Understanding Structure Induced Functional Connectivity in Brain using EEG

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***Abstract*—Phase synchronization (PS) analysis has been exhibited as an effective method to understand visually evoked functional connectivity of brain responses for basic structures. It is believed that the brain response changes with the perception of the object of an individual. Different studies have been conducted on healthy subjects to see how the brain creates a perception for dots forming a line (called as structure) as compared to random dots (called as non-structure). In this paper, we investigate how the Phase locking value (PLV) which quantifies the functional connectivity, changes for the structures and non-structures using multi-channel neural signals such as electroencephalography (EEG). The results reveal high synchronization or enhanced connectivity between the brain regions during structure compared to non-structure. These results are accompanied by the Network Measures Analysis. The low Clustering Coefficient (CC) and high Path Length (PL) in the alpha band for non-structure trials indicate loss of small-world properties. Also, minimum spanning tree (MST) network measures such as Leaf Fraction (LF) and Tree Hierarchy (TH) showed decreased value for non-structure trials symbolizing weak integration for random dots as compared to grouping perception of dots.**

***Index Terms*—EEG, Functional Connectivity, Grouping Perception, MST Analysis, Network Measures Analysis.**

I. Introduction

The ability to recognize our surroundings is due to learning through our senses. Perception is shaped by experience but it does not occur without cognitive abilities. The most powerful ability humans have is discrimination or classification of objects [1][2] class. But, the evolving question about human ability is how the brain learns object [3] [4]. The neural basis of perceptual grouping is not yet understood clearly [5]-[8]. It is believed that the object perception fundamentally depend upon the deduction of contours from the visual scene [9].

Contour integration or structure formation is nothing but the grouping of components based on similarity [10] and thus provides visual edge information [11]. The manner in which a contour is constituted can even change the response of brain (EEG response) [12]. The understanding of this concept can be elucidated through various imaging modalities such as electroencephalography (EEG) [13]-[15], magnetoencephalography (MEG), structural MRI, functional MRI, Diffusion MRI. The organisation of Brain neural network is considered as a large-scale network [16] assembled as a collection of interconnected brain regions. These regions perform their functions collectively in order to forge behavior and furnish actions [17]. Thus, there must exist some co-ordination or synchronization between these areas within this complex network [18]. This synchronization is responsible for cognition. Reduction in interactions between the areas causes psychiatric and neurological disorders [19].

Furthermore, in context of object binding problem, spatially separated processing areas of brain are coordinated and computations occurring in them combined together to form perception using a coordinating mechanism [20]. Various coordinating mechanism measures such as phase synchronization index (PSI), Phase Locked Value (PLV) [21], coherence, correlation coefficient and mutual information exists [22]-[25], which are employed to infer the connectivity between the brain regions using different techniques such as EEG (electroencephalography), fMRI (functional magnetic resonance imaging), MEG (magnetoencephalography) , diffusion tensor imaging (DTI) and others.

Phase-locking value has been applied in various types of neuroscience related research [26]-[27] to measure the strength of PS (Phase Synchronisation). As an example, [28] illustrated how the evoked responses (ERPs) obtained for the visual stimuli are characterized using PLV to determine the functional connectivity between electrodes. PLV has also been used in various neurodevelopmental research like; to examine the variation of connectivity in cortical region before seizures [29], synchrony between the neurons after stroke [30], to recognise different brain states in brain machine interface [31] [32], to inspect the deficits of mental illness [33], and to explore different approaches for help in clinical exploration [30] [34] are few.

In recent past, efforts have been made in understanding the organization of whole-brain network [35] [36], using various methods, wherein Graph theory [37] [38] is one of them. The Graph theory enables exhibiting the organization of complete-brain functional connectivity network. If the number of connections are more, the weighted matrices of the graph are thresholded [39]. This thresholding affects the network topology values in many different ways. To overcome these issues, MST has been employed extensively in the investigation of brain network organization [40] [41]. The functional connectivity analysis presented in the current study using graph theory and MST measures can provide a complete framework in evaluation of brain network organization for structure-perception.

In the present work, we have attempted to disentangle and determine the neural correlates of structure-formation/structure-perception through different studies conducted. Firstly, functional connectivity analysis is performed to find the brain areas interacting during the process of perception formation. Further, the organization of whole-brain network is identified using graph theory and minimum spanning tree analysis. Graph measures such as Path length and Clustering coefficient are evaluated to search for features of small-world properties. MST network topology measures such as Leaf fraction and Tree Hierarchy are evaluated to check for network efficiency and integration ability [42] [43].

The work carried out in this paper can provide a new insight to the existing theories of grouping perception in brain. Also, how the functional connectivity network in brain varies for structure perception at different EEG frequency bands is explained well.

II. Materials and Methods

A. Participants

Fifteen subjects in the age group of 19 to 30 years participated in the study out of which 13 were males while 2 were females. No subject suffers from any neurological deficits or illness. The participants were informed with all the details about the experiment and proper consent was taken once they agreed to perform. The proposed experiment was approved by the Indian Institute of Technology review board (IIT Delhi Ethical Clearance Committee).

