Graph Theoretical Analysis of Facial Attractiveness EEG Functional Connectivity Patterns

Nuno Fernandes
Faculty of Sciences, University of Porto
up202109069@edu.fc.up.pt

ABSTRACT

The present work aims to investigate the functional connectivity of brain networks when viewing attractive facial pictures. Despite prior research on facial attractiveness having focused on examining event-related-potentials (ERP) of EEG data, literature lacks in distinguishing the neural patterns that emerge from viewing an attractive face in comparison to a less attractive face. To perform functional connectivity analysis and graph measurements of the EEG data, a database from a prior study consisted of 23 participants was used. Firstly, the phase locking value (PLV) for the gamma frequency between each pair of electrodes was computed. Then, an exploratory data analysis of the constructed network using electrodes as nodes and PLVs as edge weights suggested complex but distinct patterns between viewing attractive and unattractive faces. The cluster-based permutation tests supported these findings, since they revealed the presence of different clusters for the two conditions. Finally, minimum spanning trees (MST) were computed for the two conditions, but no difference in graph measures (i.e., betweenness centrality, closeness centrality, tree hierarchy, modularity) were found. This work presents theoretical contributions as an initial approach towards the understanding of neural patterns response to attractive stimuli.

Keywords

Facial attractiveness; EEG; functional connectivity, MST, brain networks.

1. INTRODUCTION

When we see a face, we rapidly form an impression about its attractiveness [1]. Despite there are objective cues to facial attractiveness, such as symmetry [2] and sexual dimorphism (the preference for more masculine/feminine faces) [3], facial attractiveness has a subjective component, and individual observers can vary in their responses and preferences [4,5]. So, what are the neural mechanisms that make us feel automatically attracted to someone?

Prior research using electroencephalography (EEG) has shown that attractive (vs ordinary) faces consistently elicit a larger late positive potential (LPP) [6]. Prior studies have also revealed earlier event-related potential (ERP) components, such as the P1, N170, P2 and N250 to be sensitive to facial attractiveness [7]. Consistently, using time-resolved representational similarity analysis on the EEG data, researchers [8] revealed that representations of facial attractiveness emerge only after 150–200 ms of cortical processing, with an amplitude peak at 550 ms.

Despite the vast literature on ERP analysis of facial attractiveness, there is a lack of evidence concerning functional connectivity or graph measurements of brain networks elicited by attractive stimuli. While ERP analysis focus on the time it takes the brain to respond to a certain stimulus [9], functional connectivity tries to map the connectivity between brain regions where these potentials are elicited [10]. So, functional connectivity expresses statistical dependencies between different brain regions [10]. Additionally, the analysis of brain network characteristics has the potential to yield valuable insights into attractiveness judgments. Despite network analysis of EEG data is a relatively emerging field, its implications have been exploited in several domains. For example, concerning Alzheimer's disease [11], emotion recognition [12], or young brain maturation [13,14].

The objective of the present work is to understand whether there are statistical patterns in brain networks when people see an attractive face and try to capture these using graph theoretical network analysis. Besides theoretical relevance in the understanding of how our brain forms attractiveness judgements, results will have practical implications since attractiveness plays an important role in our daily life. In fact, in addition to mating contexts, attractiveness also plays an important role in various non-sexual social contexts such as friendship formation [15], school settings [16], and job interviews [17]. Researchers have also examined attractiveness as a potential risk factor for various mental disorders [18].

2. MATERIALS AND METHODS

To perform functional connectivity analysis and graph measurements of the brain networks associated with facial attractiveness we used a publicly available database from a prior work [8].

2.1 Database

The database consists of EEG recordings of facial attractiveness evaluations. The participants (n = 23) age ranged from 18 to 25 years old (M = 19.75, SD = 1.62). From these, 19 were females (83%) and the others were males (17%). Stimuli were full-front face photographs from the Face Research Lab London Set [19]. In each of the 604 trials, participants saw one of the faces for 1450 ms and subsequently performed attractiveness evaluations. Participants indicated whether they found the face attractive (yes/no) and how attractive they found the face on a 1-7 scale. For the present work, only binary ratings (yes/no) were considered.

