University of South Australia

Symposium on Cognitive Neuroengineering and Computational Neuroscience

11th and 12th July 2013

Computational Techniques for Characterizing Cognition using EEG Data - New Approaches

R. Vijayalakshmi

Department of Applied Mathematics and Computational Sciences

PSG Tech, Anna University

India

Agenda

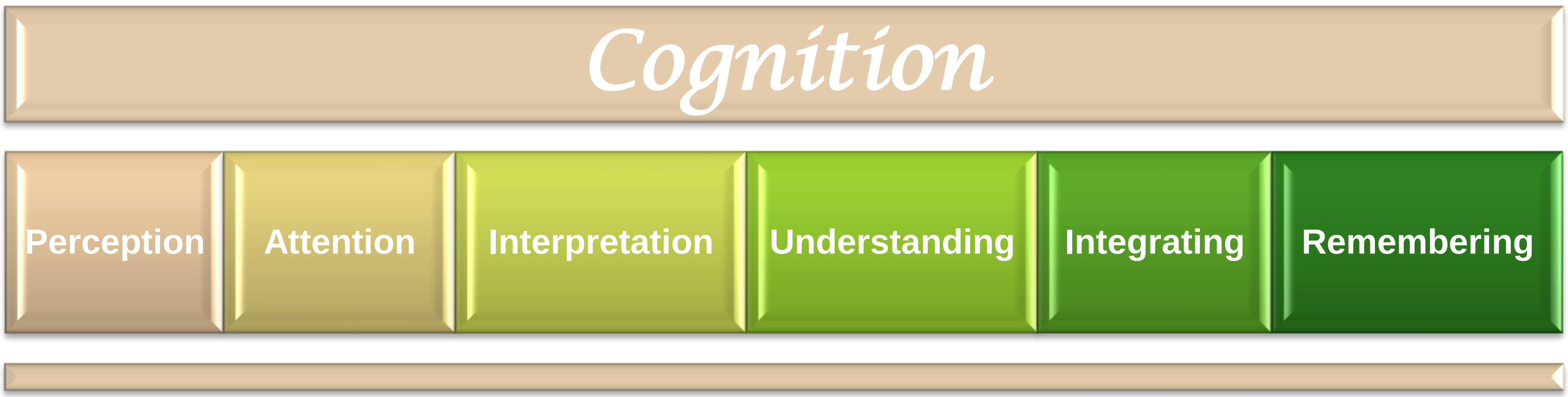
- Describing the cognitive brain theory from the perspective of large-scale complex networks and graph theory
- Reviewing computational techniques for identification and characterization of structural and functional brain networks
- Exploring the novel computational techniques that provide a coherent framework for understanding of cognition in functional brain network

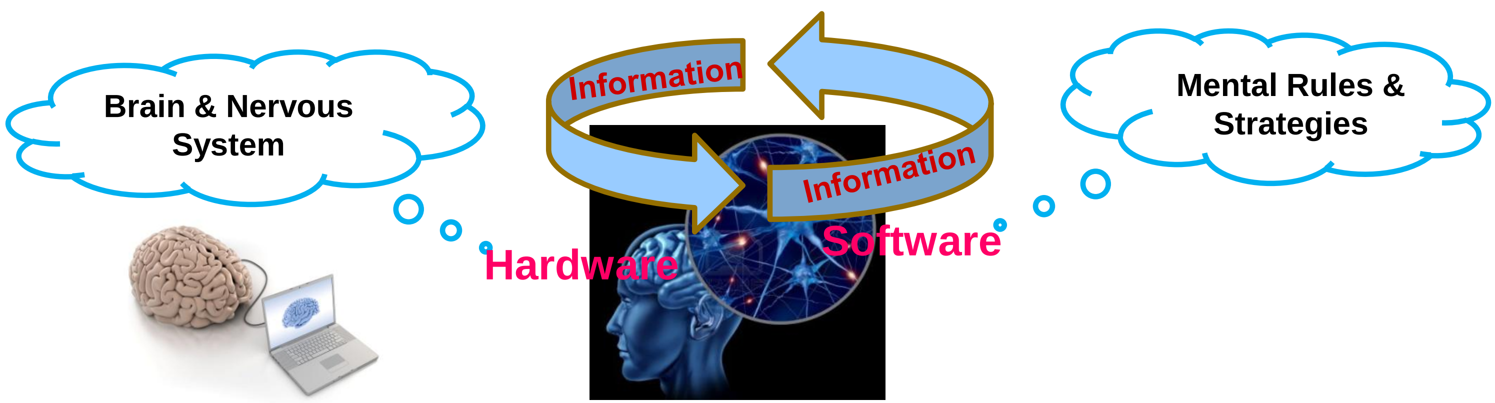
Objectives of the Talk

- Identification of changing neuronal patterns during different brain states - fusing statistical methods, information theory and network analysis
- Visualization of neural interactions and patterns in functional brain network
- A better understanding of the structural Vs. functional association of brain regions - Voronoi diagrams
- Presentation of results from dynamic interactions of distributed brain areas operating in large-scale networks