B. Stimulus Design

The stimuli was designed using two types of images viz 'Structure' and 'Non-Structure'. The 'Structure' image contains random dots few of which seems to form two straight lines while in the 'Non-Structure' image, only random dots were present. Each image appear on the screen for 1000 ms with a random gap of 1200 ms-2300 ms between them. The total number of images was 40 and each stimuli was presented randomly five times on the screen which provides 200 events (100 of structure and 100 of non-structure). Fig.1 shows the stimulus paradigm. Image presentation was controlled via a computer running on the Psychopy stimulus presentation software. Psychopy works in sync with the Brain Vision Recorder software so as to add correct labels to the raw EEG data [15].

C. EEG Acquisition

The ActiChamp Brain Vision device was used to record the EEG signals related to the stimuli shown. The sampling frequency of the recording was kept at 2500 Hz. The raw EEG data was collected using 64 channel EEG acquisition system. The sensors were pasted onto the head of participant through headcap designed according to the international 10-20 electrode placement system. The size of EEG electrode cap was decided by measuring the head circumference of the participant. These measured EEG signals from brain were then sent to the Brain Vision amplifier. Fig. 2 shows the EEG acquisition apparatus. The data was collected and stored by the Brain Vision EEG recording software running on the first computer which is connected in sync with the other computer displaying the stimulus.

In order to capture the EEG signal, the participant was seated in front of the screen of the monitor keeping a distance of about 40-60 cm. The impedance was adjusted as low as possible between the scalp and the electrode. The subjects was asked to avoid bodily movement and look at the stimuli keeping all the focus on the screen. The approximate time taken to conduct the experiment was around 45-50 minutes.

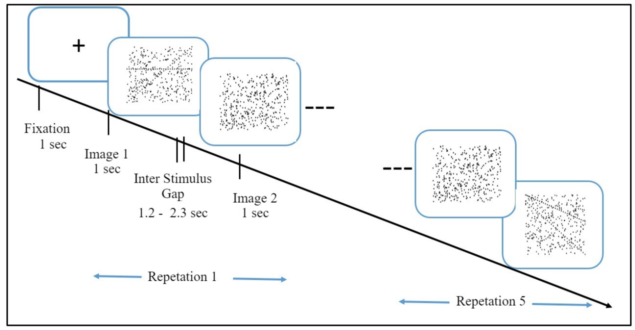


Fig. 1: Stimulus Design Overview

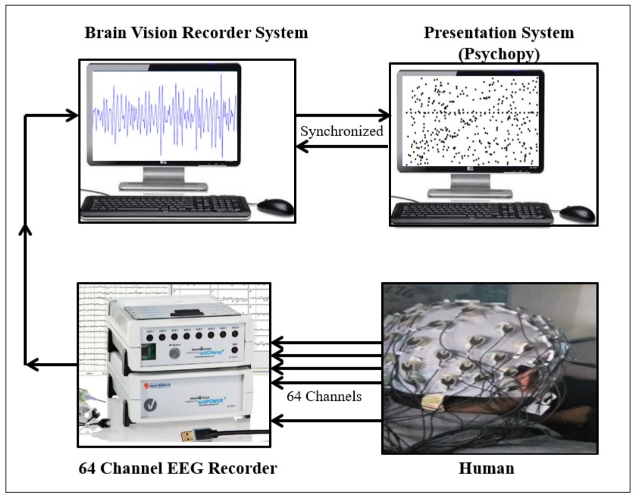


Fig. 2: EEG Acquisition Apparatus

1) Preprocessing: The collected raw EEG data was first passed through the bandpass filter having cutoff frequencies 2 Hz-45 Hz. Then each signal was re-referenced using average re-referencing followed by the epoch extraction. The epochs were segmented for the events related to structure and non-structure, as a window of length 1400 ms ranging from -200 ms before stimuli onset to 1200 ms after the stimuli onset. The mean of recorded baseline from -200 ms to 0 ms was removed from each channel.

D. Phase Synchronisation

The concept of Phase Synchronisation (PS) is used to measure the connectivity between electrodes on the scalp. The population of neurons that are phase-locked with each other are said to be wired together. It is believed that the neurons that are wired together, will fire together[46]. Thus, the PLV value reflects the existence of some wiring or functional connectivity between these neurons or the electrodes. The PLV value range lies between 0 and 1, so PLV value equal to or near to 1 indicates higher functional connectivity between the electrode pair. The phase locking value (PLV) is expressed as :

$$PLV = \frac{1}{N}\left|\sum_{n=1}^{N} exp(j(\phi_a(t) - \phi_b(t))\right| \tag{1}$$

where N is the total number of trials and $\phi_a(t)$ and and $\phi_b(t)$ denotes instantaneous phase of electrode a and electrode b respectively. Firstly, the instantaneous (wrapped) phase of each electrode signal is extracted. Then the instantaneous phase difference between the each electrode-pair, recorded as a response to stimuli is calculated across the trials. This phase difference is represented in the Euler form as $M\,e^{i\,\theta}$. The vectors are then averaged to evaluated the mean complex vector. The length of this mean vector quantify the strength of functional connectivity or phase synchronisation between the electrodes [28].
The PLV values between the electrodes are visualized by the connectivity matrix and connectivity map. For validating the results, the obtained PLV values are compared with the PLV values computed for surrogate data. The surrogate data is obtained by randomizing the phase of the original signals. The results were considered only if the difference between surrogate data PLVs and the PLVs computed on the original data was significant $(p < 0.05)$.