EEG signals were recorded using an ANT Waveguard 64-electrode system at 250 Hz sampling rate. Available data has already been preprocessed. The main preprocessing steps consisted of referencing the data to the Fz electrode (which was then discarded), epoching and cropping from -250 ms to 1450 ms relative to stimulus onset, and baseline-correction. For further details see [8].

2.2 Data Analysis

2.2.1 Functional Connectivity

Firstly, a connectivity matrix was constructed for the gamma frequencies by computing the phase-locking value (PLV) between each pair of electrodes. PLV is the most used phase interaction measure, and it expresses the absolute value of the mean phase difference between the two signals expressed as a complex unit-length vector [20,21]. So, PLV measures the similarity between two time series. If the signals are independent, the PLV will be zero. Conversely, if the phases of the two signals are strongly associated then the PLV will approach one.

2.2.2 *Cluster-Based Permutation Tests*

Cluster-based permutation tests were used to identify sub-networks of brain connectivity for the attractive and unattractive conditions. Since in the statistical analysis of EEG-data emerges the multiple comparisons problem, due to the spatiotemporal structure of the data (signal is sampled at multiple channels and time points), this procedure aims to control the family-wise error rate (FWER). The FWER is the probability of making at least one Type I error (false positive). This approach was suggested by [22] and it addresses the multidimensional problem by employing the cluster structure of the data as its unique test statistic. So, no inference is made over individual voxels. Rather, clusters are initially identified via an algorithmic approach, and the cluster structure is compared to the pattern of clusters constructed under the null hypothesis. For a detailed description of cluster-based permutation tests using EEG data see [23].

2.2.3 *Graph Measures*

The connectivity matrices were analyzed as weighted graphs using PLV's as edge weights. Each electrode was considered a node and all connections between any pair of electrodes were considered as edges. The MST was used to construct the subnetwork for graph measurements analysis (Table 1). This algorithm starts with ranking all edges weights from lowest to highest. Since the focus was on the strongest edges, similarly to [24], the edges were ranked from highest to lowest, formally reconstructing the maximum spanning tree. It starts by disconnecting all nodes and adding the edge with the highest weight. Then, it adds the edge with the second highest and this is repeated until all nodes are connected. When adding a new edge result in a cycle or loop, this edge is discarded, and the next edge in the rank is selected [24]. So, the MST is a subnetwork connecting all nodes in the network without forming any loops or cycles [25].

Table 1 Graph measures

Characteristic	**Definition**	**Interpretation**
Degree	Number of connections	Measure of region importance, i.e., important regions on the functional brain network
Betweenness centrality (BC)	BC consists of the number of shortest paths between any two nodes i, j that pass-through node u divided by the number of shortest paths. The betweenness centrality of the network was characterized by the BC_{max} (node with highest BC).	Maximum BC expresses the importance of the most central node to the brain network, which is an indicator of central network organization.
Closeness centrality	Closeness centrality is the inverse of the average shortest distance between the node and all other nodes in the network. The closeness centrality of the network was characterized by the node with the highest close centrality.	Maximum closeness centrality indicates how close the most central node is close to all other nodes in the network.
Diameter	It is the largest distance between any two nodes, divided by the total number of edges.	Measure of efficiency. Low diameter indicates that information is more efficiently passed through remote brain regions.
Leaf fraction	Leaf fraction is defined by the leaf number divided by the maximum possible leaf number. Leaf number is the number of nodes that have only one connection. The maximum leaf number is n-1 (with n being the number of nodes).	Measure of global topology which indicates whether the network has a central organization or not. Networks with a higher leaf fraction are more dependent on central nodes.
Tree hierarchy	Characterizes an optimal topology of efficient organization while avoiding information overload of central nodes.	Tree hierarchy value for a line-like topology is equal to 0, for a star-like topology is equal to 0.5, and for trees with configurations between these two extreme cases, can have values approaching 1.
Modularity	Modularity quantifies the strength of partitioning the network into communities. The Clauset-Newman-Moore greedy modularity maximization algorithm was used [26].	In brain networks, communities may represent brain regions (i.e., frontal, occipital, parietal, temporal lobes).