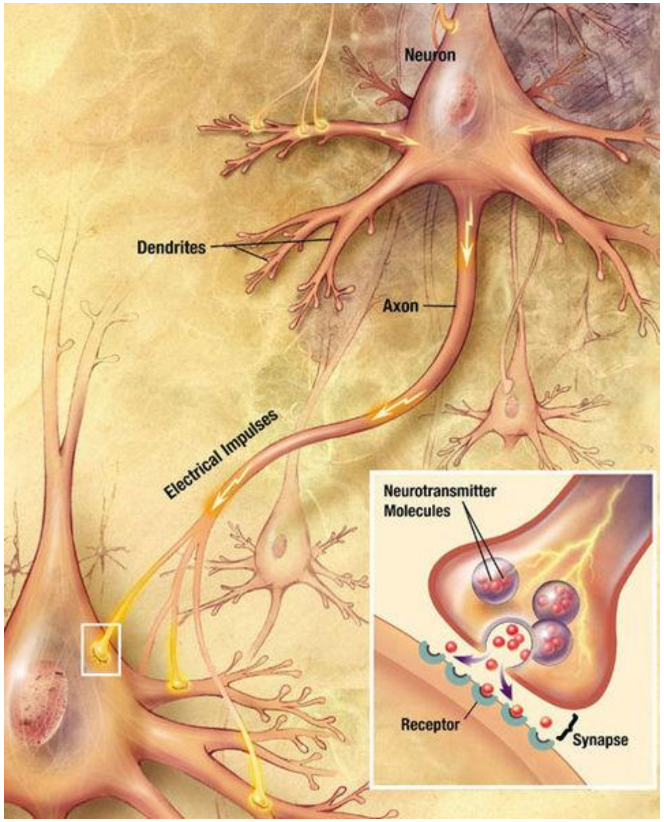
Cognition

How brain transforms sensed information into Action

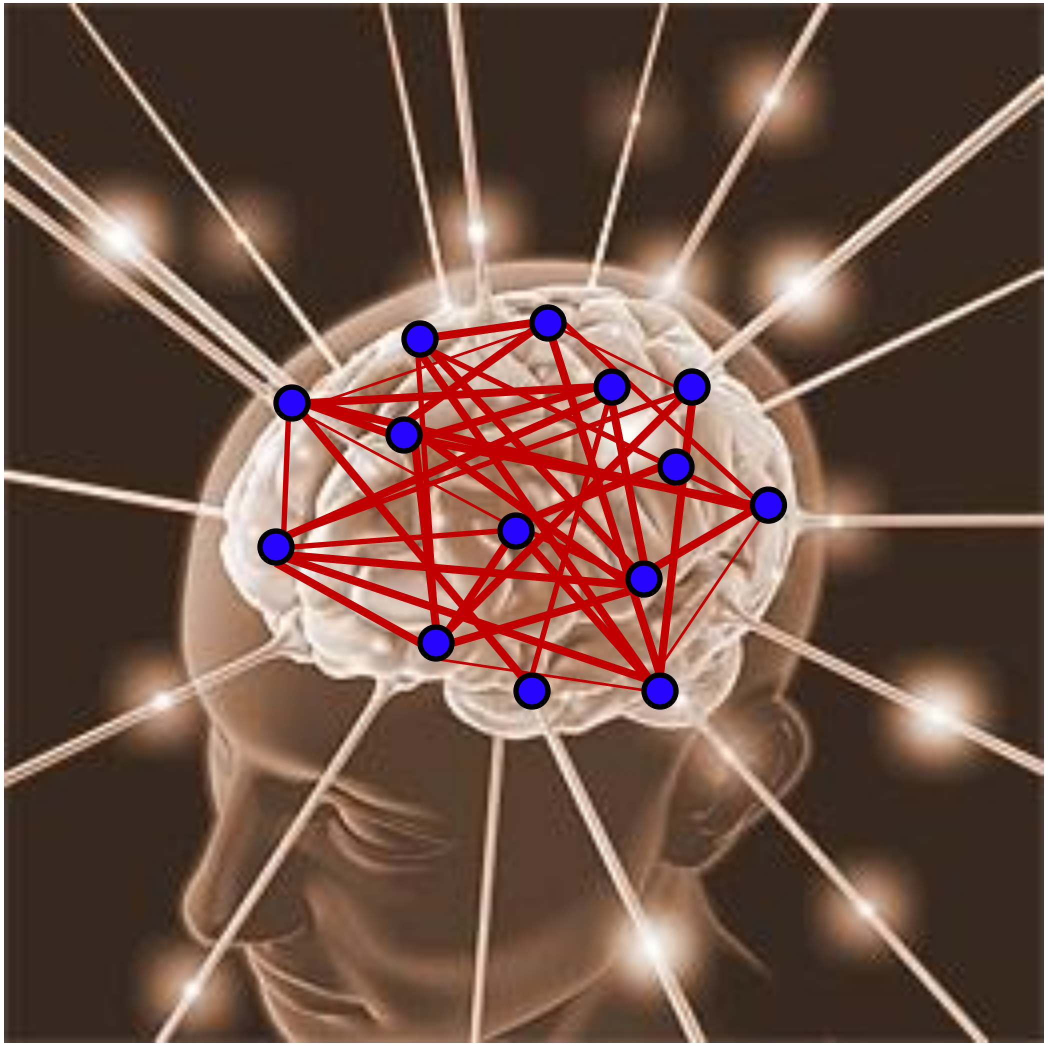




Human Brain

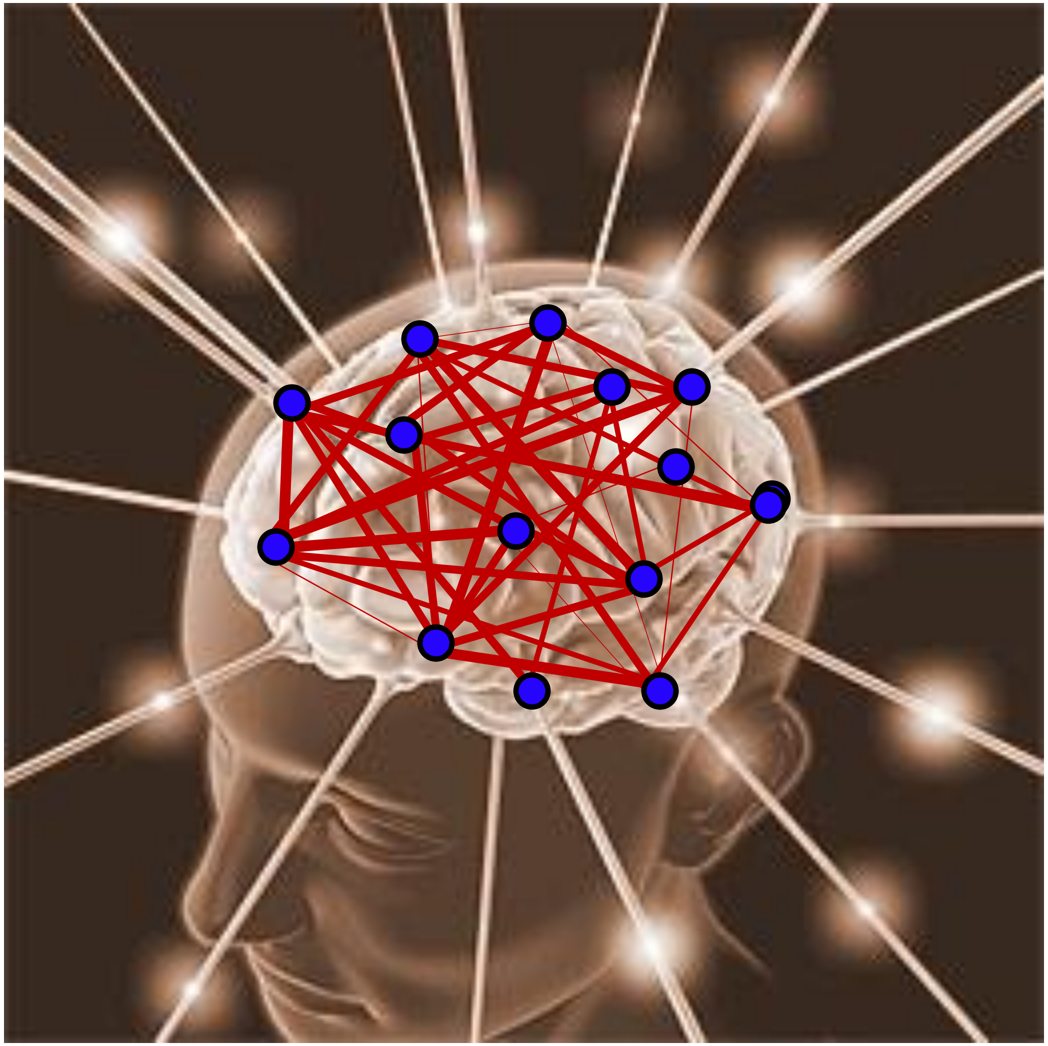

Neuron
Dendrites
Axon
Electrical Impulses
Neurotransmitter Molecules
Receptor
Synapse

Brain Network



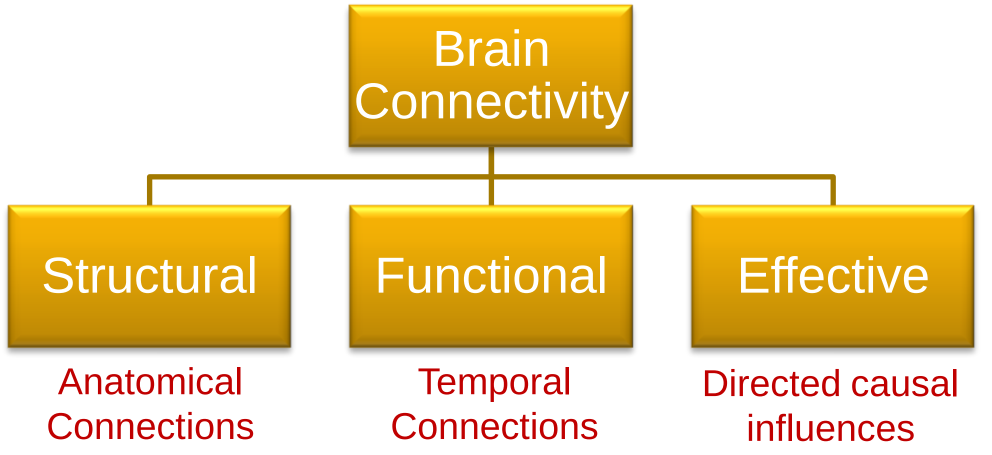
- ✓ Billions of Neurons~10^{11}
- ✓ Connections~10^{12}
- ✓ Complex and constantly changing network
- ✓ Transmit information using chemical and electrical signals

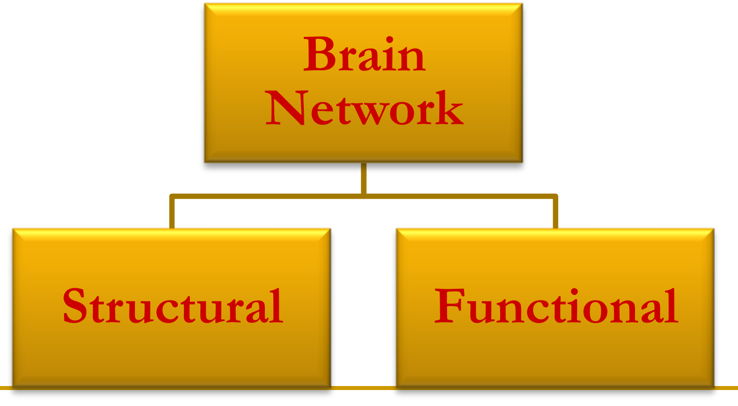
Brain Network



- ✓ Billions of Neurons~10^{11}
- ✓ Connections~10^{12}
- ✓ Complex and constantly changing network
- ✓ Transmit information using chemical and electrical signals
- ✓ Connections strengthen or weaken, or newly formed

Brain Network





Functional Magnetic Resonance Imaging (fMRI)

- Non-invasive method for measuring activity in the human brain
- Tracks brain activity by monitoring the levels of oxygenated blood (BOLD - blood-oxygen-level-dependent) that travel to active neurons
- An indirect measure of the underlying neural activity

Magnetoencephalography (MEG)

- Detects the magnetic fields (billion times smaller than the Earth's magnetic field) created by the brain's electric signals
- Carried out in a heavily shielded room – often at night, when other electrical devices are switched off.

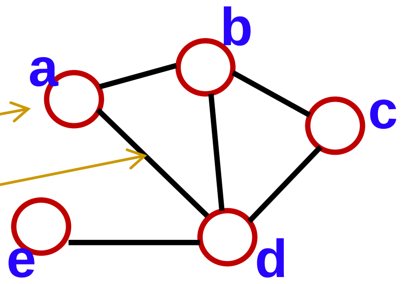
Electroencephalograph (EEG)

- Recording of electrical activity of the brain from multiple electrodes placed on the scalp.
- Useful for studying the relationship between brain activity during normal and cognitive activities.
- Valuable tool for research and diagnosis, due to its millisecond-range temporal resolution despite limited spatial resolution.

Why EEG?

- Simple and costs less
- Direct method to measure brain activity
- Portability
- Silent - Allows for better study of the responses to auditory stimuli
- No high-intensity magnetic fields
- Very high (milliseconds accuracy) Temporal Resolution
- …

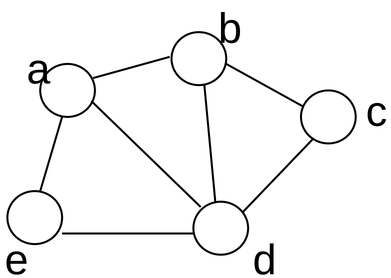
Network/Graph Theory



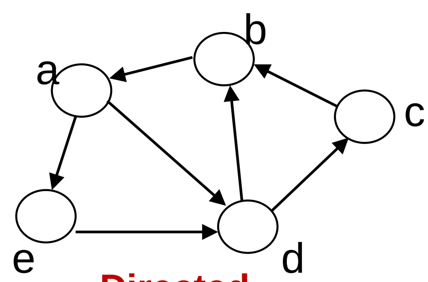
- Network /Graph - A mathematical model
  - Represents data as a collection of
    - Nodes/vertices and
    - Links/edges/connections between pairs of nodes
- Complex Network - Used to represent chaotic systems (such as brain) at different levels
    - From small ensembles of neurons and synaptic connections to macro-anatomical regions connected by white matter bundles

Network/Graph Theory

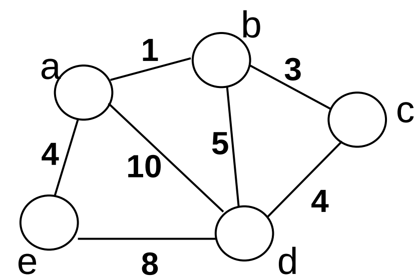
- A Network/Graph G can be defined as G=(V,E), where V is a set of Nodes, and E is a set of edges between the Nodes $E \subseteq \{(u,v) | u,v \in V\}$



Undirected



Directed



Weighted

	a	b	c	d	e
a	0	1	0	1	1
b	1	0	1	1	0
c	0	1	0	1	0
d	1	1	1	0	1
e	1	0	0	1	0

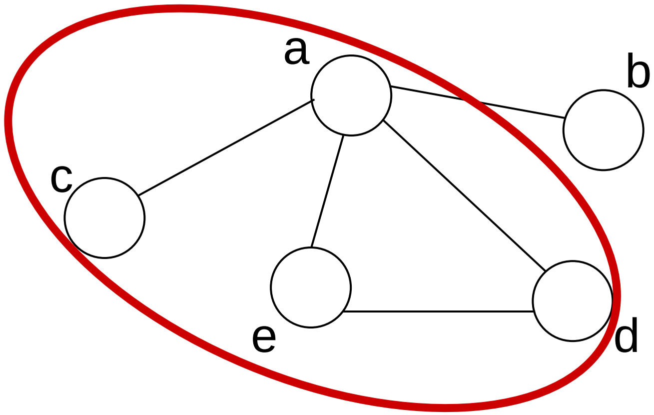
	a	b	c	d	e
a	0	0	0	0	1
b	1	0	0	0	0
c	0	1	0	0	0
d	0	1	1	0	0
e	0	0	0	1	0

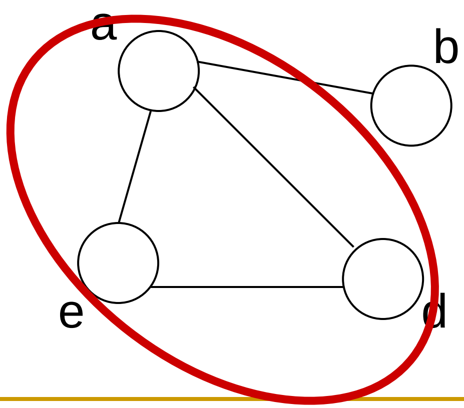
	a	b	c	d	e
a	0	1	0	10	4
b	1	0	3	5	0
c	0	3	0	4	0
d	10	5	4	0	8
e	4	0	0	8	0

Graph representation: Adjacency Matrix

Network/Graph Theory

- Subgraph:
  - A graph G_1 that has a subset of nodes and a subset of edges with respect to some base graph G. $G_1 \subseteq G$
- Clique:
  - A sub-graph with each node connected to every other node
  - A group of nodes interact with each other more regularly and intensely than others in the same network





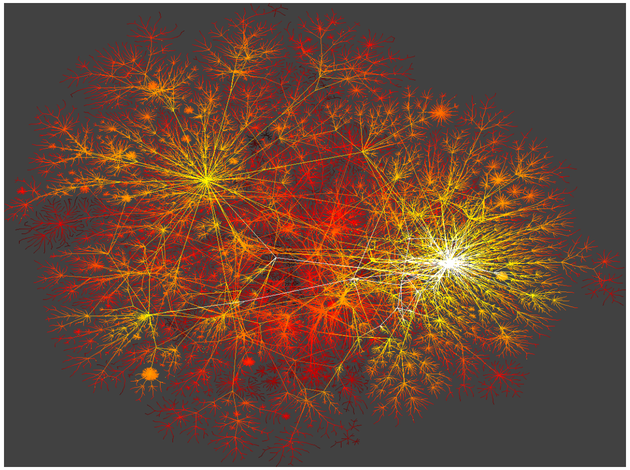
Graph Mining

- Non-trivial extraction of implicit, novel, previously unknown and potentially useful knowledge (patterns) from graph representation of data

