Visualization of Complex Functional Brain Networks during Cognitive Load

University of South Australia

DSTO & UniSA - 2 Day Symposium on Cognitive Neuro-Engineering & Neuroscience

Naga M Dasari

Naga.Dasari@mymail.unisa.edu.au

Division of IT, Engineering and Environment, University of South Australia, Adelaide, AUSTRALIA

University of South Australia

Research Objectives

- Statistical measures explored
- Changes during cognition and eyes open – detected & visualized
- Functional brain networks visualized - correlations among the various parts of the brain
- Graph measures applied on brain networks

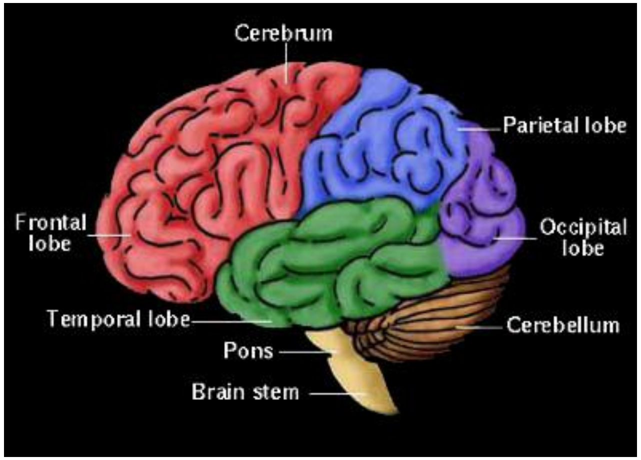
University of
South Australia

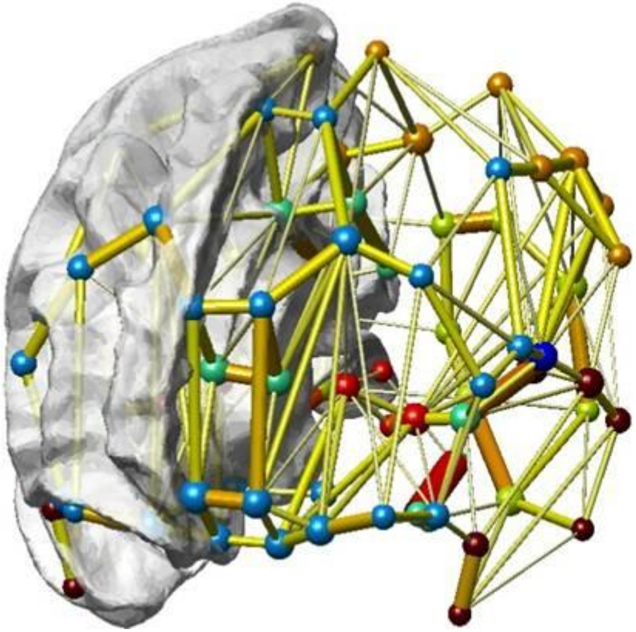
Outline

- Functional Brain Networks
- Electroencephalogram
- Signal Processing System
- Experimental setup for data acquisition
- Signal processing techniques
- Visualization
- Conclusion and future work

Functional Brain Networks

- **Human brain**
- **Functional networks**
- **Segregation and Integration**
- **Network perspective - localized and distributed aspects of the brain**





Electroencephalogram (EEG)

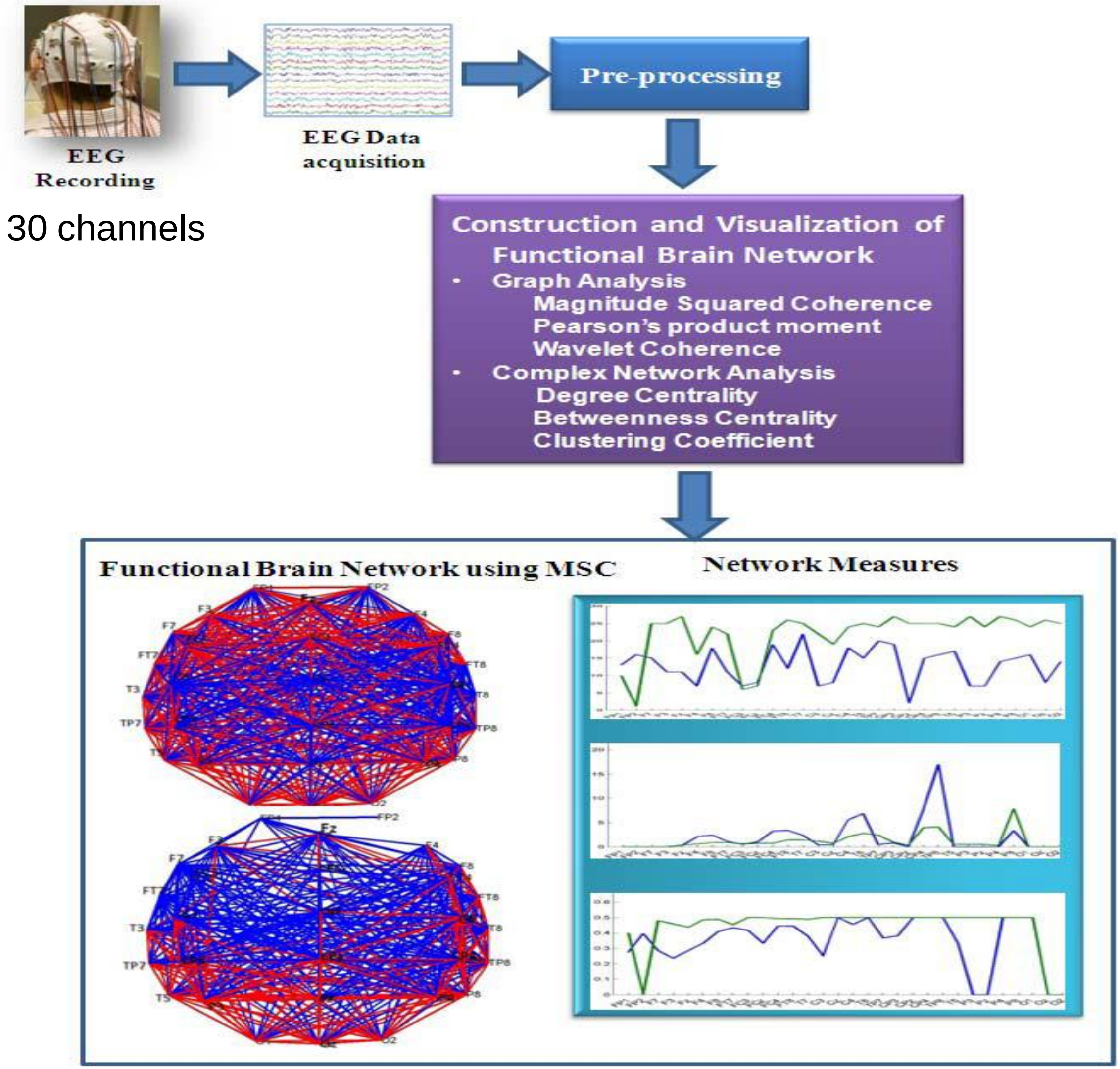
- **A recording of voltage fluctuations versus time from electrodes placed over scalp**

