EEG brain network study during resting states

Group 3: Pavan Kumar Alikana (1826777)
Dastagiri Dudekula (1826239)
Vamsi Gunturi (1794653)

Abstract:

This project focuses on understanding brain signal and connectivity patterns related to the eye states. More specifically, we analyzed brain Signals recorded by EEG for two different Eye states i.e. Eye open(EO) and Eye close(EC) respectively. We analyzed the 64-channel EEG signals from a single subject(S004) with eyes-open and eyes-closed baseline conditions. We did 4 types of analysis namely connectivity graphs, graph theory indices, motif analysis and community detection. More on this in their respective sections. At each stage of analysis, we emphasized arising differences between EO and EC states, accordingly concluded main identifiers of each state. To do this we focused on understanding the difference between the brain connectivity estimated with the MVAR estimation approaches like Partial directed coherence (PDC) and Direct Transfer Function (DTF) (the second one tends to give connectivity value little bit bigger than the first one). We also performed motif analysis using the tool mfinder and considering 3-node and 4-node motif configuration. We were able to obtain motifs and anti-motifs for the configuration with 3 and 4 nodes. We also to carried out specific analysis about information about the connection involved in a specific community detection configuration (modularity-based vs information theory-based approaches). Finally, after our observations while computing the community detection, we highlighted the weaknesses of Louvain's' algorithm in recognizing small communities compared to Info map.

Introduction:

Understanding brain functionality has been a major interest among the computational neuroscientists. Over the years different methodologies have been introduced and implemented to accomplish that. Electroencephalography (EEG) was invented in 1924 by German scientist Hans Berger and since then scientific interest to explain various human behavior and infer functional aspects of both normal and pathological brain processes with EEG has been strongly increasing. Not only different human behavior such as eye movement, attention and hand clenching can be visualized with EEG signals, but also human conditions such as schizophrenia or intelligence can be inferred from EEG signal data. All these states are associated with a particular frequency which aids us in understanding the functional behavior of complex brain structures. In this way, EEG allows us to acquire brain signals corresponding to various states. In this work, we have concentrated on determining differences in two particular states: eyes open (EO) and eyes closed(EC). We have studied 64-channels EEG signals, corresponding to a single subject (N=4). Then we performed spectral, connectivity, graph indices, motifs and community detection analysis by emphasizing arising differences between EC and EO at each stage.

Methods and Observations:

1.1 Connectivity graph:

The functional connectivity at the level of the brain structures (the connectivity derived from scalp EEG Measurements) can be estimated with the use of a spectral estimator based on the Multivariate Autoregressive Model (MVAR). In order to know the connectivity pattern in which the 64 channels are involved, we implemented both Direct Transfer Function (DTF) and Partial directed coherence (PDC) estimators, which measure the effect of a channel on another one(both direct and indirect) and only direct respectively.

This process requires the selection of the order for the model to which we used the Akaike information criterion for MVAR order estimation. We obtained best order for model to be 5 and 6 respectively for EO and EC states.

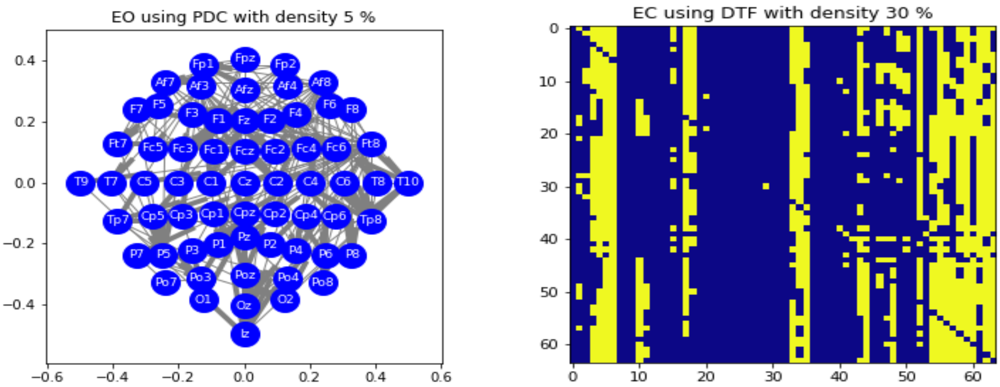

Figure 1.1: Topology representation of EO using PDC with graph density 5% and Adjacency matrix representation for Eyes closed using DTF with density 30%