- Used to describe and mine a wide variety of data such as the Internet, the web, social networks, metabolic networks, protein-interaction networks, food webs, citation networks, and many more

Graph Mining - Applications

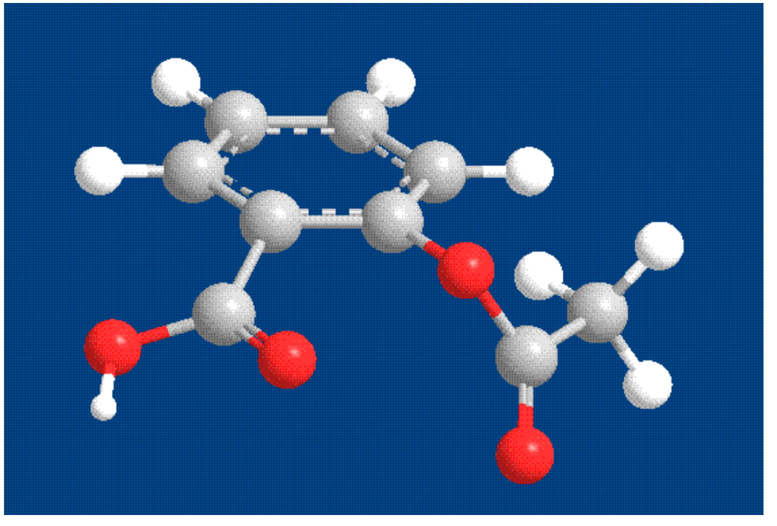
- Widespread application areas from biology and chemistry to internet applications
  - Internet / computer networks
    Nodes: computers/routers
    Edges: communication links
  - WWW
    Nodes: web pages
    Edges: hyperlinks



Internet

Graph Mining - Applications

- Chemical molecules
  - Nodes: atoms
  - Edges: chemical bonds



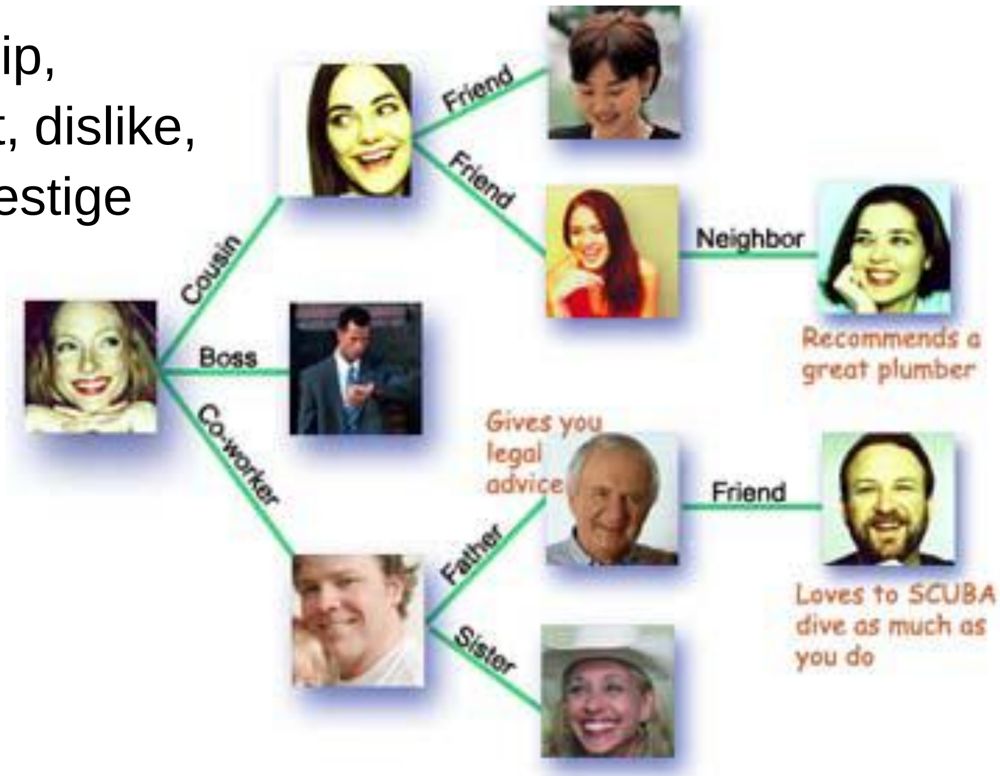
Aspirin

Graph Mining - Applications

- Social networks - Relationships and flows between people

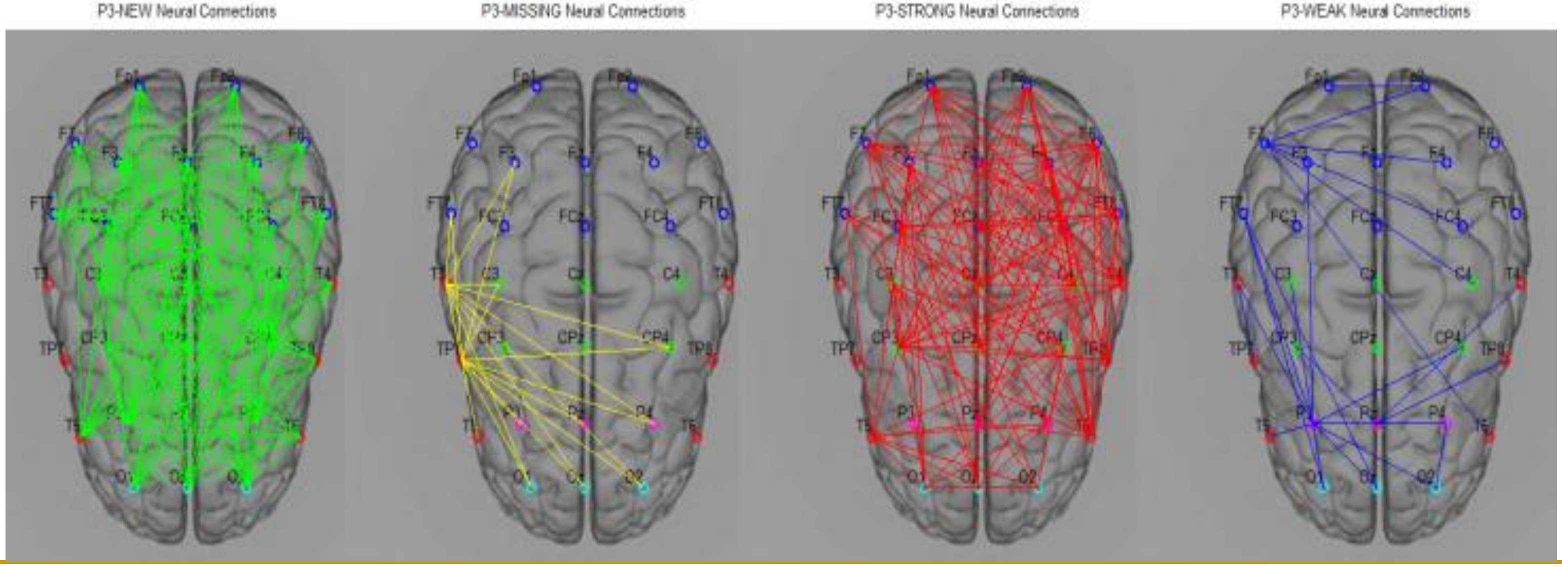
  Nodes: persons

  Edges: friendship, kinship,
  common interest, dislike,
  knowledge or prestige



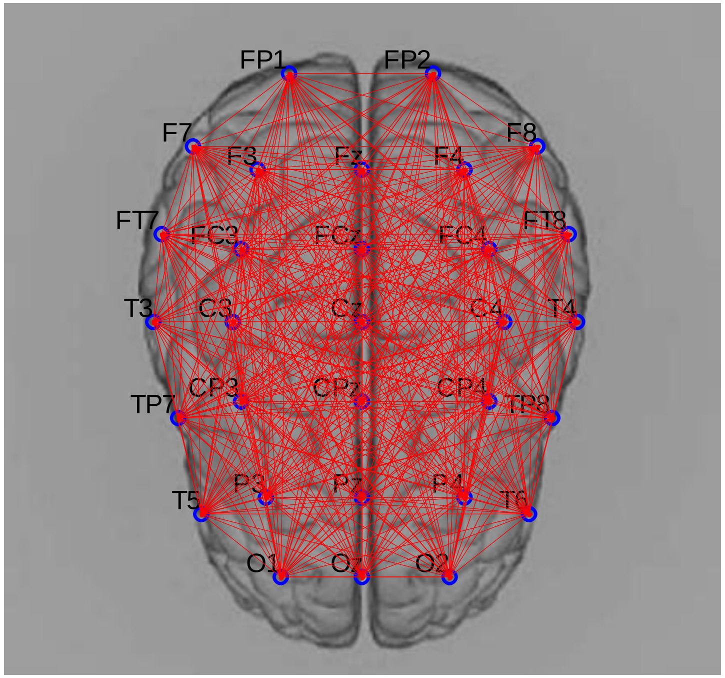
Graph Mining - Applications

- Brain Networks
  - Nodes – Multichannel EEG Electrodes/Brain Regions
  - Edges – Statistical measures of correlation(linear and non-linear)/ Physical connections (synapses or axonal projections)



EEG data to Graph Data Base

- Multichannel EEG data
  - Nodes – Electrodes containing chunks of EEG data
  - Connections – Weights computed using linear/non-linear statistical metrics(all pairs of electrodes)
  - Thresholding – to eliminate weak links



Social Network Analysis(SNA) Metrics

- Density
- Clustering Co-efficient
- Characteristic Path Length
- Centrality
  - Degree
  - Betweenness
  - Closeness

SNA Metrics applied to EEG Data

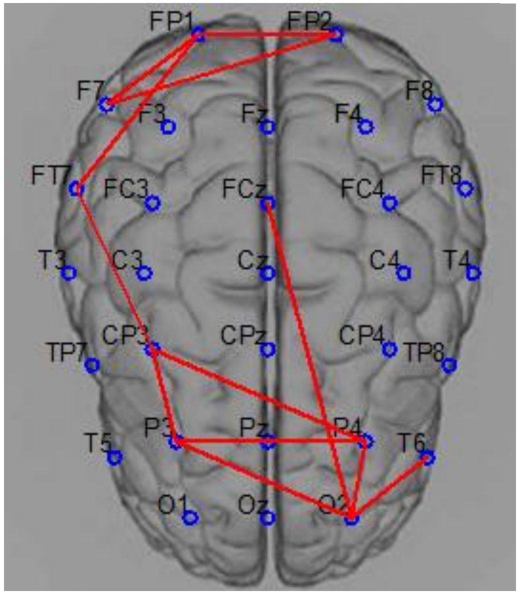
- Density
  - Density = Number of connections/Total number of possible edges between all pairs of electrodes

    Density=5/6=0.83

    (A *dense network)*
  - A perfectly connected network
    - Clique with density=1

An indication how well-connected a Functional Brain Network is.