- **Advantages**
  - **Non-invasive**
  - **No complex equipment required**
  - **No radio-active elements required for recording**
  - **Scalp is not subjected to any photo emissions**
  - **High temporal resolution**

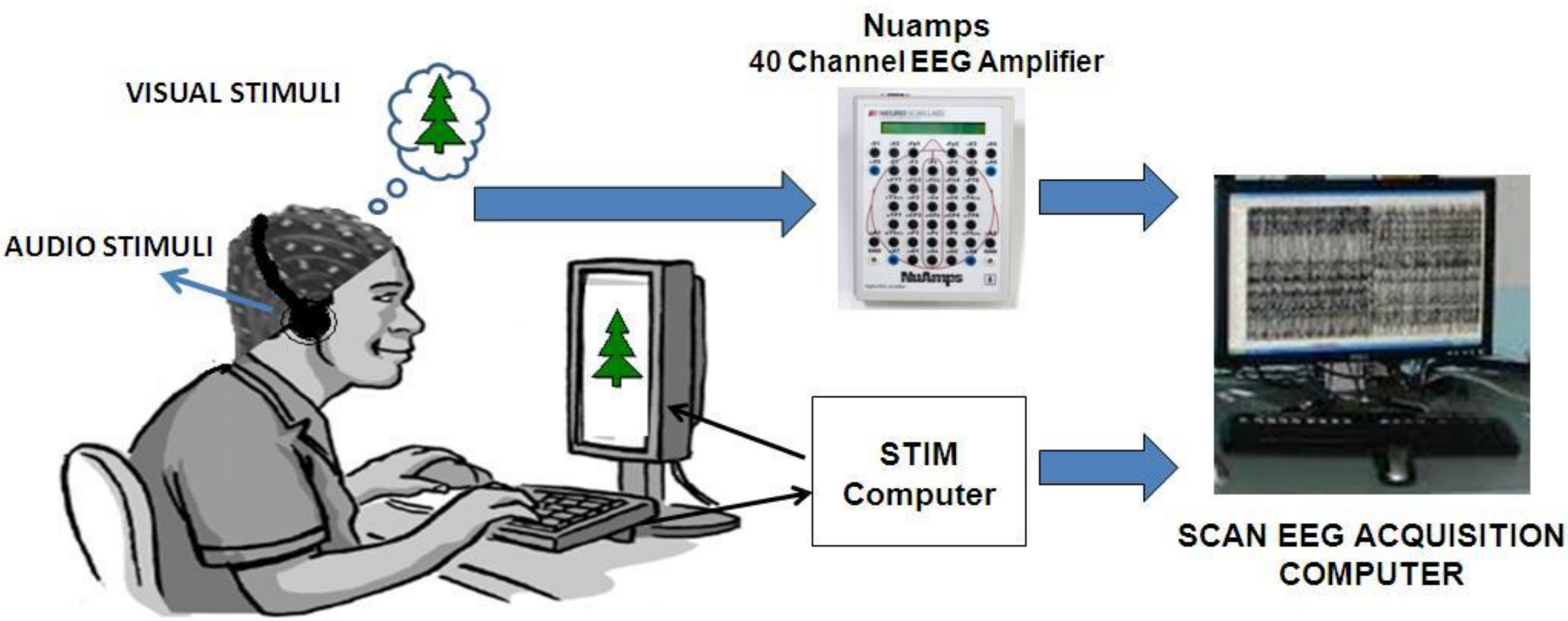
- **Disadvantages**
  - **Low spatial resolution**
  - **Prone to noise (muscle movement, eyeball movement, etc..)**

University of
South Australia

Signal Processing System



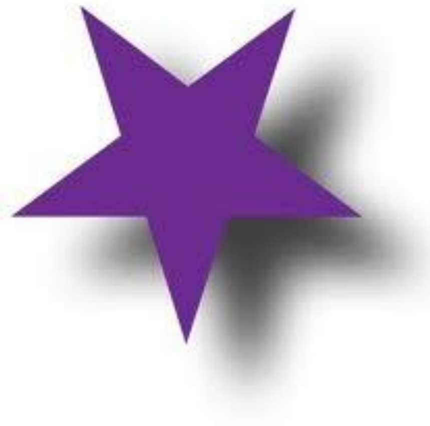
Experimental Setup

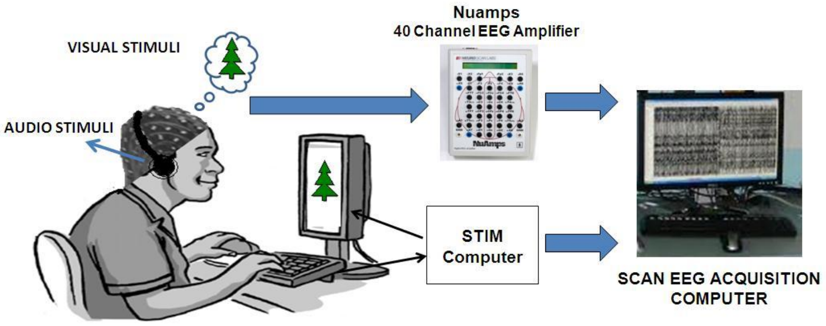


Cognitive load experimental set up

Experimental Setup

- Eyes open (Baseline)