Observations:

We dynamically calculated threshold (best alpha) for all densities mentioned in the problem statement i.e.., 1%, 5%, 10%, 20%, 30% and 50% so that we have a holistic analysis on different observations based on the parameters chosen (state, method and density). Full results can be found in Appendix A in Figure 5.1, 5.2, 5.3, 5.4 where we tried to show a topographical representation for all the 64 channels. For adjacency matrix representations please refer to Figures 5.5, 5.6,5.7, 5.8 in Appendix A

As we can see in the Figures 5.3, 5.4 with PDC estimator (two top subfigures), when the subject is in EC state we can observe that approximately 50% of the connection remains the same and the rest is changing. It seems like the network is becoming more concentrated around parietal central channels.

Since DTF is taking into account also indirect influence, it is reasonable to observe more connections in the network on the Figure 5.1 and 5.2 for DTF than topologies based on PDC in 5.3 and 5.4. Here, we see even more obvious concentration around central parietal channels than before.

1.2 Graph theory indices:

We studied the structure of the PDC and DTF networks from a macroscopic point of view using two global indices: average clustering coefficient and average shortest path length and from a microscopical point of view using local indices we measured the total degree, In-degree and out-degree of each node as shown in below figure for local indices for instance.

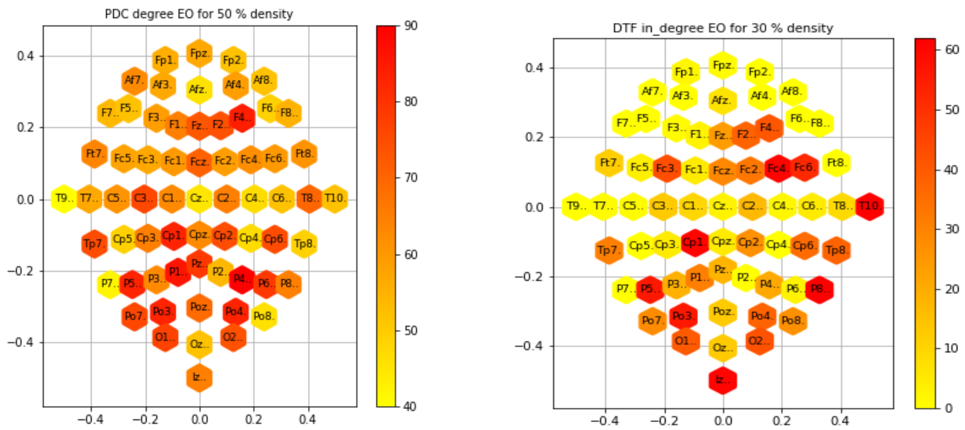

Figure 1.2.1: In degree of the nodes in EO state using DTF at 30% graph density and Degree of the nodes in EO state using PDC at 50% density

Observations:

For local indices, we tried to do all this analysis using both PDC and DTC and apply them to all the graphs with densities 1%, 5%, 10%, 20%, 30% and 50%. Full results are included in Appendix B in Figures 9,10,11,12 (for degree), Figures 13,14,15,16(for in-degree) and Figures 17,18,19,20 (for out-degree). For global indices, we tried to compare both clustering coefficient and average shortest path from both PDC and DTF at all densities. The plots for this are included above in the Figure 3.1. We observed that average shortest path length shows a regular behavior, it decreases regularly as we increase the network density. This is true for both eyes open and close states for both PDC and DTF estimators