Density = 12/45=0.27



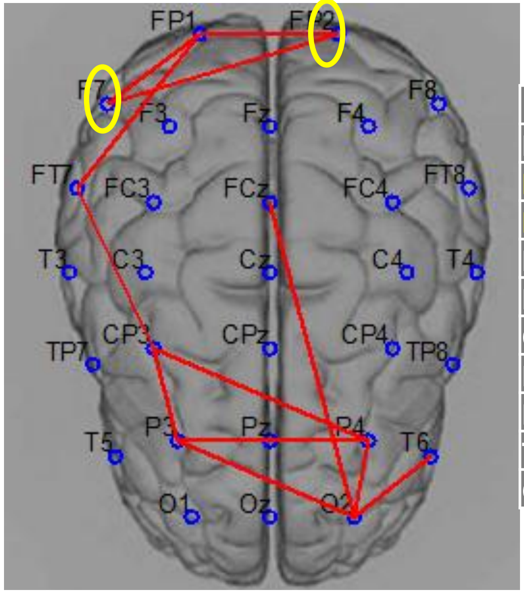
SNA Metrics applied to EEG Data

- Clustering Coefficient (C_i)
  - Number of actual connections across the neighbors of an electrode, as a percentage of all possible connections.

$$C_i = \frac{2T_i}{K_i(K_i - 1)}$$

  - k_i - neighbors of I
  - T_i - connections between its neighbors

Measures how close an electrode and its neighbors are from being a clique - Cohesiveness



	Ci
FP1	0.333
FP2	1
F7	1
FT7	0
FCz	
CP3	0.333
P3	0.667
P4	0.667
T6	
O2	0.167

SNA Metrics applied to EEG Data

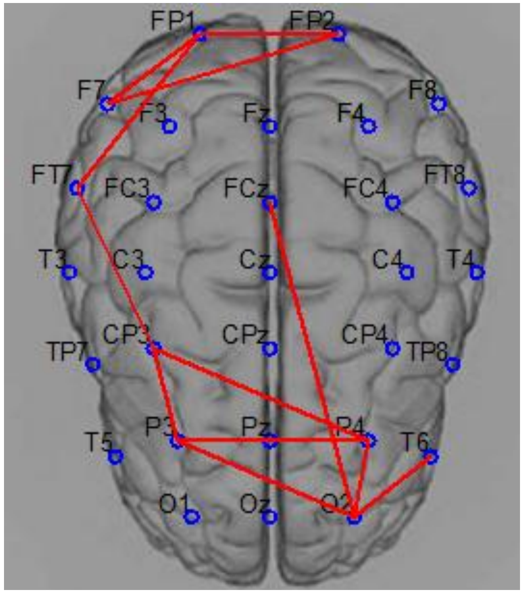
- Clustering Coefficient for Entire Network (C)
  - Average of all coefficients of its electrodes

$$C = \frac{1}{N}\sum C_i$$

C_i – Clustering Coefficient of each electrode i

Extent to which the neighbors of an electrode are the neighbors of each other

Overall Clustering Coefficient C= 0.521



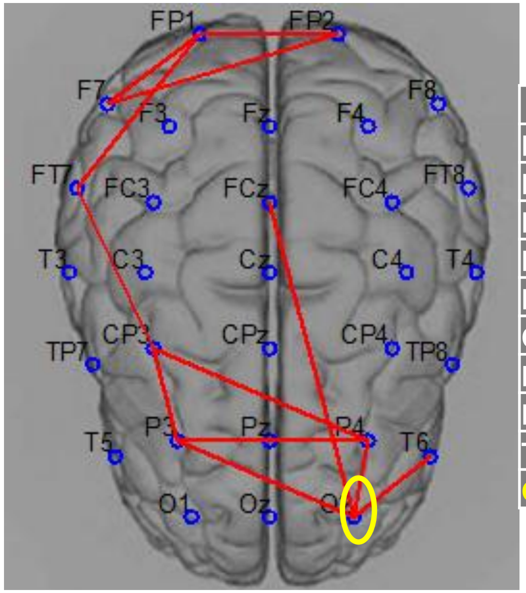
SNA Metrics applied to EEG Data

- Degree Centrality (DC)
  - Number of neighbors of an electrode.
  - Useful in assessing which electrodes are central with respect to spreading information and influencing others

$$DC(i) = \sum_{j=1}^{n} A_{ij}$$

A=Adjacency matrix

Measure of immediate influence to determine the number of direct connections of an electrode in the network



	DC
FP1	3
FP2	2
F7	2
FT7	2
FCz	1
CP3	3
P3	3
P4	3
T6	1
O2	4

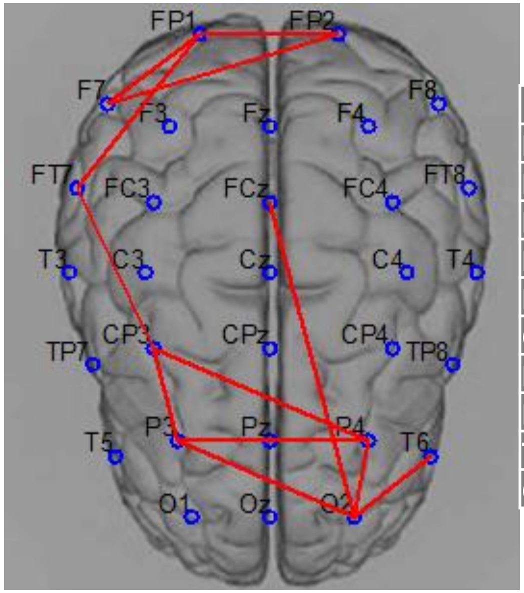
SNA Metrics applied to EEG Data

- Closeness Centrality (CC)
  - Sum of reciprocal distance of an electrode to all the other electrodes

$$CC(i) = \frac{1}{\sum_{j=1}^{n} d_G(i,j)}$$

  - Electrodes with lower closeness centrality are the electrodes having a shorter network distance to other electrodes.

Useful to find speed of information dissemination



	CC
FP1	4.64
FP2	4.589
F7	4.589
FT7	4.67
FCz	4.596
CP3	4.685
P3	4.677
P4	4.677
T6	4.596
O2	4.655

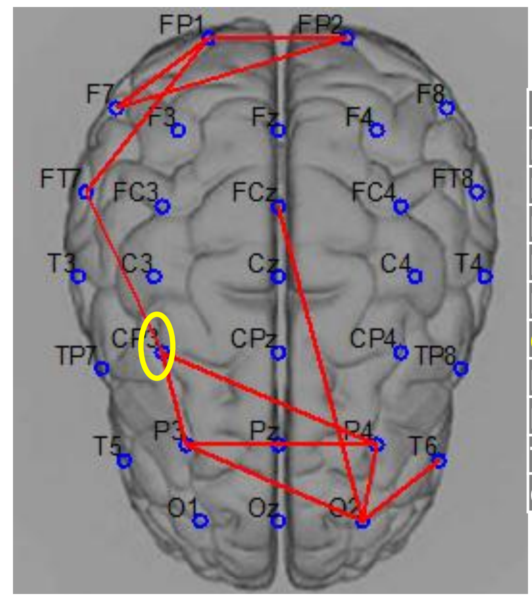
SNA Metrics applied to EEG Data

- Betweenness Centrality (BC)
  - Fraction of geodesic (shortest) paths between other electrodes in which the given electrode i falls on.

$$BC(i) = \sum_{x=1, x \neq i}^{n} \sum_{y=1, y<x, y \neq i}^{n} \frac{g_{xy}(i)}{g_{xy}}$$

  - Useful in determining points where the network would break apart - Bridge

Measures the number of times an electrode lies between the various other electrodes in the network.



	BC
FP1	14
FP2	0
F7	0
FT7	18
FCz	0
CP3	20
P3	7.5
P4	7.5
T6	0
O2	15

Construction of Functional Brain Networks

- Magnitude Squared Coherence (MSC)
  - Examines the linear relation between two signals x and y at time t.
  - Estimates the extent to which signal y(t) may be predicted from x(t) by an optimum linear least squares function.

$$C_{xy} = \frac{|G_{xy}|^2}{G_{xx}G_{yy}}$$

where G_{xy} - cross-spectral density between x and y,

G_{xx} and G_{yy} - auto-spectral density of x and y

$|G|$ - Magnitude of the spectral density

Range: [0 1]

Construction of Functional Brain Networks

- Pearson Correlation Coefficient (r)
  - Measures the linear relationship between two signals x and y
  - r = covariance / standard deviation

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

  - *x* and *y* - Electrodes

    Range: [-1 1]

Construction of Functional Brain Networks

- Entropy
- A measure of chaos/uncertainty/unpredictability/ information content in a random variable X

  - Information Theory

  - For a random variable X with n outcomes $\{x_1, ..., x_n\}$, the Shannon entropy, $H(X)$, is defined as

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log(P(x_i))$$

  - $P(x_i)$ - probability mass function of outcome x_i

Construction of Functional Brain Networks

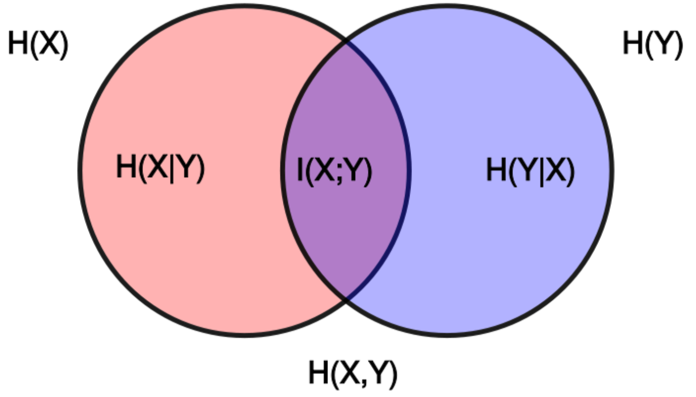
- Joint Entropy(X,Y)
  - Entropy over all possible pairs of the two random variables

$$H(X,Y) = -\sum_{x}\sum_{y} P(x,y)\log(P(x,y))$$

Construction of Functional Brain Networks

- Mutual information (MI)
  - Measures the information that two variables (Electrodes) *X* and *Y* share
  - Amount of uncertainty remaining about one variable after knowing the other.
  - I(X;Y)=H(X)+H(Y)-H(X,Y)

$$I(X;Y) = \sum_{x}\sum_{y} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right)$$



Construction of Functional Brain Networks

- Normalized variant provided by the coefficients of constraint

$$\mathrm{NMI}(X, Y) = \frac{I(X, Y)}{\min(H(X), H(Y))}$$

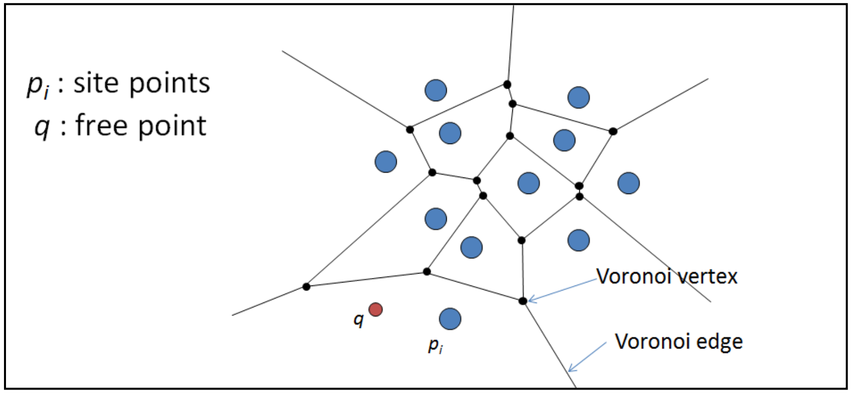
Voronoi Diagrams

- Voronoi diagram has been applied in many real time problems such as Global Positioning System (GPS) mapping, location based services, molecular biology etc.