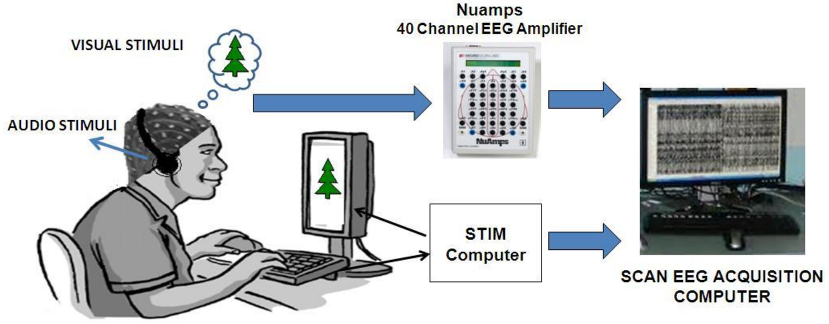
Cognitive load experimental set up

Experimental Setup

- Eyes open (Baseline)
- Cognitive Load
  - ✓ Visual stimulus
  - ✓ Audio stimulus
  - ✓ Combination of audio/visual

A 5 ↑ **A 5** ↑

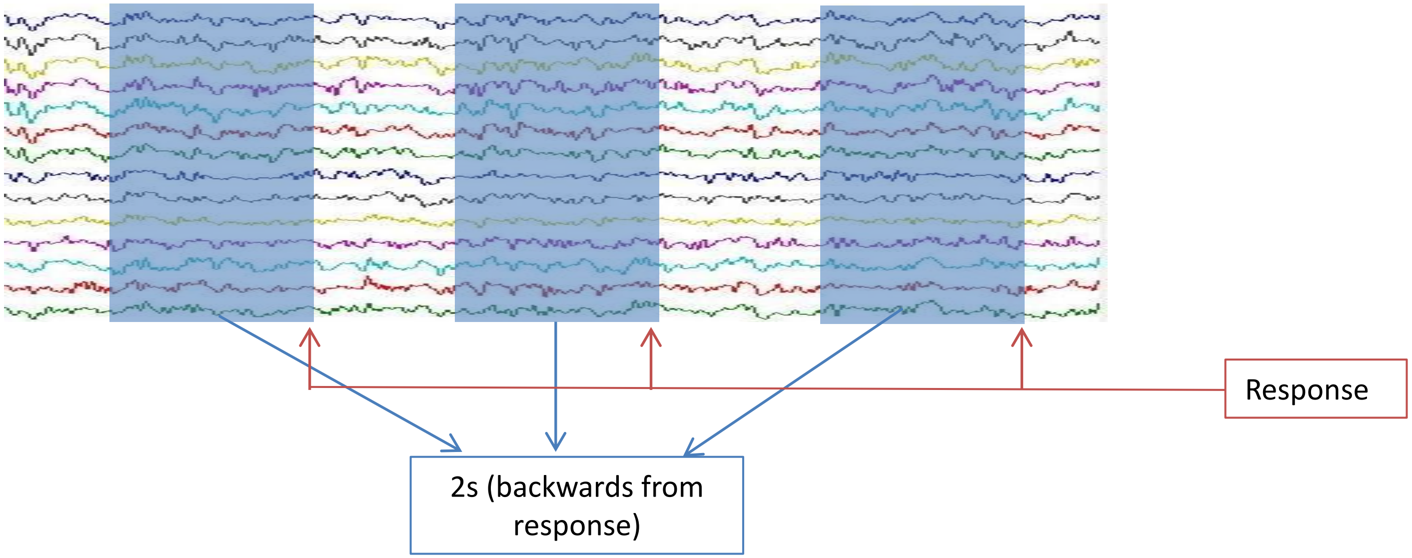
Male voice and female voice



Cognitive load experimental set up

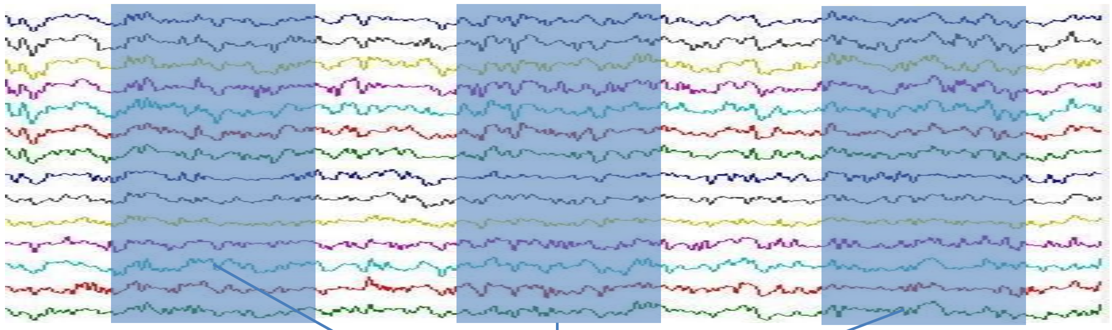
Data Processing

- Pre-Processing
  - Notch filter – 50Hz, Signal filter – 0.5Hz to 70Hz, Eye blinks removed, Bad blocks removed by visual inspection
- Chunks of 2 seconds data - averaged

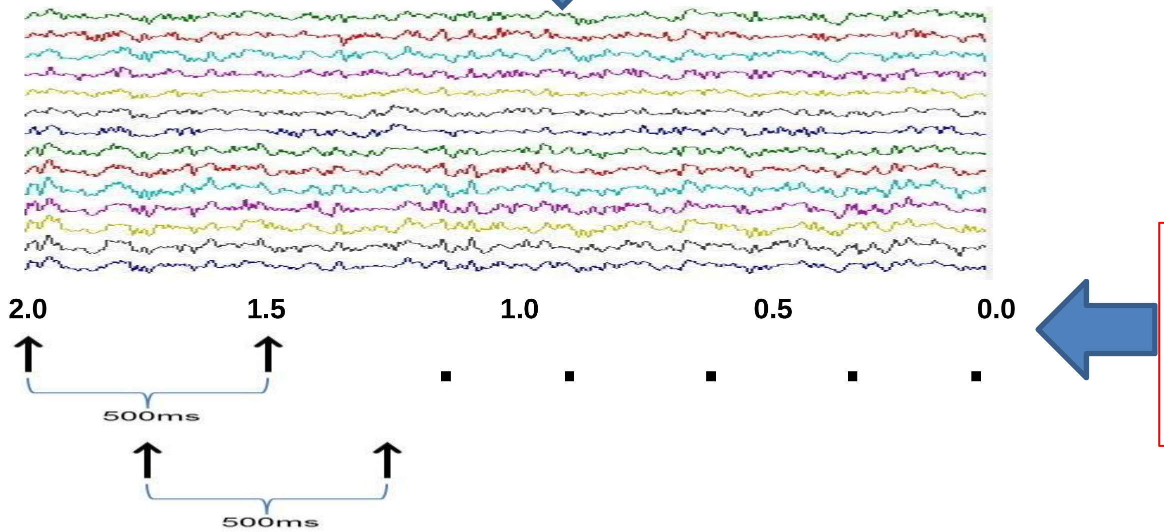


University of South Australia

Data Epoching



2s data epochs extracted and averaged



500ms overlapping epochs extraction for analysis

Processing of EEG signals

Magnitude Squared Coherence (MSC)