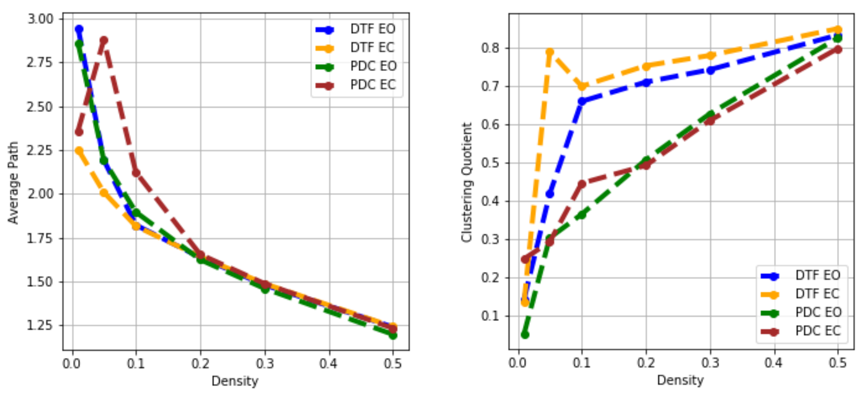

Figure 1.2.2: Global indices observed in states EO and EC using PDC and DTF at different densities

An interesting observation is that we made from above figure 3.1 is that increasing density does not always lead to increasing clustering coefficient (on interval from 10 to 15%). This effect takes place probably because the neighborhood of a single node is becoming bigger while interconnections inside the neighborhood are increasing more slowly and hence the average clustering coefficient is not keeping up with the increase in graph density. We also observed that PDC based networks tend to show less connectivity while between two PDCs(or two DTF networks) the most connected is the one that was built based on eyes closed dataset.

From the degree and in-degree topologies of both PDC and DTF in Appendix B Figures 9,10,11,12,13,14,15,16 we observed that the degree coefficients remain the same for both PDC and DTF (for both eyes open and eyes closed) but we observed a rich get's richer phenomenon for degree topologies based on PDC.

For out-degree topologies of both PDC and DTF in Appendix B Figures 17,18,19,20 we observed rather contrasting phenomenon ie.., DTF has more of nodes having more out degree than that of nodes based on PDC.

For correlating local indices as shown in Fig 5.21 in Appendix B we used the data of the highest degree node for a given graph (DTF EO, EC and PDC EO, EC). We observe that degree and outdegree remains the same for both EO and EC using PDC and DTF but there is a variation of in degree value across PDC and DTF across states (EO and EC)

Note: Tables for local indices and global indices for both PDC and DTF can be found in python notebook with name S004-Connectivity-Graph.

1.3 Motif analysis

Network motifs are defined as patterns of interconnections occurring in complex networks at numbers that are significantly higher than those in randomized networks. For the networks of both the resting conditions, EO and EC, we want to get the 3-nodes subgraph configuration and the relative frequencies and statistical significances for 3-node connected subgraph we have 13 possible combinations of configurations as shown in Figure 4.2.

A different interesting analysis can be done with the detection of 4-node connected subgraph, following the same procedure as above. Since in this case the motifs combinations are 199, we are going to show only the significant results, in particular the 10 subgraphs with higher frequency.

Observations:

3-node motifs analysis

The results on the described network are reported in the Table 1 and 2 in the Appendix C. As we can see, most of the motifs are represented in both of the networks.

For anti-motifs search we have fixed a threshold equal to 0.5 which means that a motif counts as anti-motif only if $0.5 * f_{random}(Gk) > f_{original}(Gk)$

Note: we used DTF graph with density 20% to generate these 3-node motifs

Graphs for 3 node motif analysis can be found in Appendix C Figures 21 and 22. Tables for 3 node motif analysis can be found in Appendix C Tables 1 and 2.

We performed a motif detection of type $A \rightarrow B \leftarrow C$, that is the 3-nodes network with ID 36. A graphical representation with this configuration is showed the Figures 21 and 22 in Appendix C.

4-nodes motifs:

Results for 4 node motifs can be found in motif4 folder in data/motifs folder(full path data/motifs/motif4) in our submission. Since in this case the motifs combinations are 199, we are going to show only the significant results, in particular the 10 subgraphs with higher frequency which can be found in Appendix C Tables 3 and 4.