  - Let P be a set of n distinct points (Electrode sites) on the plane.

  - Voronoi diagram of P - subdivision of the plane into n cells, one for each electrode site.

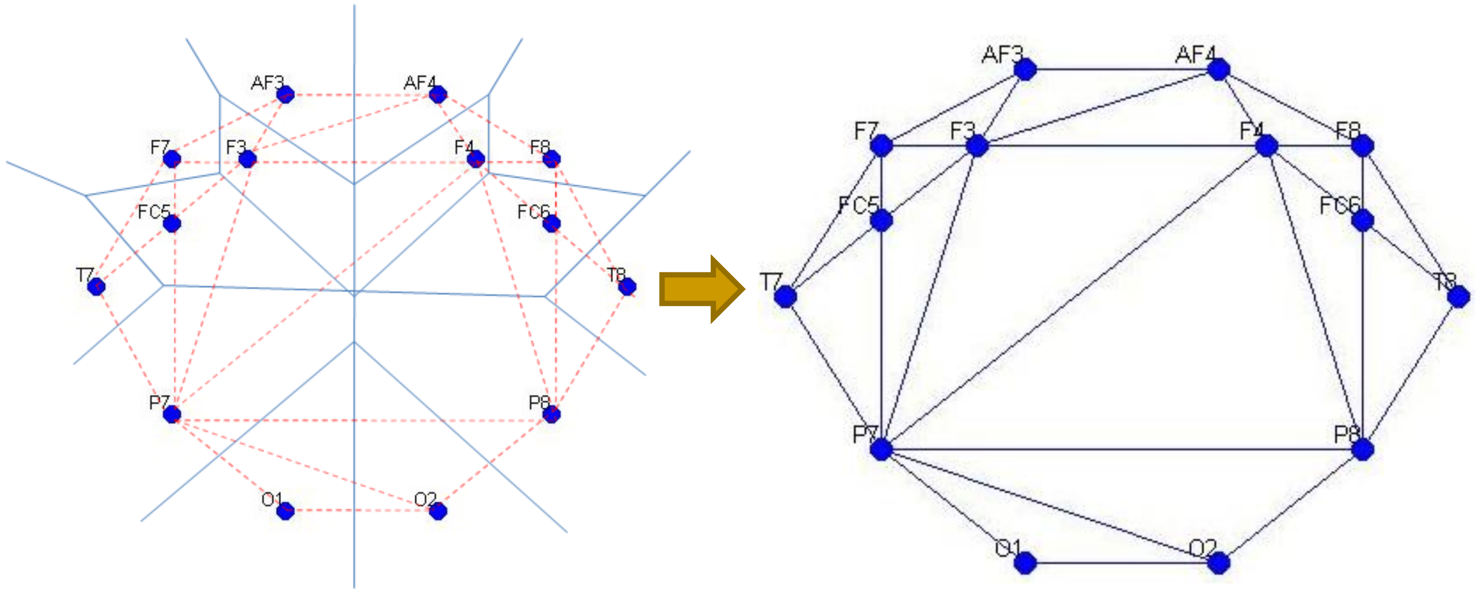
  - A point q lies in the cell corresponding to a site $p_i \in P$ *iff*



Euclidean_Distance(q,p_i)<Euclidean_distance(q,p_j), for each $p_j \in P$, $j \neq i$.

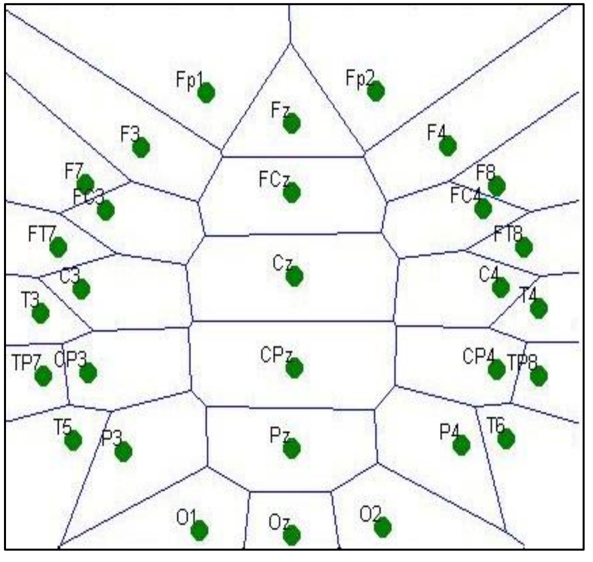
Construction of Structural Brain Network

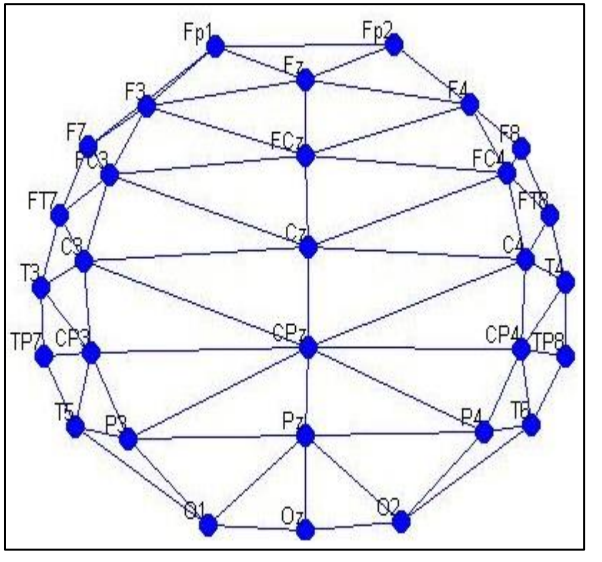
- Any two Voronoi cells x and y are said to be adjacent if they share a Voronoi edge - “Spatial Adjacency”.
- Electrodes on the scalp are connected if they are spatially adjacent - Delaunay Triangulation



Construction of Structural Brain Network

- Voronoi and Structural adjacency of 30 electrodes on the scalp





- Used to measure the influence of structural adjacency of electrodes over the functional brain network

Time Series Analysis of EEG Data

- Approximate Entropy (ApEn)
- Quantifies the amount of regularity and the unpredictability of fluctuations over time-series of data.
- High ApEn-Irregular & Low ApEn-regular
- Measures the probability of a recurrent pattern occurring within a time series even in the presence of noise and measurement inaccuracy

$$ApEn(m,r,N) = \phi^m(r) - \phi^{m+1}(r) + (r)$$

N – Number of data points

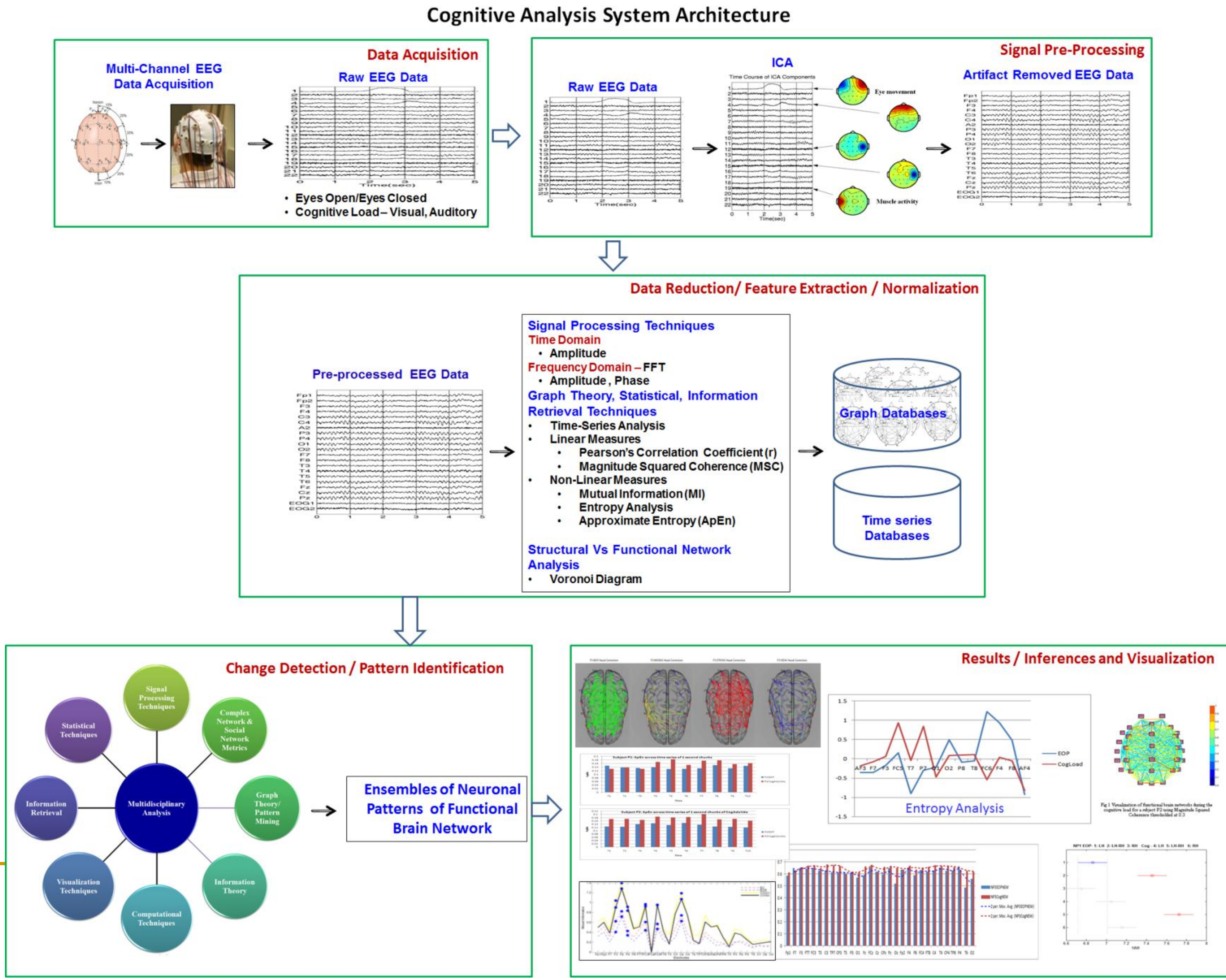
m- Length of data

r – tolerance value

$$\phi^m(r) = \frac{\sum_{i=1}^{n-m+1} \ln C_i^m(r)}{N-m+1}$$

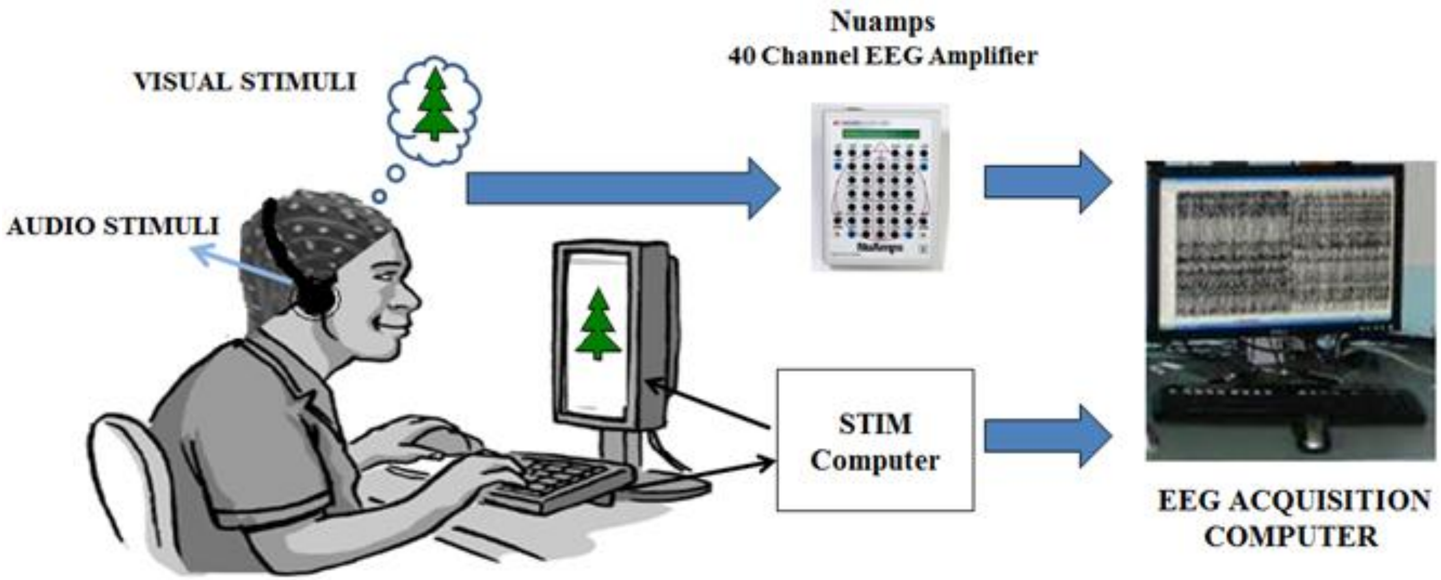
$C^m(r)$ - frequency with which patterns are encountered