E. Analysis of Network Measures

The analysis of network topology measures is done using graph theory. In a graph, a node connected to other node via edge manifests various topology measures.
The measures of network topology for connectivity (weighted) matrix are here calculated in three ways; firstly network measures like correlation coefficient and path length are calculated for connectivity(weighted) map corresponding to connectivity (weighted) matrix. In Connectivity matrix, every value denotes the strength of functional connection between a pair of electrodes such that every edge of connectivity map is assigned a weight and thus connectivity matrix is called as weighted matrix. Secondly, Binary matrix and its corresponding graph is drawn and thus the measures like path length and correlation coefficient are calculated. Binary matrix is generated using weighted matrix, by deciding a threshold value above which

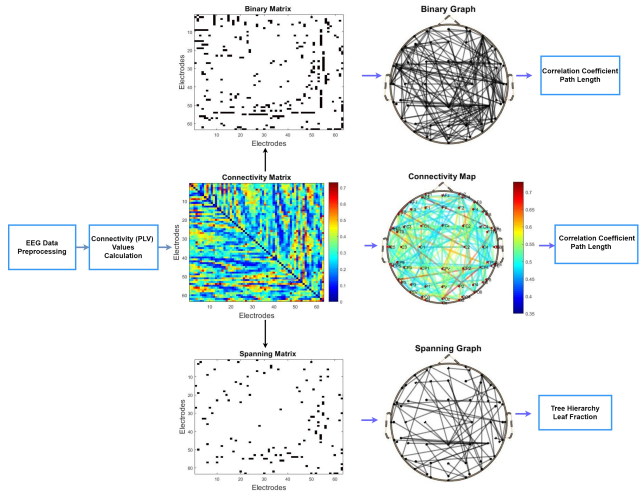


Fig. 3: Connectivity and Graph Analysis Pipeline: Schematic Overview of Graph Analysis for Connectivity Matrix in three ways

the edge weights are 1 while below are O(no edge). The third way was to calculate the minimum spanning tree(MST) matrix for connectivity (weighted) matrix and the network measures such as Leaf fraction and Tree Hierarchy related to MST graph. The connectivity and graph analysis pipeline is shown in Fig. 3.

1) Weighted Graph Analysis: In weighted graph analysis, graph containing 63 nodes and edges connecting them (depending on connectivity strength value) is drawn using Connectivity matrix. Connectivity Matrix is a 63X63 adjacency matrix specifying strength of functional connectivity between every electrode-pair. Thus, the obtained graph is weighted, fully-connected and undirected as shown in Figure 3.
The two measures of weighted matrix, Path Length (PL) and Clustering Coefficient (CC) are employed here to explore the functional brain network and characteristics it possess for a particular event occurred. The Clustering Coefficient (CC) of a network is used to determine the local modules that exist in a network. The high value of CC signifies that each node is connected to its neighboring node and is thus forming a module. Computationally, the weighted clustering coefficient is the average ”intensity” (geometric mean) of all triangles associated with each node [44]. Clustering Coefficient is given as -

$$CC = \frac{1}{N}\sum_{i=1}^{N} C_i = \frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{j,h=1}^{N}(w_{ij}w_{ih}w_{jh})^{\frac{1}{3}}}{k_i\,(k_i-1)} \tag{2}$$

where C_i is the Clustering Coefficient of node i and k_i is the degree of node.
The network characteristic path length or simply path length (PL) is the length of shortest path between every pair of nodes. The PL reflects the functional integration of information processing in the network. The small value of PL denotes