1.4 Community detection:

To detect communities, we used the Louvain algorithm which is modularity based and it was performed in two steps. First, it iterates through all the nodes in the network and assigns each node to a community as long as it increases the modularity. Afterwards, super nodes are created from the clusters of the first step and the process is repeated again until convergence.

We applied both Louvain and Infomap approaches for detecting the communities. Using Louvain, we found 4 communities for state EC and 7 communities for state EO. The list of channels on each community can be found on Tables 5 and 6 on the Appendix D. Using Info map, we found 5 communities for state EC and 6 communities for state EO. The list of channels on each community can be found on Tables 7 and 8 on the Appendix D.

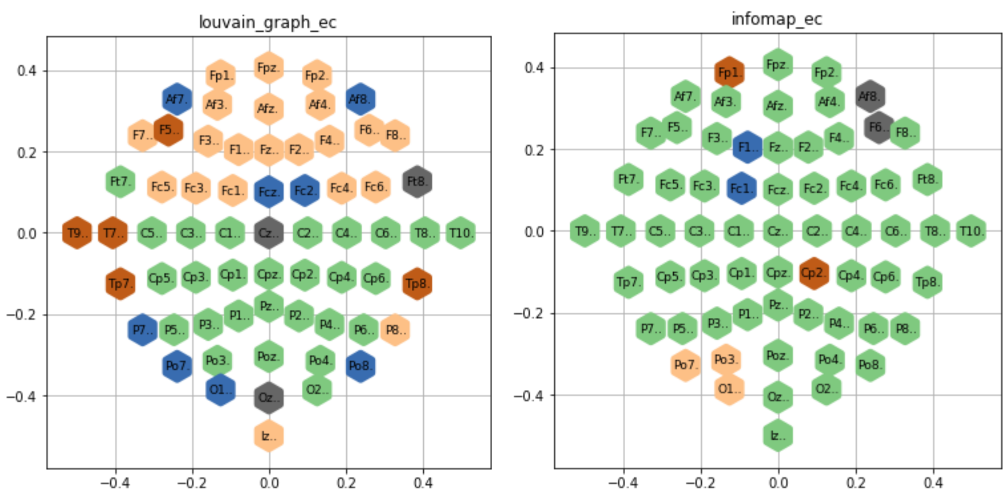

Figure 1.4: Topology diagram for community detection of DTF EC for 20% graph density using Louvain and Info map

Overall, we observed that Info map does a better job in detecting the communities since the community detection of channels using Info map is far better than the community detection using Louvain algorithm. So, it is obvious to state the weaknesses of Louvain's' algorithm in recognizing small communities compared to Info map implementation.

Conclusion:

After analyzing the EEG signals from a single subject with eyes-open and eyes-closed baseline conditions in various perspectives we found significant differences that may be taken into account while working with these base-lines. First of all, basic signal analysis showed that a frequency of 10 Hz explains the most significant difference between the two baselines. Moreover, different MVAR estimators to build the network of EEG signals can lead to very different graphs, and an estimator that involves only direct interactions seem to generate a topology where communities are physically close in the brain.

Finally, in order to be more confident about the archived results in further research we would suggest examining data from several subjects and thus we would be able to determine statistical significance of all the differences listed above from all possible view points. Also, we strongly believe that specific analysis for motifs and community detection considering both DTF and PDC for all densities and 2 states would lead to further interesting insights about the patterns in signal data. We also want to state that by doing connectivity graph analysis and graph theory indices using above ideology has yielded us better correlations for comparing and contrasting different cases because as someone stated that a picture speaks a thousand words. By this we want to conclude our report.