Cognitive Analysis Framework @ CNEL



Cognitive Stimulation

- Experimental Setup and Data Acquisition



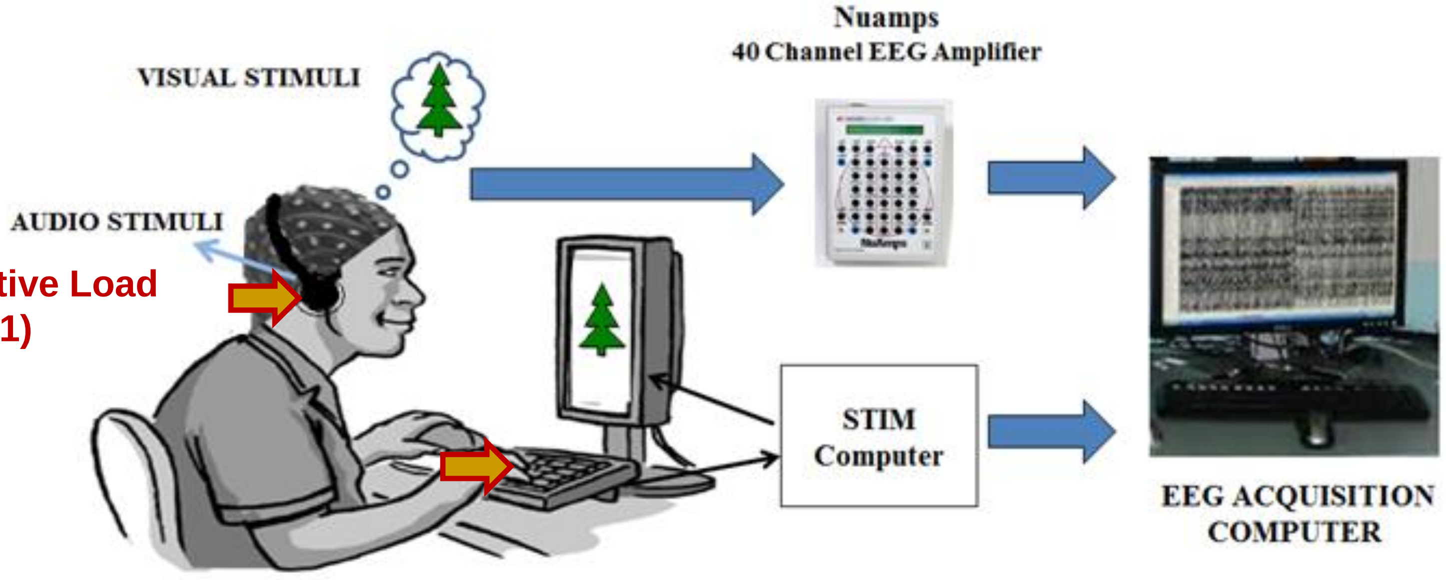
Cognitive Load Experimental Set up

Eyes Open

Cognitive Stimulation

- Experimental Setup and Data Acquisition

Audio Cognitive Load
(Cog1)



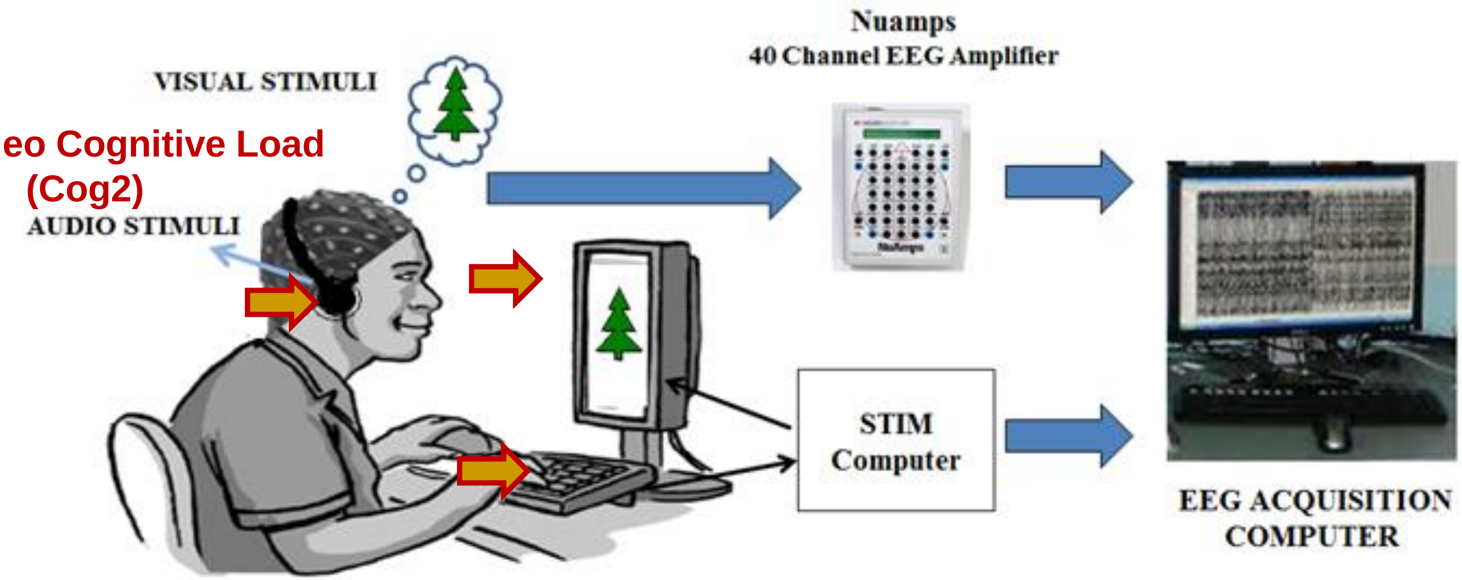
Cognitive Load Experimental Set up

Male/Female Voice
4 /A 3/S

Cognitive Stimulation

- Experimental Setup and Data Acquisition

Audio/Video Cognitive Load (Cog2)



Cognitive Load Experimental Set up

Male/Female Voice

4 /A 3/S

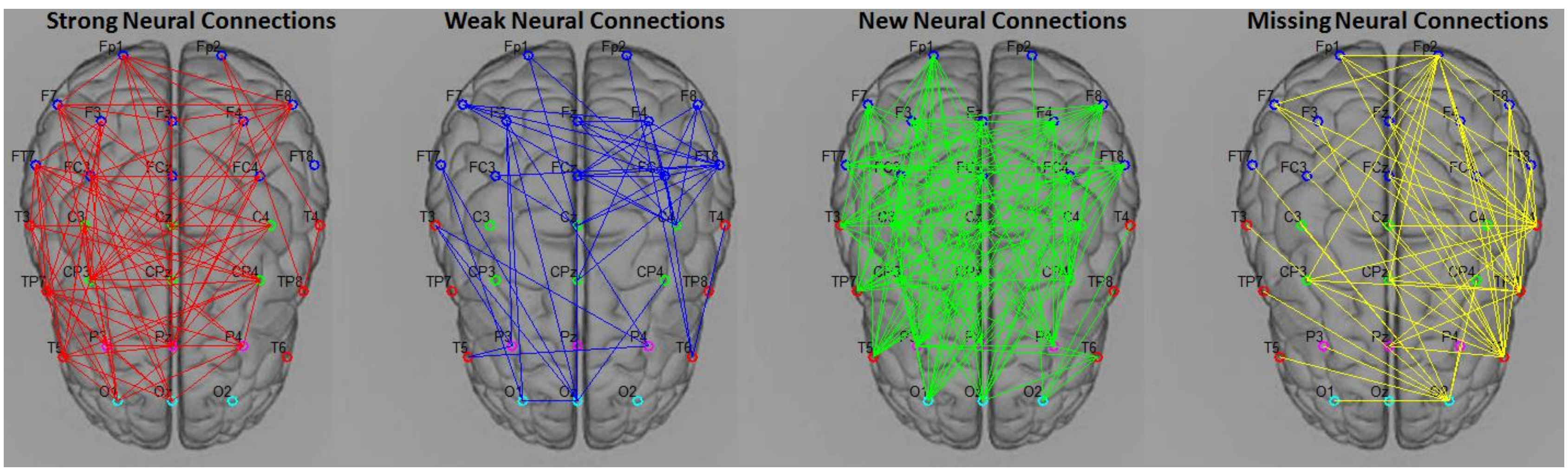
4 /A 3/S

EEG Data Filtering and Artefact Removal

- Pre-processing
  - Sampling Frequency - 1000Hz
  - Band pass filtering - 0.5Hz to 70Hz
  - 50Hz notch filter - Electrical interference removed
  - Independent Component Analysis (ICA)
  - Eye-blink artifacts removed
  - Bad blocks removed

Results and Discussion
Functional Brain Networks

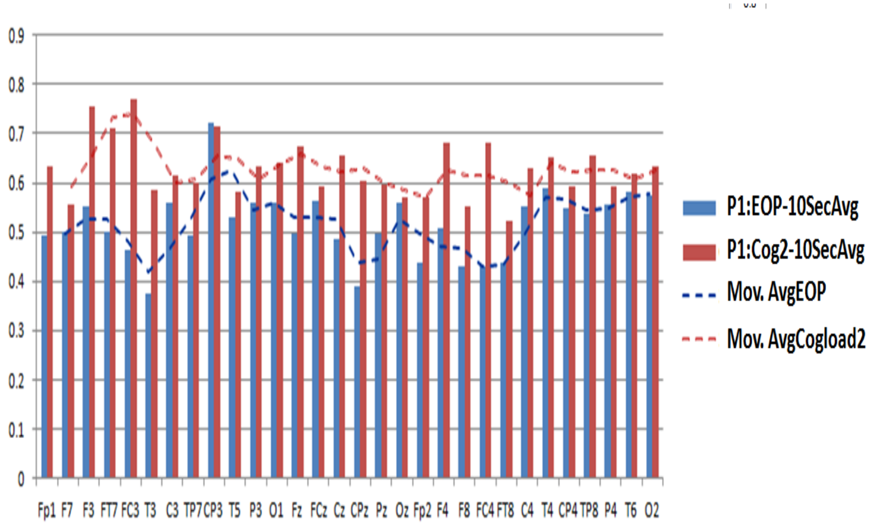
- Positive phase correlations (using r) – demonstrate highly cohesive neuronal clusters formed during cognition when compared to eyes open state.