MST measures and definitions [27, 28].

3. RESULTS

3.1 Functional Connectivity Analysis

A PLV functional connectivity matrix was calculated for each subject between all the electrodes (Figure 1.).

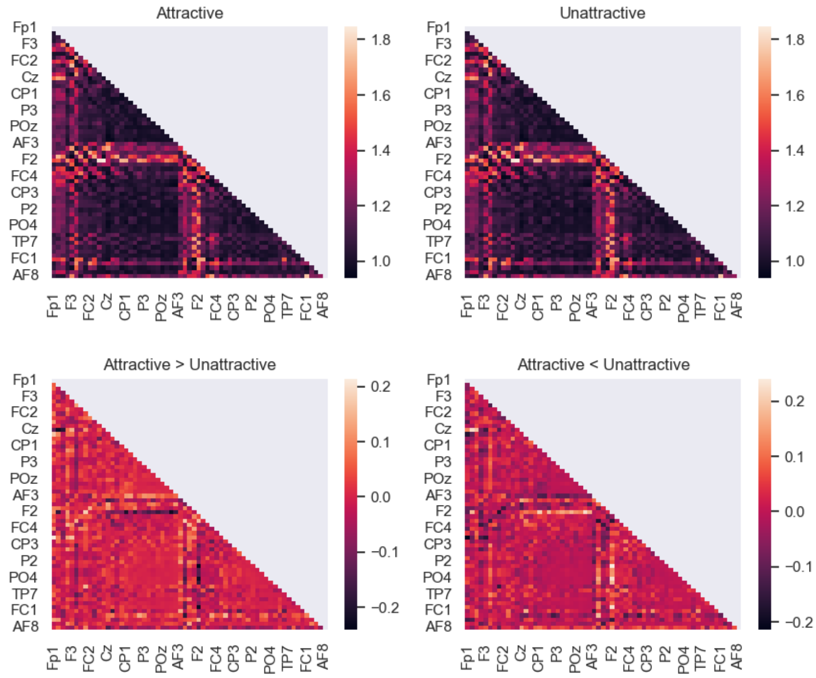

FIGURE 1. Phase locking value functional connectivity network measured with the gamma frequency band EEG. (a) Mean functional connectivity matrices for the attractive faces. (b) Mean functional connectivity for the unattractive faces. (c) and (d) shows the difference matrix of attractive and unattractive faces, (c) attractive > unattractive, (d) attractive < unattractive. In the matrix map, the horizontal and vertical axes denoted electrodes channels, and each chromatic point represented the PLV of two corresponding channels.

To better understand brain patterns, the functional connections between left and right hemisphere are represented in Figure 2.