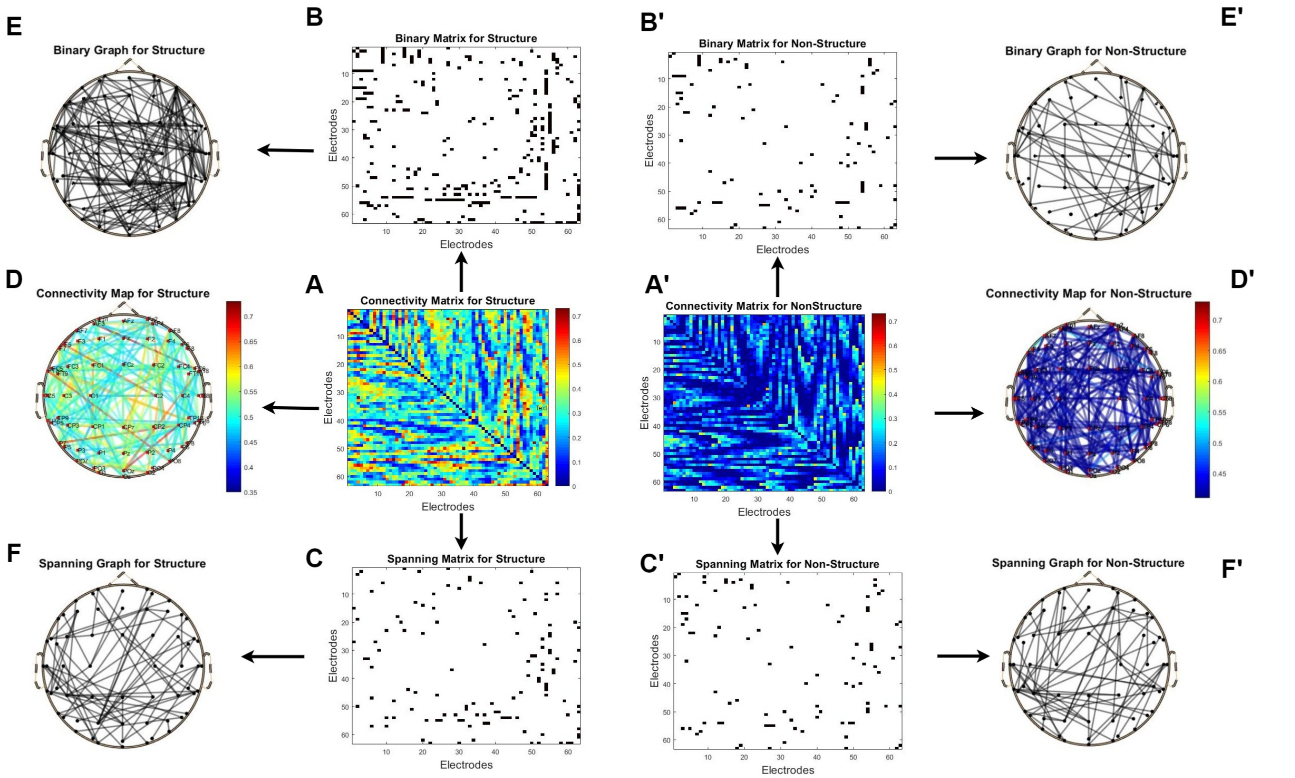


Fig. 4: **Connectivity Matrix and Connectivity Map :** A and D denotes Weighted Connectivity Matrix and Weighted Connectivity Map respectively for Structure, B and E denotes Binary Connectivity Matrix and Binary Connectivity Map respectively for Structure, C and F denotes Spanning Matrix and Spanning Map respectively for Structure while A' and D' denotes Connectivity Matrix and Connectivity Map respectively for Non-Structure, B' and E' denotes Binary Connectivity Matrix and Binary Connectivity Map respectively for Non-Structure, C' and F' denotes Spanning Matrix and Spanning Map respectively for Non-Structure

high global efficiency of information transfer between any two nodes. For calculating path length, firstly distance matrix is computed which is the inverse of original connectivity matrix. The shortest path is the path with largest total weight. Path Length (PL) for weighted network is given as

$$PL = \frac{1}{N}\sum_{i=1}^{N} L_i = \frac{1}{N}\sum_{i=1}^{N} \frac{\sum_{j=1,\, j\neq i}^{N} d_{ij}}{N-1} \tag{3}$$

where L_{ij} is the average distance between node i and all other nodes. These measures of network topology also claims whether the network has Small World (SW) properties.A SW network is defined as a network in which neighbour of every node are neighbour to each other even if the nodes are not neighbour to one another; also implies that most nodes can be reached from every other node with a small number of hops or steps. It is a property which brain connectivity network should possess as network of brain neurons is a small world network.

2) Binary Graph Analysis: Binary Connectivity Matrix is computed using Original Connectivity Matrix, for which a certain threshold value is chosen above which the connectivity values are set to 1 otherwise are set to 0. Using this Binary Connectivity matrix, a binary graph is drawn such that a edge is present only if the connectivity value is equal to 1. The topology network parameters such as Clustering Coefficient (CC) and Path Length (PL) are calculated for the obtained binary graph.

3) MST Graph Analysis: Spanning Tree is a tree in which all nodes are connected without any loop formation. Minimum Spanning Tree (MST) is evaluated using Prim's Algorithm such that starting with a node the closest neighbor is found out and all edges are marked for remaining nodes,continue to mark edges for next closest cluster until no nodes remain. A MST containing 63 nodes was constructed using MST matrix which was derived from original connectivity matrix.

Network parameters such as Leaf Fraction (LF) and Tree Hierarchy (TH) are calculated for the MST graph. Leaf Fraction measures the integration of information in the network. The low value of the leaf fraction specifies decrease in the global efficiency in the network. Leaf fraction is defined as-

$$LF = \frac{L}{N-1} \tag{4}$$

where L is number of leaf nodes (i.e. nodes with degree 1) in the network and N is total number of nodes. Tree Hierarchy indicates the balance between efficient communication paths and overload of hub nodes. Tree Hierarchy is defined as-

$$TH = \frac{L}{2mBC_{max}} \tag{5}$$

where m=N-1, N is total number of nodes, L is number of leaf nodes in the network and BC is Betweenness Centrality. Leaf node is a node with degree 1. Betweenness Centrality is defined as the number of shortest paths between any two nodes passing it, divided by the total number of shortest paths in the network.

