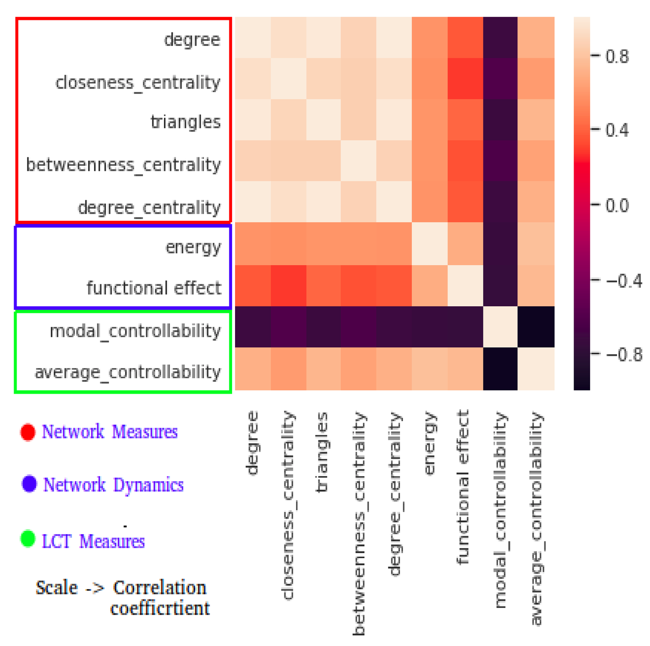
Modal Controllability

Modal controllability refers to the ability of a node to control each evolutionary mode of a dynamical network, and can be used to identify states that are difficult to control from a set of control nodes.



Network Measures and Correlations

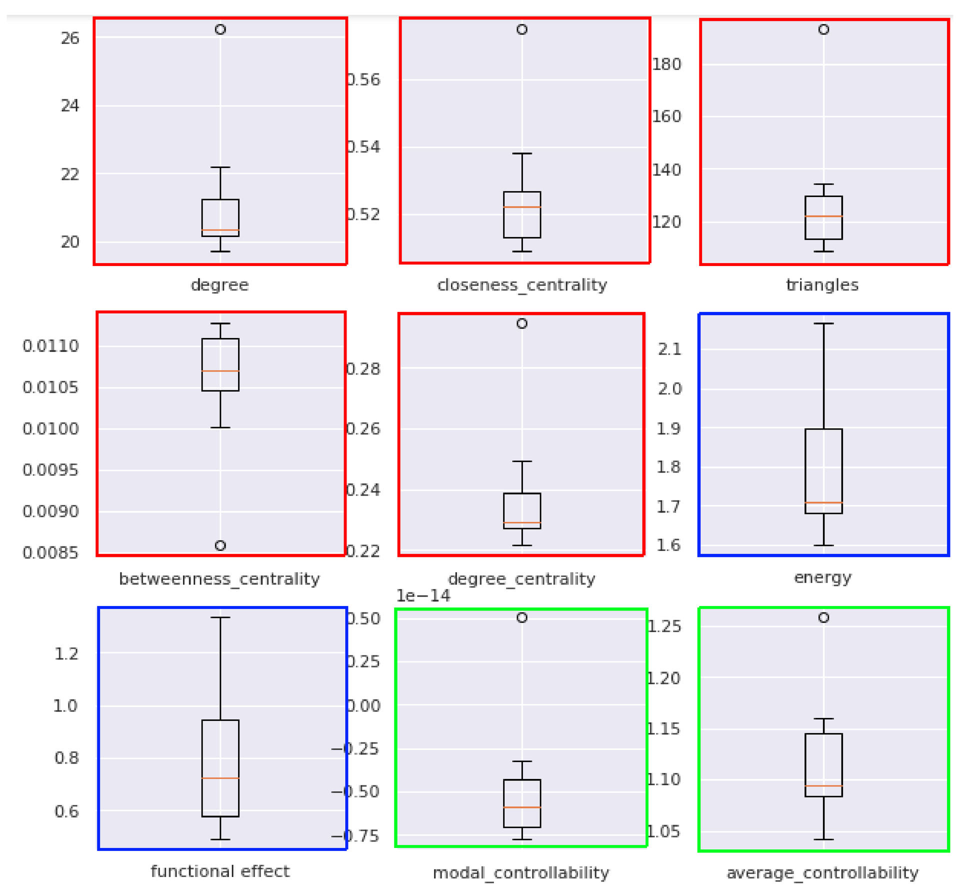
We characterize different aspect of the network using various network such as Degree, Closness Centrallity, Betweenness Centrality and Triangles. We prepared a correlation matrix between network measures, LCT measures and dynamics measures. We also tried to find the variability of these measures between subjects. We observe a strong positive correlation between energy, functional effect and average controllability but a negative correlation between modal controllabiliy and the rest.



Correlation matrix between network measures, LCT measures and dynamics measures.

Variability Between Subjects

It was found that the measures show a lot of variability between subjects. But the network dynamics measures really stood out among all other measures.



Variability of measures between subjects.

Inferences

It is observable that linear model can successfully approximate the regional controllability. It is also observable that nodes with high average controllability have high functional effect. Which means they controlling these nodes can effect the entire network. It is also observed that the LCT measures, network dynamics and network control measures vary between subjects. Though the scale of variability is larger with measures of non-linear dynamics than the LCT measures. Therefore, it is recommended to calculate the control measures for each individual rather than doing it for a mean structural connectivity matrix.

References

[1] Muldoon SF, Pasqualetti F, Gu S, Cieslak M, Grafton ST, et al. (2016) Stimulation-Based Control of Dynamic Brain Networks. PLOS Computational Biology 12(9): e1005076. https://doi.org/10.1371/journal.pcbi.1005076