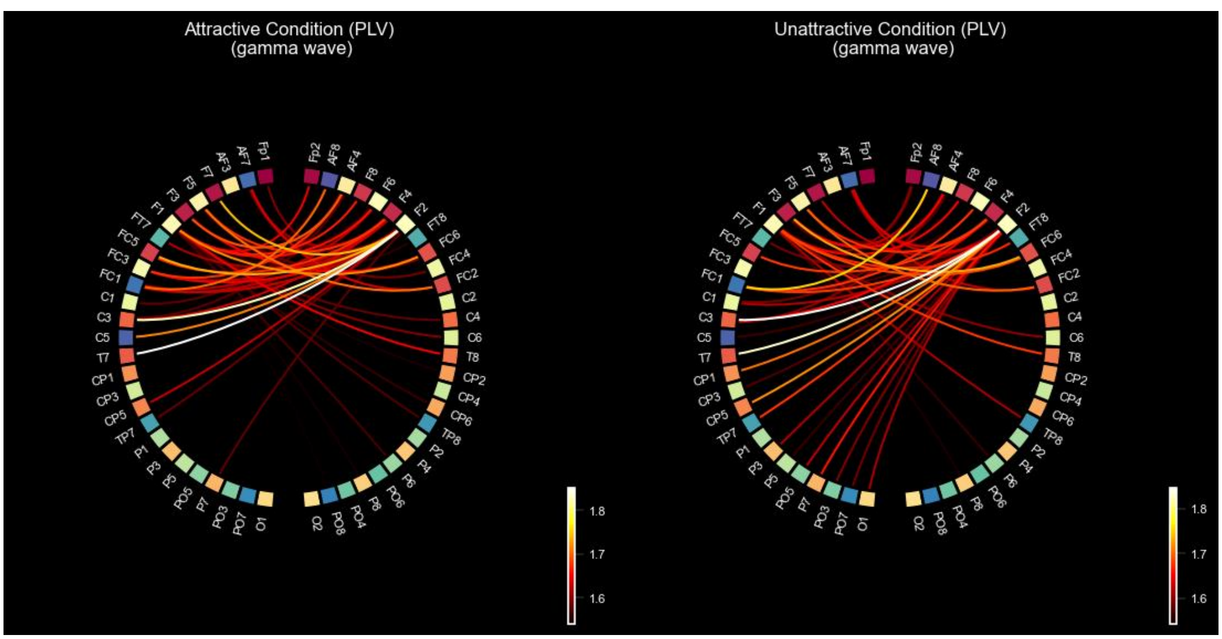

FIGURE 2. Circular functional connectivity plot.

From the functional connectivity adjacency matrix (Figure 1.), one may observe a complex but similar pattern between the two conditions. Although, by focusing on the top 100 connections (Figure 2.), it suggests that participants when viewing attractive faces exhibited an increased degree synchronization, but in a smaller area compared to viewing unattractive faces. In general, there are fewer connections for the attractive condition than the unattractive condition, but the strength is large.

3.2 Network Construction

The functional connectivity brain network was constructed using the 61 electrodes as nodes, and the PLV as edge weights. For visualization purposes, Figure 3. shows only the top 100 connections. Similar to what was observed in the prior visualizations, in the attractive condition there are stronger connections, but in the unattractive condition there are more connections between distant regions of the brain, i.e., between the frontal lobe with the parietal and occipital.

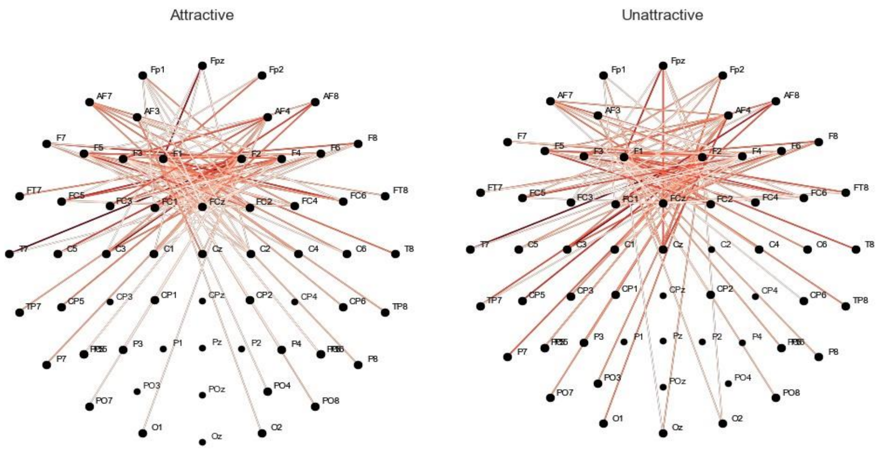

FIGURE 3. Functional connectivity networks for attractive and unattractive conditions (top 100 connections).

3.3 Cluster-Based Permutation Tests

From the cluster-based permutation tests, it is possible to infer that there were significant differences between the two conditions. As it is possible to observe, there were found 16 significant clusters in the data (p-value < .05). Supporting the prior visualizations, parietal, occipital and parieto-occipital channels were the ones contributing the most for the observable differences between the two conditions.