- Power spectrum - Power carried by each frequency
- Coherence (Cross power spectrum) - Checks the degree at which two signals are similar
- Magnitude squared coherence - Squared value of cross power spectrum divided by the product of the power of the spectra of both the signals

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}$$

where x and y are electrodes

Processing of EEG signals

Pearson Product-Moment Correlation Coefficient (r)

- A measure of linear correlation between two variables X and Y (electrodes)
- Covariance between two signals divided by the product of their standard deviations

$$r = \frac{\sum_i^n((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_i^n (y_i - \bar{y})^2}}$$

where $X = x_i \ldots\ldots x_n$ and $Y = y_i \ldots\ldots y_n$

- Range: -1 to +1

  +1 - perfectly correlated; Y increases as X increases

  0 - no correlation

  - 1 – Negatively correlated; Y decreases as X increases

Construction of Functional Brain Network

- Computation of pairwise relationships using MSC and r

	FP1	T5	O2
FP1	1	0.7	0.8
T5	0.7	1	0.2
O2	0.8	0.2	1

MSC

	FP1	T5	O2
FP1	1	0.8	-0.4
T5	0.8	1	0.6
O2	-0.4	0.6	1

r

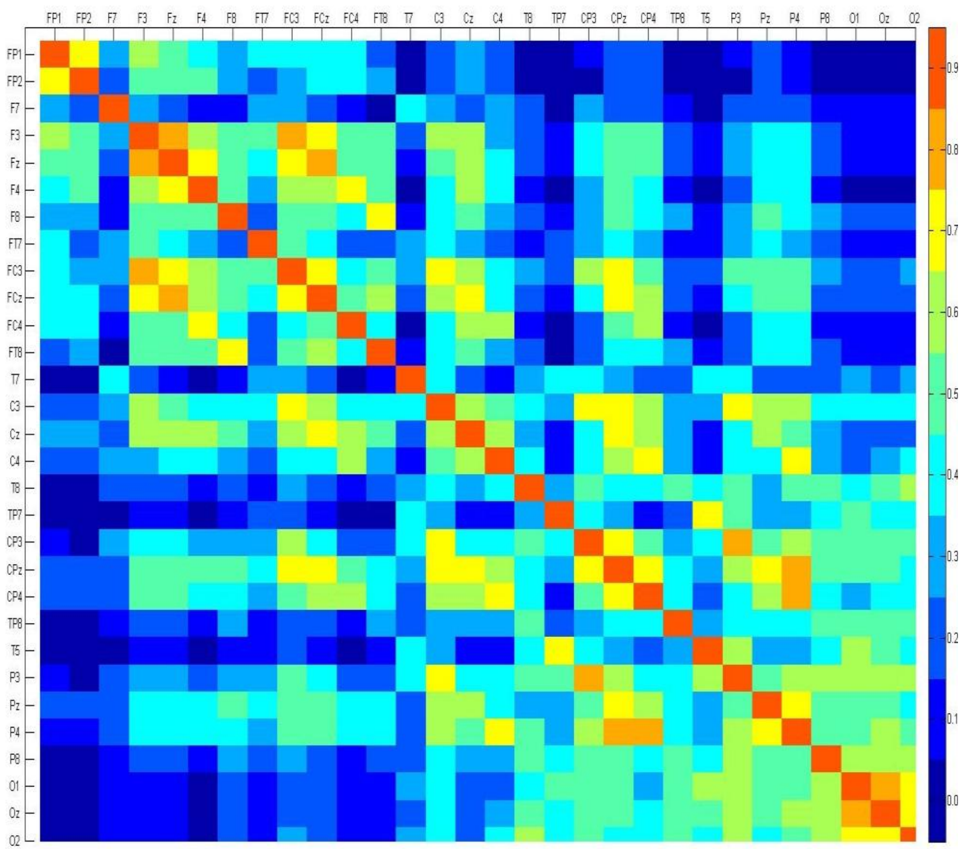
- Visualization
  - Graph (network) - Electrodes as vertices and correlation value between pairs of Electrodes as edges
  - Complex Network metrics - degree of the nodes, betweenness centrality, clustering coefficient