III. Results

A. More Phase Synchronisation between electrodes for structure event epochs

In Synchronisation study, synchronisation between every pair of electrodes for the two events is found out using Phase Locked Value (PLV). These synchronisation (PLV) values were calculated for each trial and then averaged over trials and subjects. The PLV values thus are represented in form of matrix known as Connectivity Matrix. The Connectivity Maps are drawn for these event specific matrices. A statistical difference $(p < 0.05)$ was reported between target and non-target trials using Wilcoxon test. Figure 4 shows the Connectivity Matrix and Connectivity Graph after averaging over trials and subjects for Structure and Non-Structure conditions.

B. Alpha Band shows more Functional Connectivity for 'Structure' trials

The EEG band analysis is performed to see the behaviour of evoked response at different frequencies for two events. For every subject, the functional connectivity was calculated for each electrode pair in four EEG frequency bands; theta, alpha, beta and gamma.The functional connectivity was averaged over all subjects in all the bands for the two events, structure and non-structure separately. The topology of this mean functional connectivity is shown in Figure 5 for different bands. The topology reflects more functional connectivity in alpha band[47] for the structure trials as compared to non-structure trials. The topology for difference between two conditions as in Figure 5 also proves the existence of greater functional connectivity in alpha band.

Mean PLV values in each frequency band are averaged over all electrodes and thus box plot is drawn for each frequency band. The box plot is shown in Figure 6 to show the mean functional connectivity for two events in different frequency bands. Significant difference $(p < 0.05)$ was found between structure and non-structure trials in Alpha and Gamma Band is shown in Figure 6.

C. Significant difference in Weighted Network measures for the two events

The CC is calculated for every node using the mean PLV matrix in each band, separately for the events-structure and non-structure. The Boxplot for CC is illustrated in Figure 7a for the two events in theta, alpha, beta and gamma EEG frequency bands where red box denotes structure while green box denotes non-structure. The Boxplot of Clustering Coefficient shows a clear visual difference between the events structure and non-structure in alpha band. Also, the CC values are statistically different with $(p < 0.05)$ for the two events in alpha band. Path Length(PL) is computed by taking the harmonic mean of distance matrix which was calculated using mean PLV matrix. The Boxplot for PL is illustrated in Figure 7b for the two events in theta, alpha, beta and gamma EEG frequency bands where red box denotes structure while green box denotes non-structure.The Boxplot of PL shows a clear visual difference as well as statistically significance with $(p < 0.05)$ between the events structure and non-structure in alpha band.

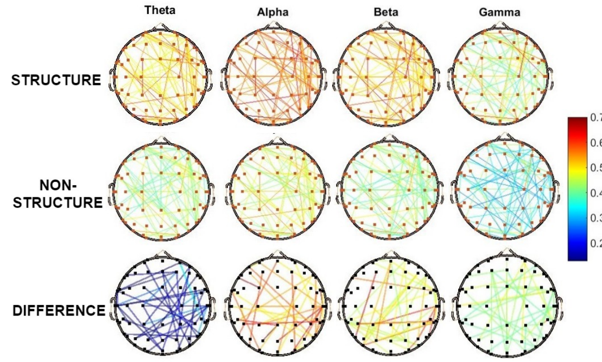


Fig. 5: Functional Connectivity in 4 EEG Frequency Bands

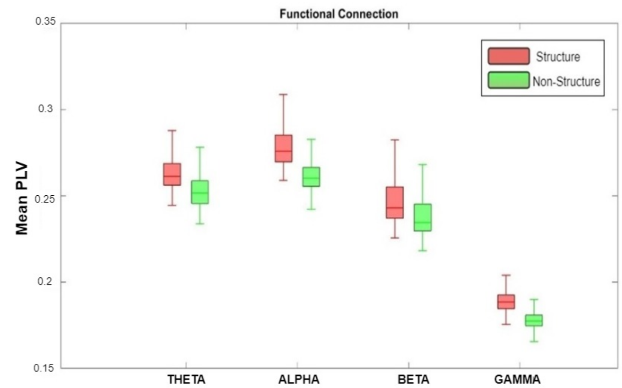
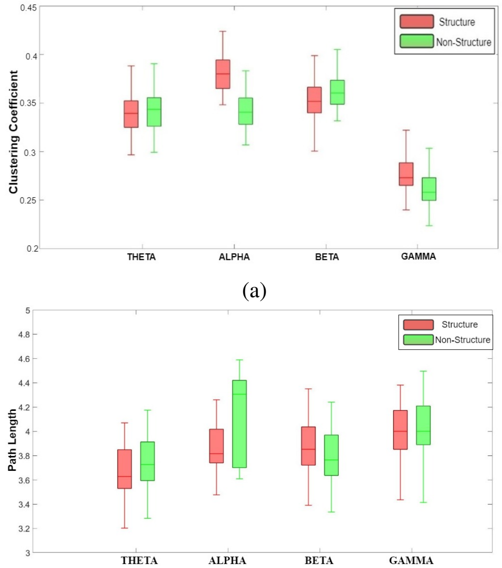