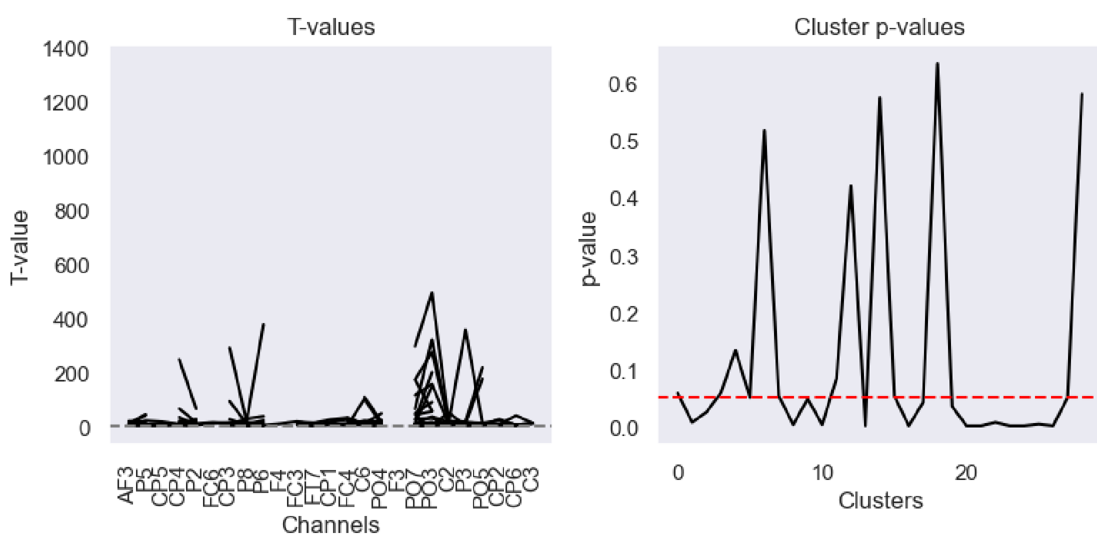

FIGURE 4. Cluster-Based Permutation Tests results based on channel locations and cluster formations.

3.4 Graph Measures

MSTs were constructed for each condition (attractive/unattractive) per subject, which makes a total of 46 MSTs. Additionally, for having a comprehensible insight into the trees topology, an overall MST for each condition was computed (Figure 5.).