University of South Australia

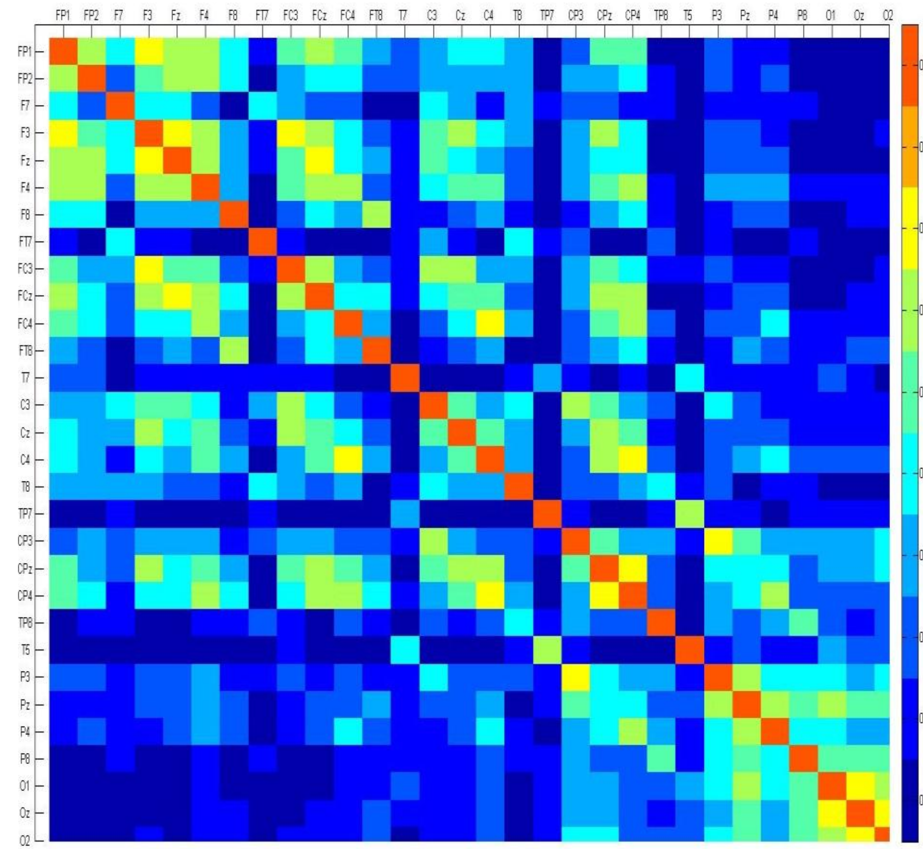
Pairwise relationships - Example

Pairwise relationships using MSC

Cognitive load



Eyes Open

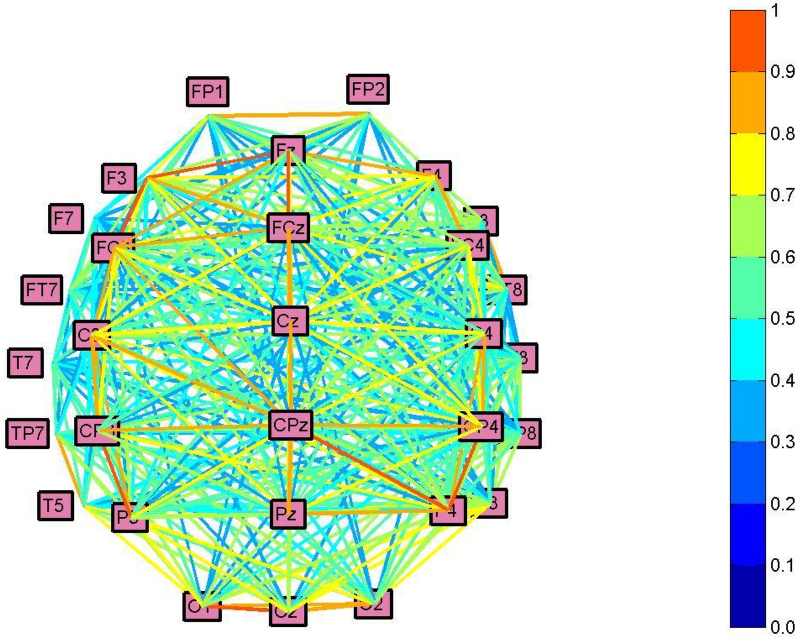


Complex Network Metrics

- Degree of a node
  - Number of edges connected to each vertex
  - Edge – existence of correlation between two electrodes
- Betweenness centrality (BC)
  - Number of shortest paths between all other node pairs in the network that pass through it
- Clustering coefficient (CC)
  - Proportion of links between the vertices within its neighbourhood to the number of links that could possibly exist between them.
  - Measure of segregation

University of South Australia

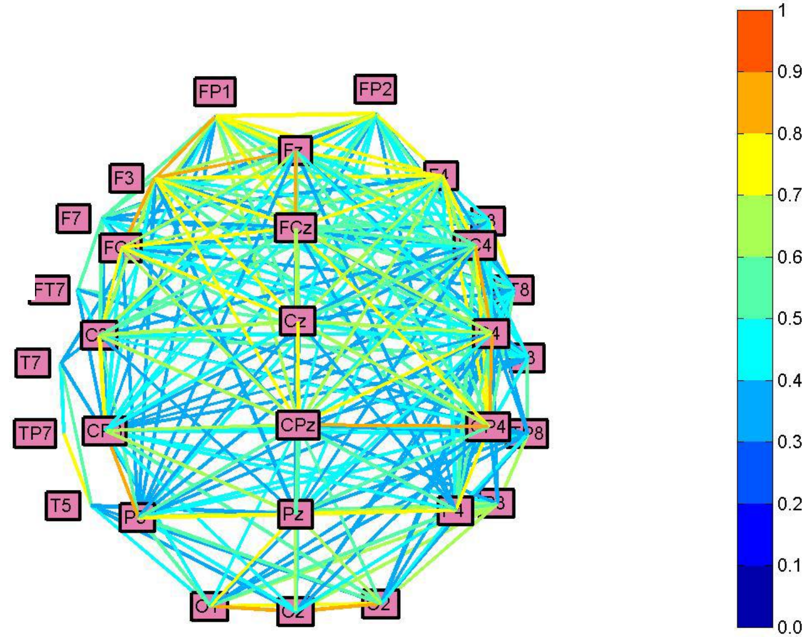
Visualization of Functional Brain Network



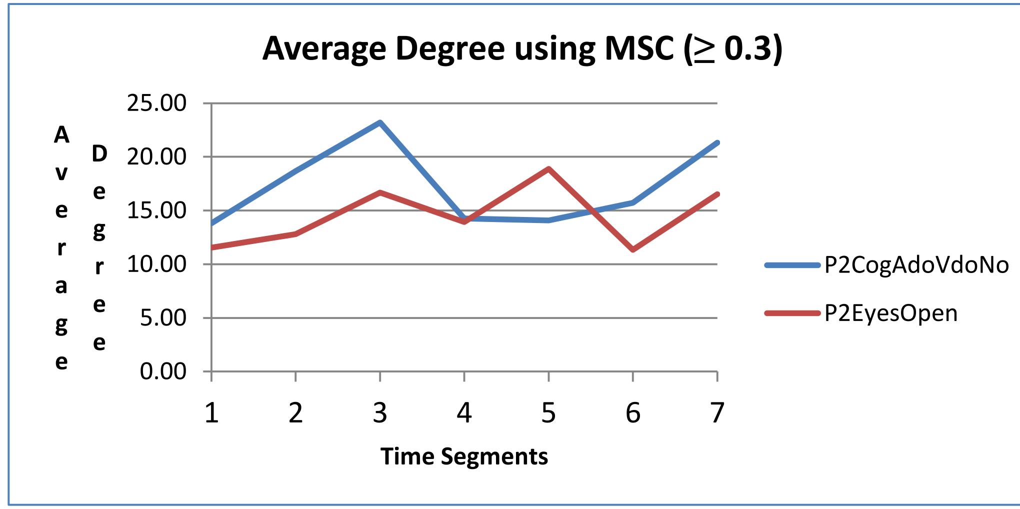
Subject: P2
Functional brain network during eyes open - MSC Threshold: 0.3