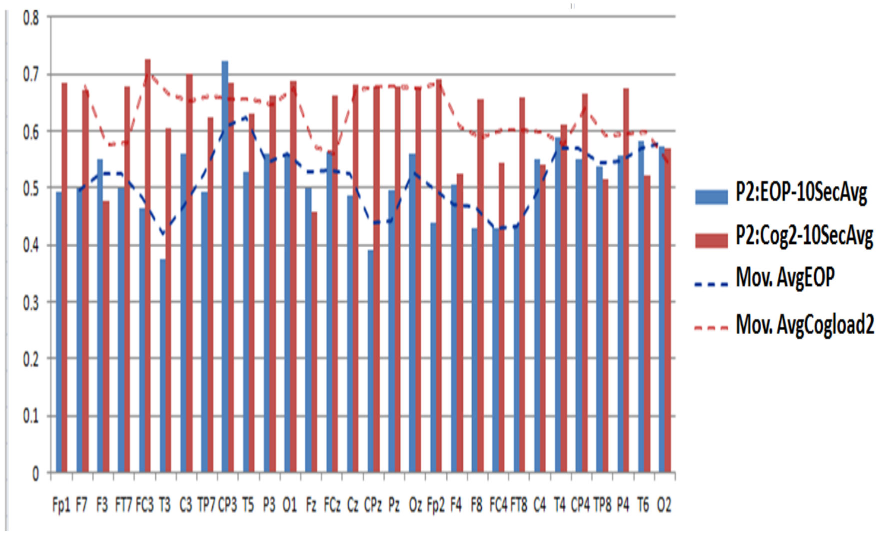


Results and Discussion

Information Sharing between electrodes

- Averaged NMI – Information sharing between electrodes comparatively higher during cognitive load

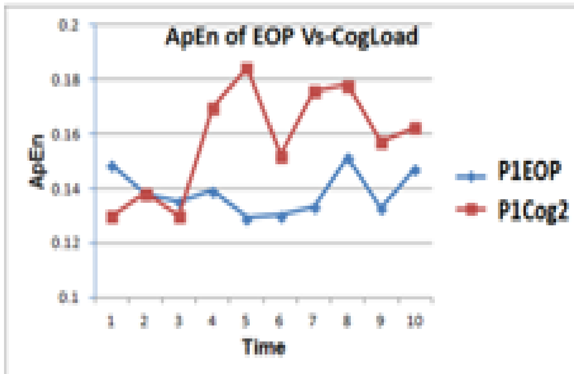


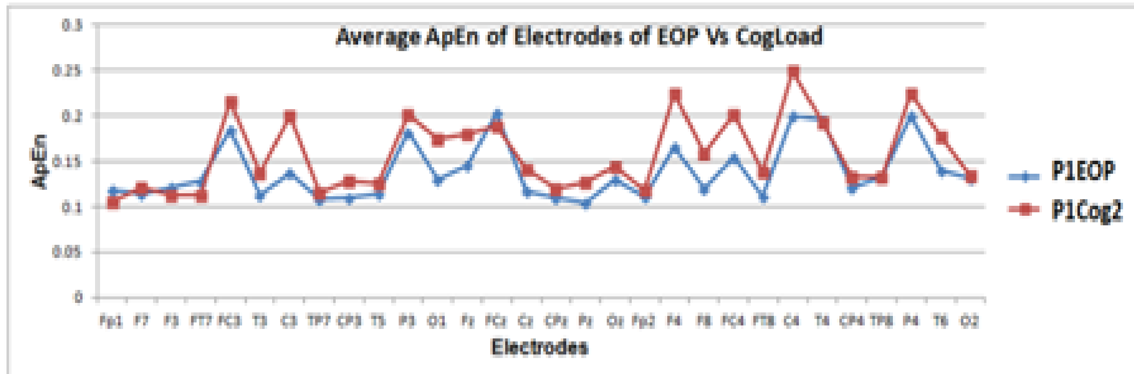


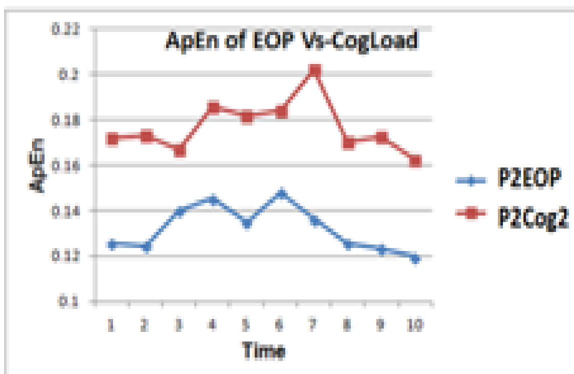
Results and Discussion
Brain Entropy

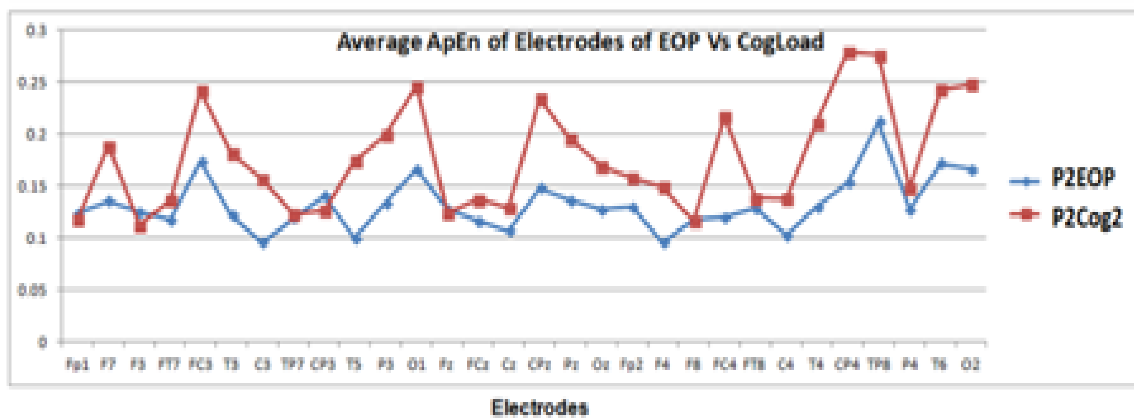
- Average ApEn of all electrodes across time, and ApEn values averaged over 10 chunks for all electrodes for two subjects
- Higher ApEn during cognition across many of the electrodes
- Comparatively higher ApEn at right hemisphere electrodes during cognitive load

Results and Discussion
Brain Entropy



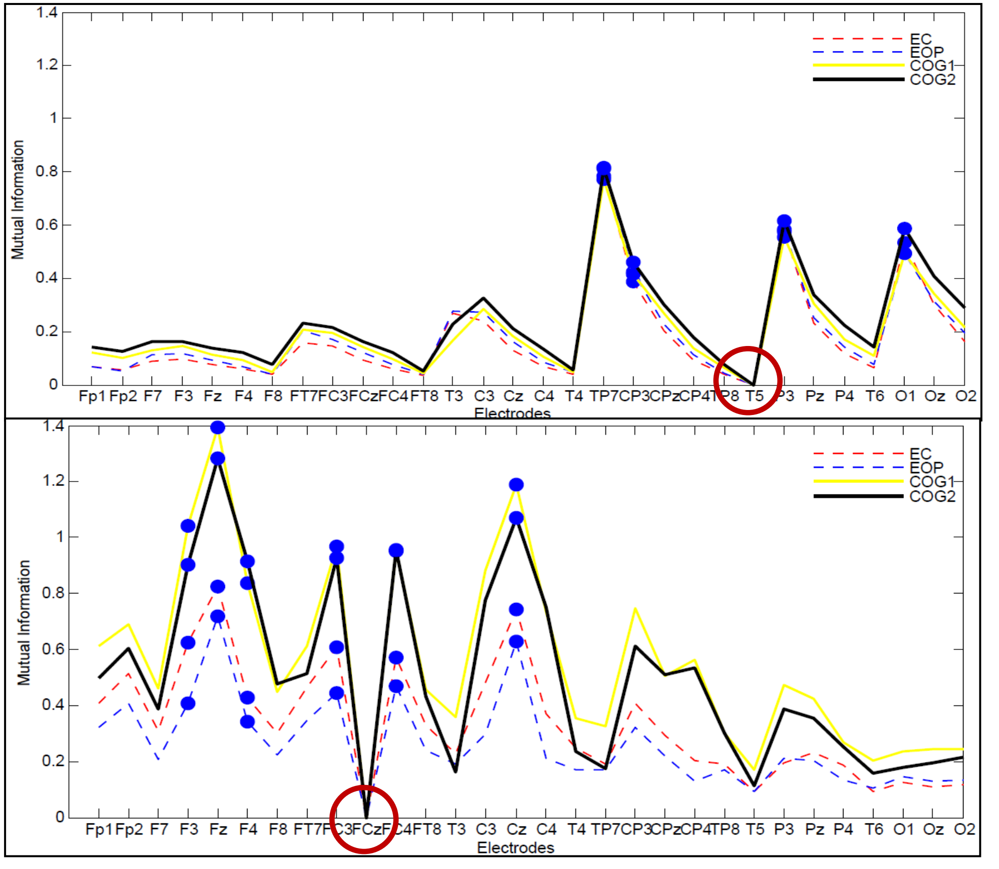






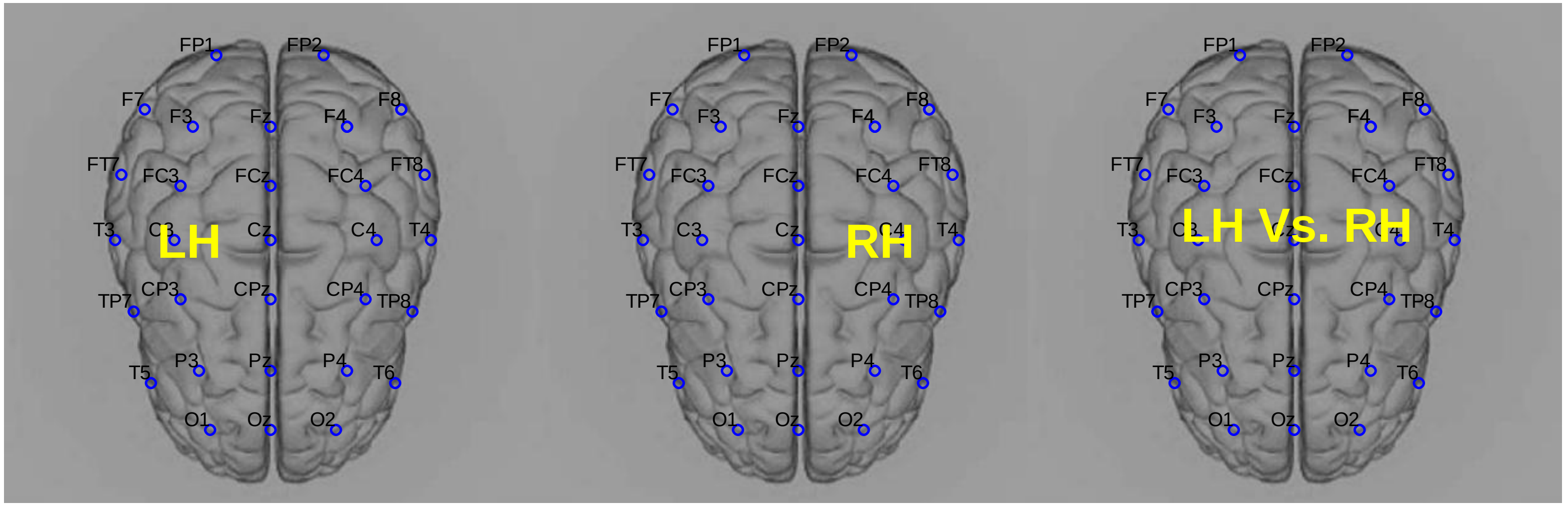
Results and Discussion
Structural Adjacency

- Voronoi Adjacency
- Structural adjacency between electrodes strongly influenced the functional adjacency between them.
- High values of information exchange at the structurally adjacent nodes



Results and Discussion Hemispherical Interactions

- Measuring the different intensities of interactions of the electrodes of left and right hemispheres during cognitive load using Total NMI



Results and Discussion
Hemispherical Interactions

- Multicomparison test –

  Interaction of electrodes across the hemispheres is moderately different from that of right hemisphere at the confidence interval of 0.95.