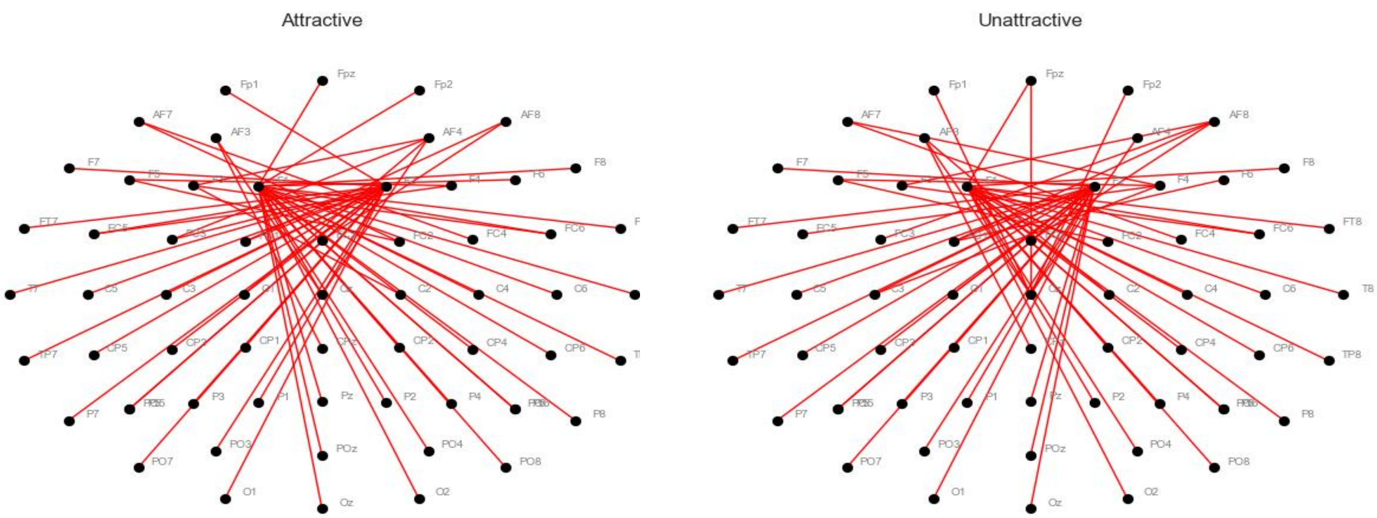

Figure 5. MST for the overall attractive and unattractive faces.

To compare MST measures, paired Wilcoxon signed rank tests were performed. However, no significant differences were found.

Table 2. MST graph measures. Both mean (standard deviation) results for the two conditions and paired Wilcoxon signed rank tests.

Characteristic	**Attractive**	**Unattractive**	**Wilcoxon signed rank test (p-value)**
$Degree_{max}$	19.48 (6.33)	19.70 (7.97)	258.5 (.90)
Betweenness centrality (BC_{max})	0.74 (0.08)	0.75 (0.10)	285.5 (.90)
Closeness $centrality_{max}$	0.38 (0.10)	0.38 (0.11)	252 (.79)
Diameter	9.61 (2.52)	9.91 (2.77)	269 (.93)
Leaf fraction	0.77 (0.09)	0.76 (0.09)	268 (.95)
Tree hierarchy	0.53 (0.07)	0.52 (0.07)	290 (.59)
Modularity	0.66 (0.05)	0.65 (0.07)	282 (.71)

4. Discussion

The present work aimed to compare brain patterns when viewing an attractive vs. an unattractive face. Therefore, functional connectivity matrixes were computed using the PLV, and MSTs were computed to extract graph measures.

The cluster-based permutation tests suggest differences in the functional connectivity patterns between the two conditions. However, no differences were found for the graph measures. A possible reason for the lack of differences could be due to the time interval that was used for computing the PLV. PLV was computed for the entire trial duration (1450 ms), although prior ERP analysis [8] revealed that facial attractiveness is processed only after 150–200 ms, with an amplitude peak at 550 ms. So, further research may find suitable to crop the time interval to 150-550 ms before computing the functional connectivity matrix. Future studies may replicate this procedure but using regions of interest (ROI), which are formed by clusters of electrodes ([29] for a review), instead of having a functional connectivity matrix constituted by all the pairs of electrodes.

Furthermore, other metrics, like the phase lag index (PLI), are also considered adequate for calculating the cross-correlation between EEG time-series (see [30] for a comparison of PLV and PLI). So, the choice of the metric may influence the construction of the MST, and consequently graph measures.

Also, there are some limitations associated with the sample's demographics. The sample was consisted of only four male participants, which makes it difficult to generalize our results to the male population. Additionally, no information was provided in the original work [8] about sexual orientation. So, both same-sex and opposite-sex trials were considered. Although, an alternative strategy to analyze graph measures could be consider only opposite-sex evaluations (men rating women, and vice-versa), as this possibly may enhance the differences in the observable brain patterns (see [31] for details on gender differences responses to same-sex and opposite-sex stimuli).

Moreover, this work only focused on binary ratings of attractiveness (yes/no), but it may be replicated using the ordinal ratings (1-7). By this way, one could explore if brain patterns differ when viewing an average looking person vs. a highly attractive/unattractive one, or if our brain is hard-wired to solemnly respond to highly attractive individuals.

This work presents theoretical contributions as an initial approach towards the understanding of brain patterns when viewing attractive faces. Finally, it poses a challenge for further research to predict whether a person would be considered attractive or not based on these results. For example, functional connectivity matrixes could serve as inputs for convolutional neural networks (CNN), and/or graph measures used to train machine learning models.