Fig. 6: Functional Connectivity

D. Significant difference in MST Network measures for the two events

The network measures Leaf Fraction (LF) and Tree Hierarchy (TH) were calculated for the MST matrices. The Boxplots for LF and TH are illustrated in Figure 8a and Figure 8b for the two events in theta, alpha, beta and gamma EEG frequency bands where red box denotes structure while green box denotes non-structure.The Boxplot of LF and TH shows a clear visual

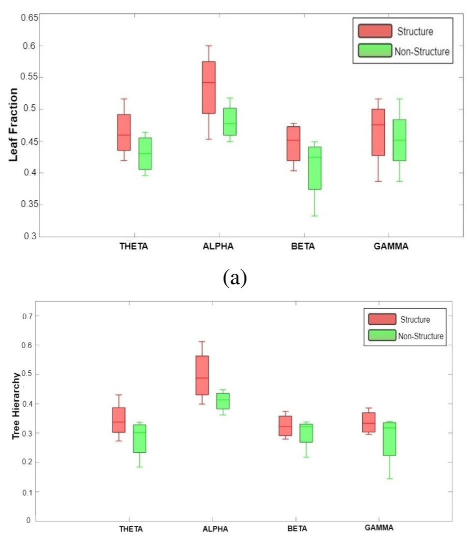


(a)

(b)

Fig. 7: Clustering Coefficient and Path Length

difference as well as statistically significance with $(p < 0.05)$ between the events structure and non-structure in alpha band.



(a)

(b)

Fig. 8: Leaf Fraction and Tree Hierarchy

IV. Discussion

Our results illustrates that there exist a visual as well as statistical difference between brain responses for structures and non-structures. It can be stated that perceptual grouping of dots for line formation as in case of structures produces high activation in brain as compared to the condition of random dots. It also reflects the figure-ground concept which here implies to the dots forming line(structure) in midst of random dots as figure while random dots are considered as background clutter or ground [10] [48].

The connectivity analysis [28] and graph analysis [42] are performed to provide different aspects of grouping/structure-formation perception in brain. Therefore, this study can be considered as first study to investigate functional connectivity of brain for perception of basic structures together with SW (Small-World) properties and MST properties of connectivity topology.

Furthermore, Phase Synchronisation (PS) results suggests higher connectivity for structure which illustrates increased mental processing at perceptual level. Phase Synchronisation of electrodes implies to wiring between them. It is believed that these electrodes which are wired together are intended to fire together functionally [20]. So, the phase synchronisation [28] between electrodes reflects the functional connectivity between brain areas related to a particular task. The graph theory [37] [38] furnish a means to evaluate the reorganization of functional connectivity between brain regions at a higher and integrative network topology level. High path length and low clustering coefficient for non-structures in alpha band was found for both weighted and binary graphs, suggests a less segregated and less integrated organization of network in the brain which is due to the absence of grouping perception in the event. Thus, weighted and binary graph reflects loss of small-world properties for non-structures [42] [43].

In addition to regular standard methods, MST analysis is also included in network measure study as a reliable and unbiased graph theoretical approach. Higher value of leaf fraction for structure in alpha band indicates highly integrated brain connectivity network for grouping perception. Increased value of Tree Hierarchy (TH) in alpha band for structures expresses balance between efficient communication path and overload of hub nodes [43]. The obtained structure-formation perception connectivity brain network was more efficient. The results of all the studies conducted for healthy controls can be used as a reference in case of neurological disorders.

There are a few shortcomings to the studies conducted in present work. First, the present study used a normal sized EEG montage with 64 electrodes. Although the connectivity strength and the network density does not affect MST metrics, still some parameters depends on the size of the network. Thus, the results presented can be reproduced by using more number of electrodes, to judge the significance of more number of nodes in the network performance [38]. Secondly, PLI can be used for measuring connectivity and to avoid problems like volume conduction [38]-[50], whilst it is not clear yet how it can be more effective method. Lastly, the EEG data can be collected for a large set of subjects to obtain more accurate results.

V. Conclusions

In conclusion, the present study elucidate a deeper insight to existing contour integration/perception mechanism. Phase

Synchronization results reveal clear difference between the two events; Structure and Non-Structure and also specifies more synchronisation between electrodes for structure as compared to non-structures. It thus elucidates, increased functional connectivity for Structure as compared to Non-Structure which occurs mainly in alpha band. The current findings for weighted graph analysis reveals the emergence of small-world network for perceptual grouping in brain. The findings from MST analysis of current study reports about good efficiency and strong information integration in the network for structures as compared to non-structures. Therefore, more specifically, it can be claimed that there exist a significant difference between the structure and non-structure evoked activation in brain. These findings evaluated for healthy subjects in terms of basic structure formation can help in further understanding several aspects of different neurological disorders. Furthermore, it would be interesting to explore the changes in functional network connections for neurologically challenged subjects over longitudinal developmental trajectories.