Subject: P2

Functional brain network during cognitive load – MSC Threshold: 0.3

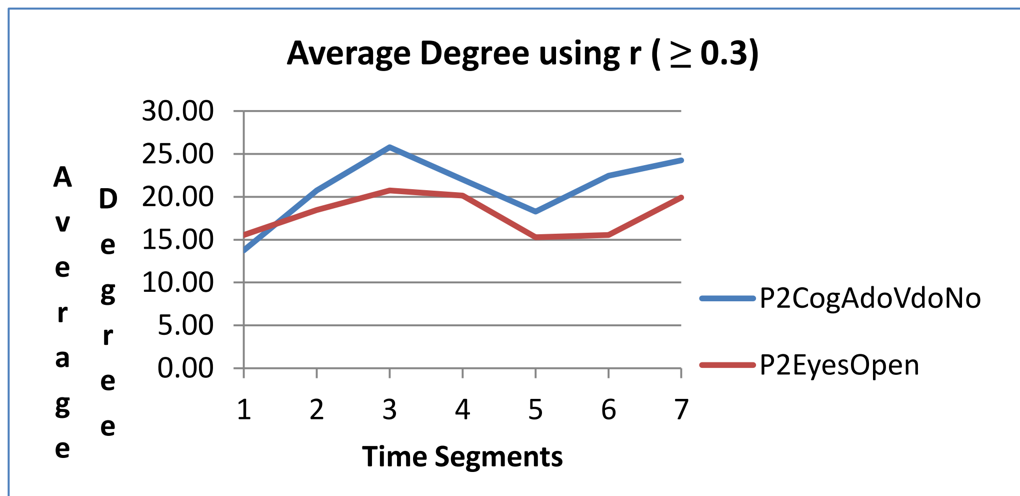


Visualization of Functional Brain Network



<u>Average Degree</u>

Average of individual degrees of the nodes



<u>Inferences</u>

Increase in average degree (Blue) - High cognitive activity during a specific epoch (1.5s-1.0s)

Visualization of Functional Brain Network

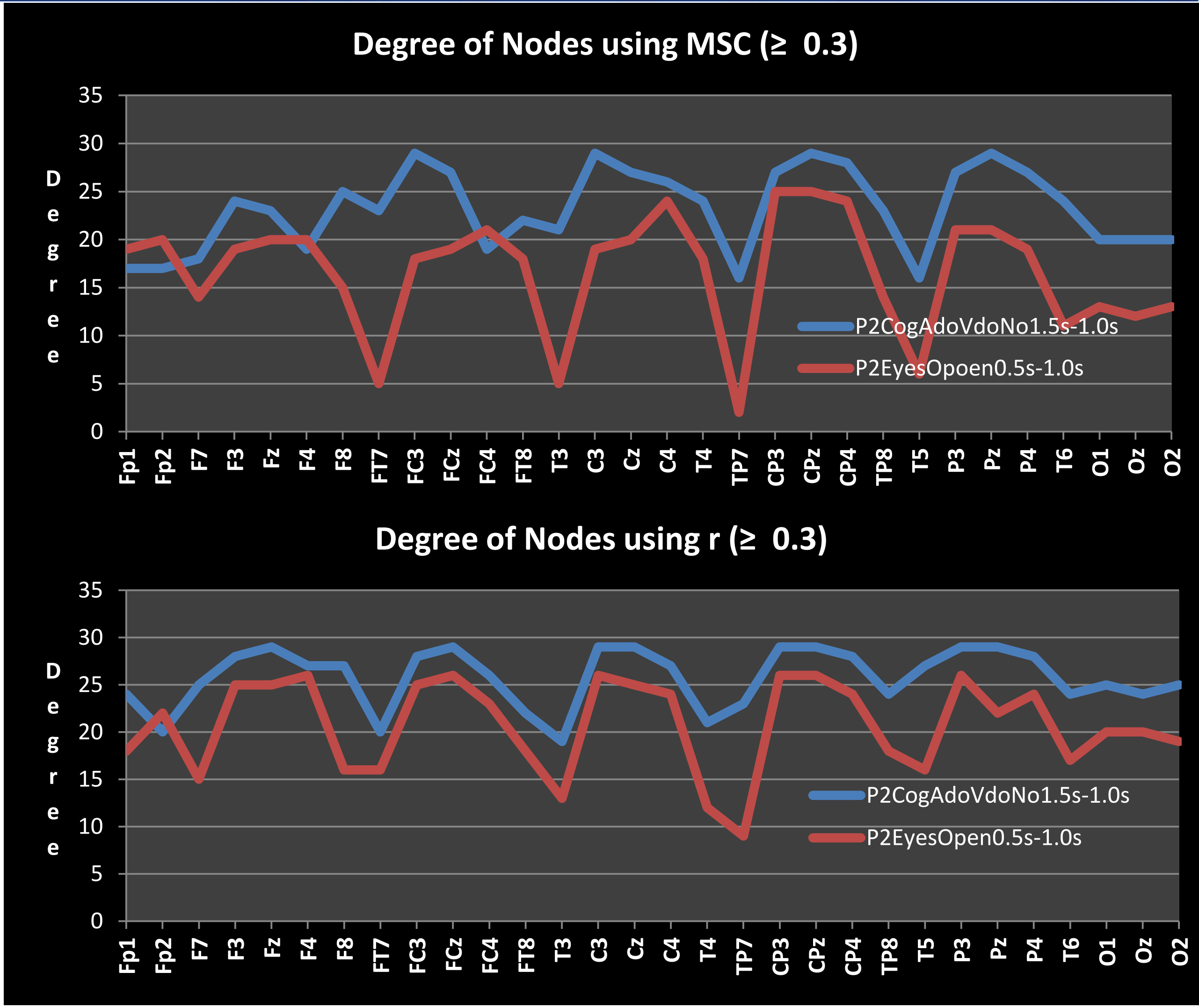
University of
South Australia

Degree of Nodes

Number of edges connected to each vertex

Observations

Degree of most of the electrodes is higher during cognitive load than during eyes open