5. REFERENCES

[1] Olson, I. R. & Marshuetz, C. Facial attractiveness is appraised in a glance. Emotion 5, 498–502 (2005). https://doi.org/10.1037/1528-3542.5.4.498

[2] David I Perrett, D.Michael Burt, Ian S Penton-Voak, Kieran J Lee, Duncan A Rowland, Rachel Edwards, Symmetry and Human Facial Attractiveness, Evolution and Human Behavior, Volume 20, Issue 5, 1999, Pages 295-307, ISSN 1090-5138, https://doi.org/10.1016/S1090-5138(99)00014-8.

[3] Perrett, D., Lee, K., Penton-Voak, I. et al. Effects of sexual dimorphism on facial attractiveness. Nature 394, 884–887 (1998). https://doi.org/10.1038/29772

[4] Hönekopp, J. Once more: Is beauty in the eye of the beholder? Relative contributions of private and shared taste to judgments of facial attractiveness. J. Exp. Psychol. Hum. Percept. Perform. 32, 199–209 (2006).

[5] Penton-Voak, I. & Perrett, D. I. Consistency and individual differences in facial attractiveness judgments: An evolutionary perspective. Soc. Res. 67, 219–244 (2000).

[6] Thiruchselvam, R., Harper, J., & Homer, A. L. (2016). Beauty is in the belief of the beholder: cognitive influences on the neural response to facial attractiveness. Social Cognitive and Affective Neuroscience, 11, 1999–2008.

[7] Zhang, Y., Wei, B., Zhao, P., Zheng, M., & Zhang, L. (2016). Gender differences in memory processing of female facial attractiveness: evidence from event-related potentials, Neurocase, 22, 317-323. https://doi.org/10.1080/13554794.2016.1151532

[8] Kaiser, D., Nyga, K. Tracking cortical representations of facial attractiveness using time-resolved representational similarity analysis. Sci Rep 10, 16852 (2020). https://doi.org/10.1038/s41598-020-74009-9

[9] Nidal, K., & Malik, A. S. (2015). EEG/ERP Analysis. Methods and Applications. CRC Press, Boca Raton.

[10] Stephan, K E; Friston, K J (2009). Functional connectivity. In: Squire, L R. Encyclopedia of Neuroscience. New York: Elsevier, 391-397.

[11] Francesca Miraglia, Fabrizio Vecchio, Paolo Maria Rossini, Searching for signs of aging and dementia in EEG through network analysis, Behavioural Brain Research, Volume 317, 2017, Pages 292-300, ISSN 0166-4328. https://doi.org/10.1016/j.bbr.2016.09.057.

[12] Xefteris VR, Tsanousa A, Georgakopoulou N, Diplaris S, Vrochidis S, Kompatsiaris I. Graph Theoretical Analysis of EEG Functional Connectivity Patterns and Fusion with Physiological Signals for Emotion Recognition. Sensors (Basel). 2022 Oct 26;22(21):8198. doi: 10.3390/s22218198. PMID: 36365896; PMCID: PMC9656224.

[13] Boersma, M., Smit, D. J., Boomsma, D. I., de Geus, E. J., Delemarre-van der Waal, H. A., & Stam, C. J. (2010). Network analysis of resting state EEG in the developing young brain: Structure comes with matu ration. Human Brain Mapping, 32, 413–425.