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References

[1] Treisman A., and Kanwisher N.K. "Perceiving visually-presented objects: recognition, awareness, and modularity," *Current Opinion in Neurobiology,* 8:218-226, 1998.

[2] Hoffman K.L and Logothetis N.K, "Cortical mechanisms of sensory learning and object recognition," Philosophical Transactions R. Soc. B. 2008.

[3] Fields C "Editorial: How Humans Recognize Objects: Segmentation, Categorization and Individual Identification," Frontier Psychology 2016 7:400.

[4] Tanaka, K. "Neuronal mechanisms of object recognition," Science 29 Oct 1993: Vol. 262, Issue 5134, pp. 685-688.

[5] Grill-Spector "The neural basis of object perception," Curr Opinion Neurobiology 13:159–166 (2003).

[6] Hans P. Op de Beeck and Chris I. Baker, The Neural Basis of Visual Object Learning Trends Cogn Sci. 2010 January.

[7] Gutnisky DA, Dragoi V. Adaptive coding of visual information in neural populations. Nature 2008;452:220–224. March 2008

[8] Sporns O., Tononi G., and Edelman G.M. "Modeling perceptual grouping and figure ground segregation by means of active reentrant connections,". Proc. Natl. Acad. Sci. Vol. 88, pp. 129-133, January 1991, Neurobiology.

[9] Hess R, Field D "Integration of contours: New insights," Trends in Cognitive Sciences(1999) 3: 480–486.

[10] Srimant P. Tripathy, Alexander J. Mussap, Horace B. Barlow, "Detecting collinear dots in noise",Vision Research 39 (1999) 4161–4171.

[11] Kovacs I, Julesz B "A closed curve is much more than an incomplete one: Effect of closure in figure-ground segmentation," Proc. Natl. Acad. Sci. USA Vol. 90, pp. 7495-7497, August 1993.

[12] Machilsen B, Novitskiy N, Vancleef K, Wagemans J "Context Modulates the ERP Signature of Contour Integration," PLoS ONE (2011) 6(9): e25151.

[13] Martinovic J, Mordal J, Wuerger SM "Event-related potentials reveal an early advantage for luminance contours in the processing of objects," Journal of Vision 2011 Jun 1;11(7).

[14] Van Hoogmoed AH, van den Brink D, Janzen G "Electrophysiological Correlates of Object Location and Object Identity Processing in Spatial Scenes," PLoS ONE 7(7): e41180. July 18, 2012.

[15] Daliri MR, Taghizadeh M, Niksirat KS. "EEG Signature of Object Categorization from Event-related Potentials," J Med Signals Sens. 2013 Jan;3(1):37-44.

[16] Bressler SL, Menon V. "Large-scale brain networks in cognition: emerging methods and principles," Trends in cognitive sciences. 2010; 14(6):277–90.

[17] Vuilleumier, P. and Driver, J. "Modulation of visual processing by attention and emotion: windows on causal interactions between human brain regions," Philos. Trans. R. Soc.(2007) Lond. B Biol. Sci. 362, 837–855.

[18] Wolf Singer "Neuronal Synchrony: A Versatile Code for the Definition of Relations?," Neuron, Vol. 24, 49–65, September, 1999, Cell Press

[19] He, B.J. et al. "The role of impaired neuronal communication in neurological disorders. Curr. Opin. Neurol.(2007) 20, 655–660

[20] Zeki, S., and Shipp, S."The functional logic of cortical connections," Nature(1988) 335, 311–317.

[21] Wei Q, Wang Y, Gao X, Gao S. "Amplitude and phase coupling measures for feature extraction in an EEG-based brain—computer interface," Journal of Neural Engineering. 2007; 4(2):120.

[22] R. Q. Quiroga, A. Kraskov, T. Kreuz, and P. Grassberger, "Performance of different synchronization measures in real data: a case study on electroencephalographic signals," Physical Review E, vol. 65, no. 4, Article ID 041903, 14 pages, 2002.

[23] T. Kreuz, F. Mormann, R. G. Andrzejak, A. Kraskov, K. Lehnertz, and P. Grassberger, "Measuring synchronization in coupled model systems: a comparison of different approaches," Physica D, vol. 225, no. 1, pp. 29–42, 2007.

[24] L. Astolfi, F. De Vico Fallani, F. Cincotti et al., "Estimation of effective and functional cortical connectivity from neuroelectric and hemodynamic recordings," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 17, no. 3, pp. 224–233, 2009

[25] J. Dauwels, F. Vialatte, T. Musha, and A. Cichocki, "A comparative study of synchrony measures for the early diagnosis of alzheimer's disease based on EEG," Neuroimage, vol. 49, no. 1, pp. 668–693, 2010.

[26] J. Fell and N. Axmacher, "The role of phase synchronization in memory processes," Nature Reviews Neuroscience, vol. 12, no. 2, pp. 105–118, 2011.

[27] F. Varela, J. P. Lachaux, E. Rodriguez, and J. Martinerie, "The brain web: phase synchronization and large-scale integration," Nature Reviews Neuroscience, vol. 2, no. 4, pp. 229–239, 2001.