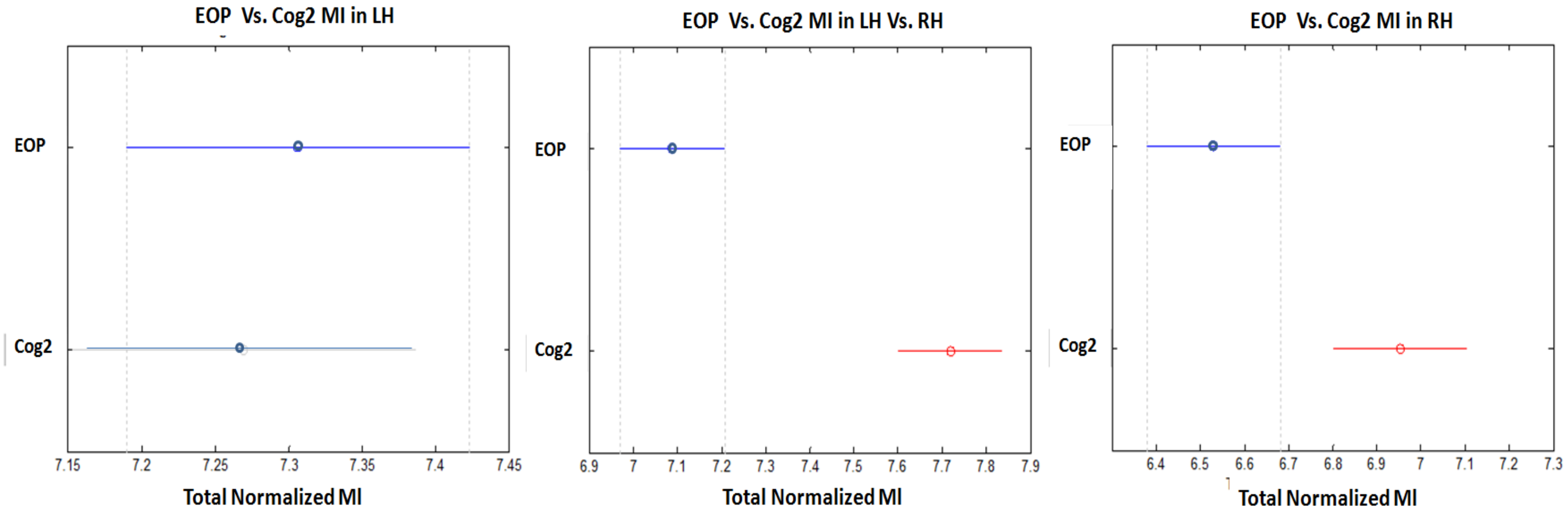
Subjects	Hemispheres Compared		Mean Difference	95% CI
P2	LH	LH-RH	-0.5457	[-0.8523, -0.2392]
	LH	RH	0.0608	[-0.2458, 0.3674]
	LH-RH	**RH**	**0.6066***	**[0.3000, 0.9132]**
P3	LH	LH-RH	-0.5870	[-0.7987, -0.3754]
	LH	RH	-0.0095	[-0.2212, 0.2022]
	LH-RH	**RH**	**0.5775***	**[0.3659, 0.7892]**

*Mean difference is significant at p<.05 level

Results and Discussion

Hemispherical Interactions

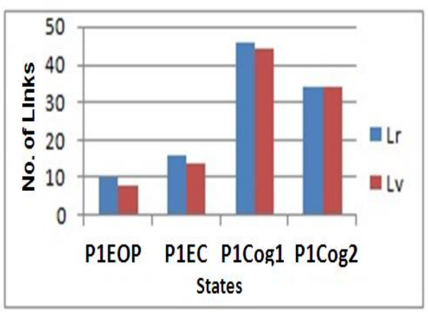
- Statistical validation using multicompare procedure to find difference in interactions between EOP and cognitive load
- High NMI values during Cognitive Load



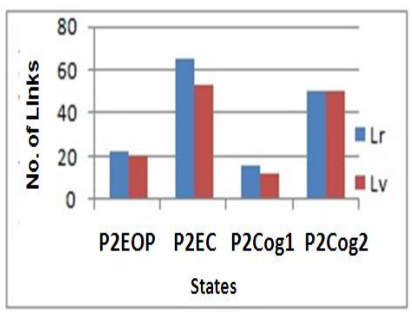
Results and Discussion

Structural & Functional Adjacency

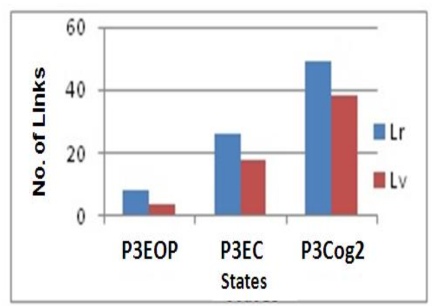
- Comparison between the Structural and Functional Adjacency in information dissemination
  - Adjacent brain regions transfer more information to each other when compared to more distant regions.
  - Number of structural brain network links(using voronoi diagram on scalp) Vs. Functional brain network links using thresholded MI remained almost the same.



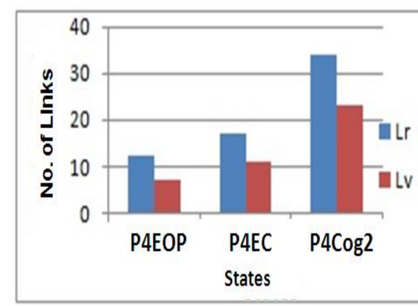
(a)



(b)



(c)



(d)

Conclusion and Future Work

- Linear and Nonlinear multivariate computational techniques to identify and quantify cognition using EEG
- Extensive study of information theory, graph data mining, and the study of the role of structural adjacency of the electrode sites in estimating cognition and 3 dimensional Voronoi diagrams
- Increased sample size and more tightly controlled variations of the cognitive load tasks provide further insights into the hidden neuronal patterns that represent cognition

References

1. Reber, A.S. 1995. The Penguin Dictionary of Psychology, (2nd Ed.), London, UK: Penguin Books Ltd.
2. Savoy, R.L. 2002. Functional Magnetic Resonance Imaging: (fMRI), in Ramachandran, V.S. (Ed. In Chief), Encyclopaedia of the Human Brain, 327-351, downloaded from http://www.sciencedirect.com/science/referenceworks/9780122272103 [31/7/2012]
3. Herculano-Houzel S., Lent R. 2005. Isotropic fractionator: a simple, rapid method for the quantification of total cell and neuron numbers in the brain. Journal of Neuroscience, 25, p. 2518 – 2521.
4. World Health Organisation, 2001. World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects, Bulletin of the World Health Organization, 79, p. 373-374.
5. Australian Government, 2010. Revision of the joint NHMRC/AVCC Statement and Guidelines on Research Practice: Australian Code for the Responsible Conduct of Research, downloaded from http://www.nhmrc.gov.au/_files_nhmrc/publications/attachments/r39.pdf, 22nd November.
6. Mukamel, R., Ekstrom, A.D., Kaplan, J., Iacoboni, M. & Fried, I. 2010. Single-Neuron Responses in Humans during Execution and Observation of Actions, Current Biology, 20, p. 750–756.
7. Dumermuth G. 1974. Quantification and analysis of the EEG, Schweiz Arch Neurol Neurochir Psychiatr. 115(2), p. 175-92.
8. Fagg, A. H., & Arbib, M. A. 1998. Modelling Parietal-Premotor Interactions in Primate Control of Grasping, Neural Networks, 11, p. 1277-1303.
9. Atallah, H.E., Frank, M.J. & O'Reilly, R.C, 2004. Hippocampus, cortex, and basal ganglia: Insights from computational models of complementary learning systems, Neurobiology of Learning and Memory, 82, p. 253–267.
10. Bullmore, E. and Sporns, O, 2009. Complex brain networks: Graph theoretical analysis of structural and functional systems. Nat. Reviews, 67, p.735-748.

References

11. J. Zhang, W. Cheng, Z. Wang, Z. Zhang, W. Lu, et al. 2010. Pattern Classification of Large-Scale Functional Brain Networks: Identification of Informative Neuroimaging Markers for Epilepsy. PLoS ONE 7(5): e36733. doi:10.1371/journal.pone.0036733, 2012.
12. M.E.J. Newman, Networks an Introduction. Oxford University Press, Oxford.
13. D. J. Smit, C. J. Stam, D. Posthuma, D.I. Boomsma, and E. J. de Geus, 2008. Heritability of “small-world” networks in the brain: a graph theoretical analysis of resting state EEG functional connectivity. Hum. Brain Mapp. 29, p. 1368–1378.
14. K. J. Friston, C.D. Frith, P.F. Liddle, R.S. Frackowiak. 1993. Functional connectivity: the principal-component analysis of large (PET) data sets. J Cereb Blood Flow Metab 13, p. 5–14.
15. A.A. Fingelkerts, S. Kahkonen. Functional connectivity in the brain – is it an elusive concept? 2005. Neuroscience and biobehavioural Reviews. 28(8), p. 827-836.
16. S. Fortune. A sweepline algorithm for Voronoi diagrams, 1986. In SCG ’86: Proceedings of the second annual symposium on Computational geometry, ACM Press, p.13–322.
17. Pablo A. Estévez, Michel Tesmer, Claudio A. Perez, and Jacek M. Zurada, 2009. Normalized Mutual Information Feature Selection, IEEE Transactions On Neural Networks, 20.
18. Pincus, S. M, 1991. "Approximate entropy as a measure of system complexity," *Proceedings of the National Academy of Sciences*, p. 88.
19. Johnson, M. L, Straume, M., and Lampl, M, 2001. The use of regularity as estimated by approximate entropy to distinguish, saltatory growth, Annals of Human Biology, 28 (5), p. 491-504.
20. Pincus, S. M, 2001. ‘‘Assessing serial irregularity and its implications for health,’’ Ann. NY Acad.Sci., 954, p. 245–267.
21. Delorme A., Makeig S, 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neuro. Methods* 134, p. 9–21.

Invited Talk

17th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems, Kitakyushu, Japan, September 9 – 12, 2013.

Nanda(D) Nandagopal, Vijayalakshmi R, Bernie Cocks, Nabaraj Dahal, Naga Dasari, Thilaga M, 'Computational Techniques for Characterizing Cognition using EEG - New Approaches'


Thank You!