[14] Boersma, M., Smit, D. J., Boomsma, D. I., Geus, E. J., Delemarre-van de Waal, H. A., & Stam, C. (2012). Growing trees in child brains: Graph theoretical analysis of EEG derived minimum spanning tree in 5 and 7 year old chil dren reflects brain maturation. Brain Connectivity, 3(1), 50–60

[15] Wang, S. S., Moon, S.-I., Kwon, K. H., Evans, C. A., and Stefanone, M. A. (2010). Face off: implications of visual cues on initiating friendship on Facebook. Comput. Hum. Behav. 26, 226–234. doi: 10.1016/j.chb.2009.10.001

[16] Lerner, R. M., and Lerner, J. V. (1977). Effects of age, sex, and physical attractiveness on child-peer relations, academic performance, and elementary school adjustment. Dev. Psychol. 13, 585–590. doi: 10.1037/0012-1649.13.6.585

[17] Watkins, L. M., and Johnston, L. (2000). Screening job applicants: the impact of physical attractiveness and application quality. Int. J. Sel. Assess. 8, 76–84. doi: 10.1111/1468-2389.00135

[18] Davis, C., Claridge, G., and Fox, J. (2000). Not just a pretty face: physical attractiveness and perfectionism in the risk for eating disorders. Int. J. Eat. Disord. 27, 67–73.

[19] DeBruine, Lisa; Jones, Benedict (2017). Face Research Lab London Set. figshare. Dataset. https://doi.org/10.6084/m9.figshare.5047666.v3

[20] Lachaux JP, Rodriguez E, Martinerie J, Varela FJ. Measuring phase synchrony in brain signals. Hum Brain Mapp. 1999;8(4):194-208. doi: 10.1002/(sici)1097-0193(1999)8:4<194::aid-hbm4>3.0.co;2-c

[21] Sergul Aydore, Dimitrios Pantazis, Richard M. Leahy. A note on the phase locking value and its properties, NeuroImage, Volume 74, 2013, 231-244. https://doi.org/10.1016/j.neuroimage.2013.02.008.

[22] Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. Journal of Neuroscience Methods, 164(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

[23] Han CE, Yoo SW, Seo SW, Na DL, Seong JK. Cluster-based statistics for brain connectivity in correlation with behavioral measures. PLoS One. 2013 Aug 19;8(8):e72332. doi: 10.1371/journal.pone.0072332. PMID: 23977281; PMCID: PMC3747142.

[24] van Dellen E, Sommer IE, Bohlken MM, Tewarie P, Draaisma L, Zalesky A, Di Biase M, Brown JA, Douw L, Otte WM, Mandl RCW, Stam CJ. (2018). Minimum spanning tree analysis of the human connectome. Hum Brain Mapp. 2018 Jun;39(6):2455-2471. doi: 10.1002/hbm.24014.

[25] Wang, H., Hernandez, J. M., & Van Mieghem, P. (2008). Betweenness centrality in a weighted network. Physical Review E, 77(4), 046105.

[26] Clauset, A., Newman, M. E., & Moore, C. “Finding community structure in very large networks.” Physical Review E 70(6), 2004.

[27] Boersma, M., Smit, D. J., Boomsma, D. I., Geus, E. J., Delemarre-van de Waal, H. A., & Stam, C. (2012). Growing trees in child brains: Graph theoretical analysis of EEG derived minimum spanning tree in 5 and 7 year old chillren reflects brain maturation. Brain Connectivity, 3(1), 50–60.

[28] van Dellen, E, Sommer, IE, Bohlken, MM, et al. Minimum spanning tree analysis of the human connectome. Hum Brain Mapp. 2018; 39: 2455– 2471. https://doi.org/10.1002/hbm.24014

[29] Schoffelen, J.-M. and Gross, J. (2009), Source connectivity analysis with MEG and EEG. Hum. Brain Mapp., 30: 1857-1865. https://doi.org/10.1002/hbm.20745

[30] Sergul Aydore, Dimitrios Pantazis, Richard M. Leahy, A note on the phase locking value and its properties, NeuroImage, Volume 74, 2013, Pages 231-244, ISSN 1053-8119, https://doi.org/10.1016/j.neuroimage.2013.02.008.

[31] Michela Sarlo, Giulia Buodo, To each its own? Gender differences in affective, autonomic, and behavioral responses to same-sex and opposite-sex visual sexual stimuli, Physiology & Behavior, Volume 171, 2017, Pages 249-255, ISSN 0031-9384, https://doi.org/10.1016/j.physbeh.2017.01.017.