Visualization of Functional Brain Network

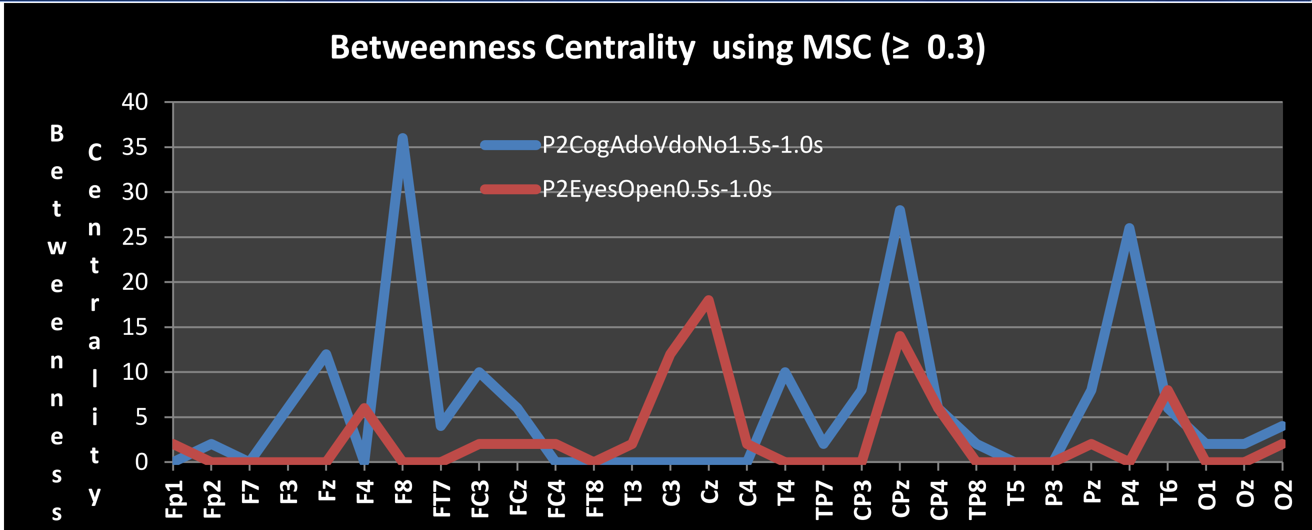
University of South Australia

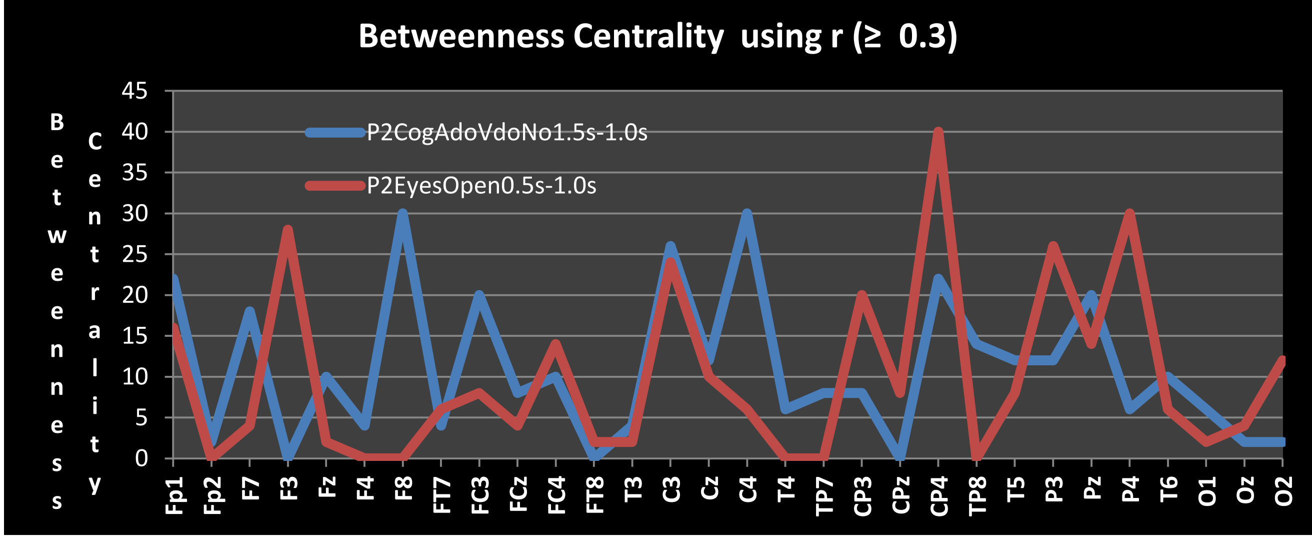
Betweenness Centrality

Number of shortest paths between all other node pairs in the network that pass through it