[28] Kabbara A, Khalil M, El-Falou W, Eid H, Hassan M "Functional Brain Connectivity as a New Feature for P300 Speller," PLoS ONE(2016) 11(1):e0146282.

[29] M. Chávez, M. Le Van Quyen, V. Navarro, M. Baulac, and J. Martinerie, "Spatio-temporal dynamics prior to neocortical seizures: amplitude versus phase couplings," IEEE Transactions on Bio-medical Engineering, vol. 50, no. 5, pp. 571–583, 2003.

[30] W. Wu, J. Sun, Z. Jin et al., "Impaired neuronal synchrony after focal ischemic stroke in elderly patients," Clinical Neurophysiology, vol. 122, no. 1, pp. 21–26, 2011.

[31] E. Gysels and P. Celka, "Phase synchronization for the recognition of mental tasks in a brain-computer interface," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 12, no. 4, pp. 406–415, 2004.

[32] C. Brunner, R. Scherer, B. Graimann, G. Supp, and G. Pfurtscheller, "Online control of a brain-computer interface using phase synchronization," IEEE Transactions on Biomedical Engineering, vol. 53, no. 12, pp. 2501–2506, 2006.

[33] P. J. Uhlhaas and W. Singer, "Neural synchrony in brain disorders: relevance for cognitive dysfunctions and pathophysiology," Neuron, vol. 52, no. 1, pp. 155–168, 2006.

[34] C. Hammond, H. Bergman, and P. Brown, "Pathological synchronization in parkinson's disease: networks, models and treatments," Trends in Neurosciences, vol. 30, no. 7, pp. 357–364, 2007.

[35] CJ Stam, ECW Van Straaten, "The organization of physiological brain networks", Clinical neurophysiology, 2012.

[36] Bullmore Edward, Sporns Olaf "Complex brain networks: Graph theoretical analysis of structural and functional systems," Nature reviews. Neuroscience(2009). 10. 186-98. 10.1038/ nrn2575.

[37] CJ Stam, JC Reijneveld, "Graph theoretical analysis of complex networks in the brain", Nonlinear biomedical physics, 2007.

[38] G. Fraga González , M.J.W. Van der Molen, G.Zaric´, M. Bonte, J. Tijms, L. Blomert, C.J. Stam, M.W. Van der Molen "Graph analysis of EEG resting state functional networks in dyslexic readers," Clinical Neurophysiology 127 (2016) 3165–3175.

[39] Chennu S, O'Connor S, Adapa R, Menon DK, Bekinschtein TA "Brain Connectivity Dissociates Responsiveness from Drug Exposure

during Propofol-Induced Transitions of Consciousness," PLoS Comput Biol(2016) 12(1):e1004669.

[40] van Dellen E, Sommer IE, Bohlken MM "Minimum spanning tree analysis of the human connectome" Hum Brain Mapp. 2018;39:2455–2471.

[41] Tewarie P, Van Dellen E, Hillebrand A, Stam CJ. The minimum spanning tree: an unbiased method for brain network analysis. NeuroImage 2015;104:177–88.

[42] Ke Zeng, Jiannan Kang, Gaoxiang Ouyang, Jingqing Li, Junxia Han, Yao Wang, Estate M. Sokhadze, Manuel F. Casanova, Xiaoli Li "Disrupted Brain Network in Children with Autism Spectrum Disorder" , Scientific Reports(2017), 7: 16253.

[43] Wang Y, Tao F, Zuo C, Kanji M,Hu M and Wang D "Disrupted Resting Frontal–Parietal Attention Network Topology Is Associated With a Clinical Measure in Children With Attention-Deficit/ Hyperactivity Disorder", Front. Psychiatry(2019) 10:300.

[44] Watts D., Strogatz S. "Collective dynamics of 'small-world' networks," Nature 393, 440–442, 1998.

[45] Maris E, Oostenveld R "Nonparametric statistical testing of EEG- and MEG-data," Journal of Neuroscience Methods(2007) 164: 177–190.

[46] Pascal Fries "Rhythms For Cognition: Communication Through Coherence," Neuron 2015 October 7; 88(1): 220–235.

[47] Bays, B. C., Visscher, K. M., Le Dantec, C. C., Seitz, A. R. (2015). Alpha-band EEG activity in perceptual learning. Journal of Vision, 15(10):7, 1–12.

[48] Lamme V.A. "The neurophysiology of figure-ground segregation in primary visual cortex," J. Neurosci.(1995) 15, 1605–1615.

[49] Cornelis J. Stam, Guido Nolte, and Andreas Daffertshofer "Phase Lag Index: Assessment of Functional Connectivity From Multi Channel EEG and MEG With Diminished Bias From Common Sources," Human Brain Mapping 28:1178–1193 (2007).

[50] Matteo Fraschini, Matteo Demuru, Alessandra Crobe, Francesco Marrosu, Cornelis J Stam, Arjan Hillebrand "The effect of epoch length on estimated EEG functional connectivity and brain network organisation," J. Neural Eng. 13 (2016) 036015 (10pp).