Observations

MSC showing significant increase in BC for cognitive load





Visualization of Functional Brain Network

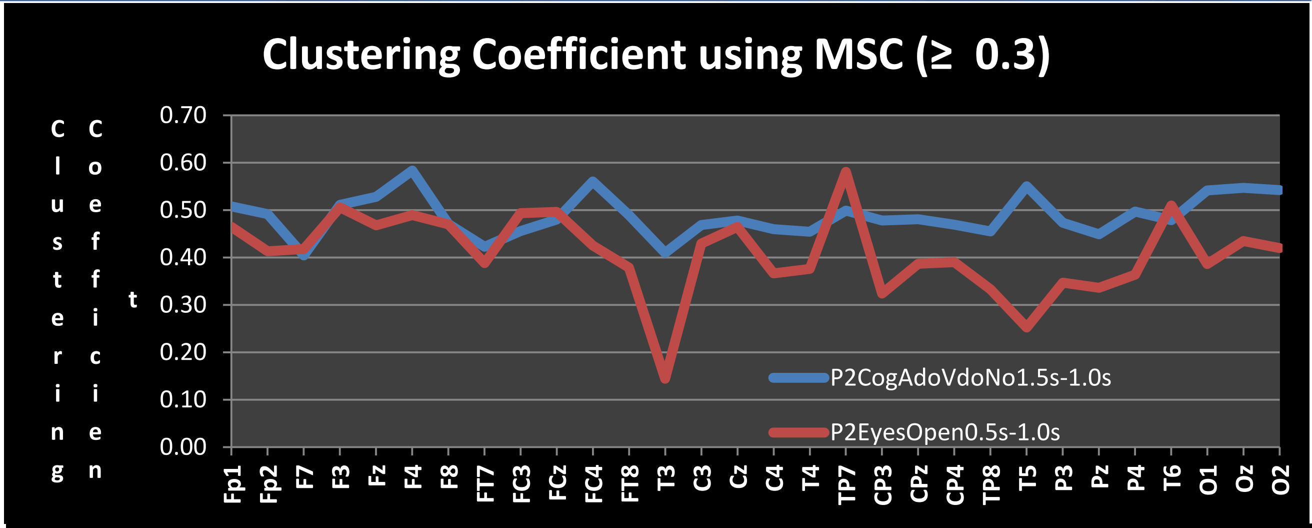
University of
South Australia

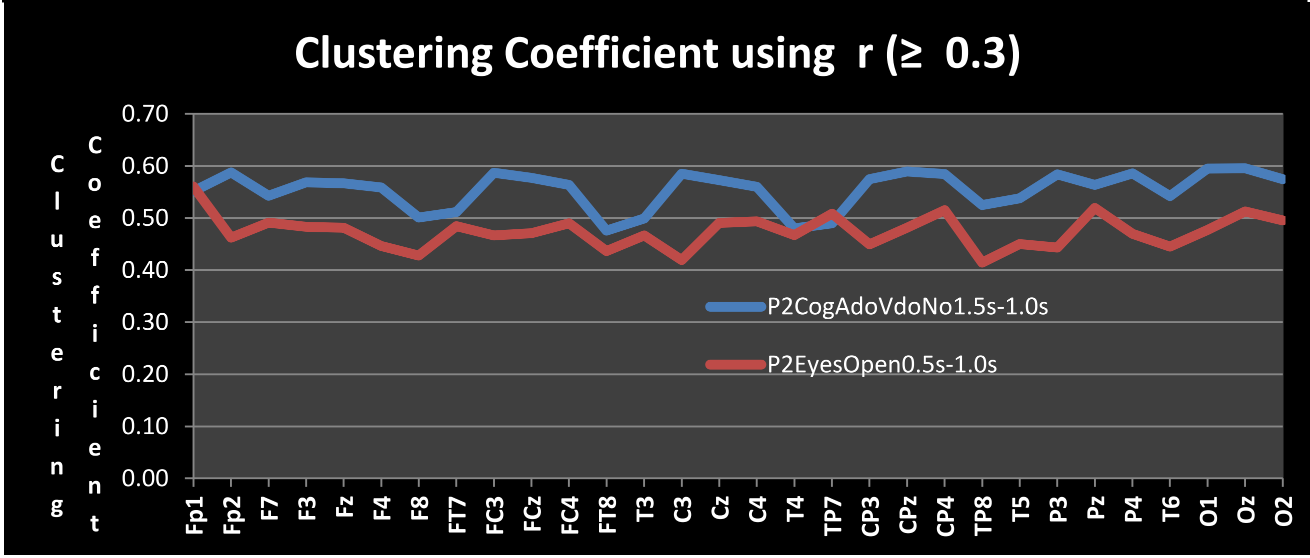
Clustering Coefficient

Proportion of links between the vertices within its neighbourhood to the number of links that could possibly exist between them

Observations

Pearson correlation exhibits higher CC for almost all the electrodes during cognitive load where as it is high for majority of electrodes using MSC.





Conclusion and Future Work

- Higher Average degree– identified the time segment of cognitive processing
  - Larger number of temporal correlations in functional brain network
  - Increase in cortical processing
- Higher Degree of Nodes – identified the electrodes involved in higher amount of processing during cognitive load
- Higher clustering coefficient – Identified the electrodes that form clusters (segregation)
  - Faster dissemination of the information in the neighbourhood
- Betweenness Centrality – identified the electrodes involved in integration principle
  - Electrodes with high BC support integration principle of the functional brain network
- Statistical testing on Analysis of Variance (ANOVA) confirmed difference between eyes open and cognitive load tasks
- Nonlinear measures and techniques will be explored further to understand the underlying neuronal interactions better

University of South Australia

University of South Australia

References

1. O. Sporns, “Network analysis, complexity and brain function,” Complexity, vol. 8(1), pp. 56–60, 2002.
2. A. R. Lauria, *Higher Cortical Functions in Man*, Basic Books: Newyork, 1966.
3. G. Tononi, O. Sporns, and G.M. Elderman, “A measure for brain complexity:a relating functional segregation and integration in the nervous system,” in Proceedings of the National Academyof Sciences, vol. 91(11), 1994, pp. 5033–5037.
4. G. Tononi, G.M. Elderman, and O.Spornts, “Complexity and coherencey: integrating information in the brain,” Trends in Cognitive Sciences, vol. 2(12), 1998, pp.474-484.
5. F.L. Varela, J.-. Lachaux, E. Rodriguez, and J. Martinerie, “The brainweb: phase synchronization and large-scale integration,” Nat Rev Neurosci, Vol.2, pp-229-239.
6. A.A. Fingelkurts, and S. Kähkönen, “Functional connectivity in the brain—is it an elusive concept?,” Neuroscience and biobehavioral review, vol. 28(8), pp.827-836, 2005.
7. B. Horwitz, “The elusive concept of brain connectivity,” NeuroImage,vol.28(8), pp. 466-470. 2003.
8. V. Sakkalis, “Review of advanced techniques for estimation of brain connectivity measured with EEG/MEG,” Computers in Biology and Medicine, Vol. 41(12), pp.1110-1117.
9. M.I. Posner, and M.E. Raichle, *Images of Mind*, Scientific American Libray/ Scientific American Books, 1994.
10. C. Büchel and K.J. friston, “Modulation of connectivity in visual pathways by attention: cortical interactions evaluated with structural equation modelling and fMRI,” Cerebral Cortex, vol. 7(8), pp.768-778, 1997.
11. O. Sporns, D.R. Chialov, M. Kaiser and C.C. Hilgetag, “Organization, development and function of complex brain networks,” Trends in Cognitive Sciences, vol. 8(9), pp. 418-425, 2004.
12. G. Nolte, O. Bai, Z. Mari, S. Vorbach and M. Hallet, “Identifying true brain interaction from EEG data using the imaginary part of coherency,” clinical Neurophysiology, vol. 115(10), pp. 2292-2307, 2004.
13. D.S. Bassett, E. Bullmore, “Small-World Brain Networks,” The Neuroscientist, vol. 12(6): pp. 512-523, 2006.
14. D.J. Watts, and S.H. Strogatz,“Collective dynamics of ‘small-world’ networks”. Nature, vol. 393, 440–442, 1998.
15. L.C. Freeman, “Centrality in social networks: conceptual clarification,” Social Networks. 1,pp.215–239, 1978.
16. O.M. Razoumnikova, “Functional organization of different brain areas during convergent and divergent thinking: an EEG investigation,” Cognitive Brain Research, vol. 10(1–2): pp. 11-18, 2000.
17. Sporns, O. and J. Zwi, “The small world of the cerebral cortex,” Neuroinformatics,vol. 2(2): p. 145-162, 2004.
18. B. Libet, E.W. Wright Jr, and C.A. Gleason, “Readiness-potentials preceding unrestricted ‘spontaneous’ vs. pre-planned voluntary acts”, Electrencephalography and Clinical Neurophysiology, vol.54, pp.322-335,1982.