Below are the tasks covered in our work:

Task	Class
1.1	Mandatory
1.2	A
1.3	A
1.4	D
1.5	C
2.1	Mandatory
2.2	D
2.3	B
2.4	C
2.5	B
3.1	Mandatory
3.2	C
3.4	E
4.1	Mandatory
4.2	B
4.3	C

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[9] NETWORK MOTIF SOFTWARE
https://www.weizmann.ac.il/mcb/UriAlon/download/network-motif-software

[10] Photocollage
https://www.photocollage.com/

[11] Sergio Ballesteros, Olga Lazareva "Brain Oscillatory and Network Activity duringresting states"
https://www.dropbox.com/s/g4mzis1syi2vyil/Ballesteros_Lazareva_EEG_Analysis.pdf?dl=0

[12] Pyedflib library: read/write EDF+/BDF+ files based on EDFlib
Github repository:https://github.com/holgern/pyedflib

[13] Network motifs
https://www.cs.helsinki.fi/u/lmsalmel/bio-models/NetworkMotifs.html

[14] ConnectiviPy
https://connectivipy.readthedocs.io/en/latest/tutorial.html

Appendix A: Connectivity graph

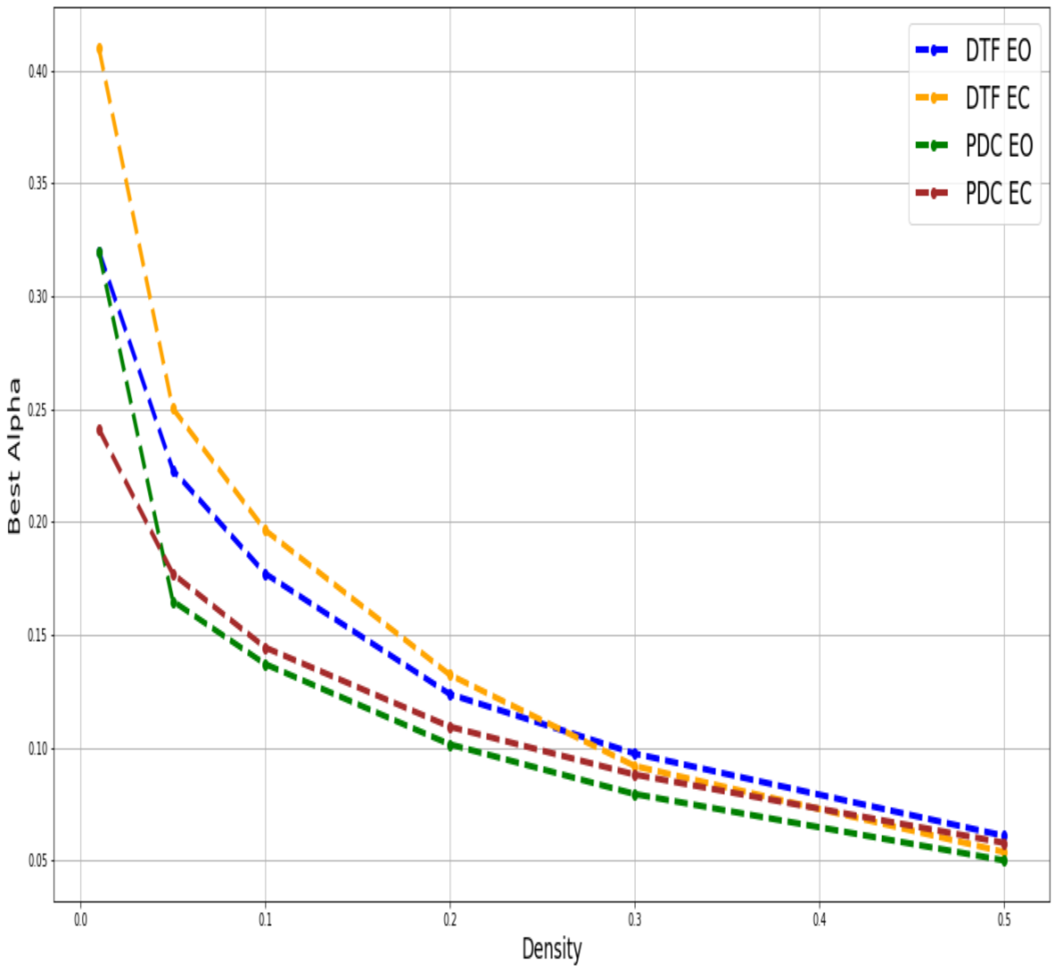

Figure 5.0: Best alpha vs Density for different states using PDC and DTF

Topology diagrams using DTF:

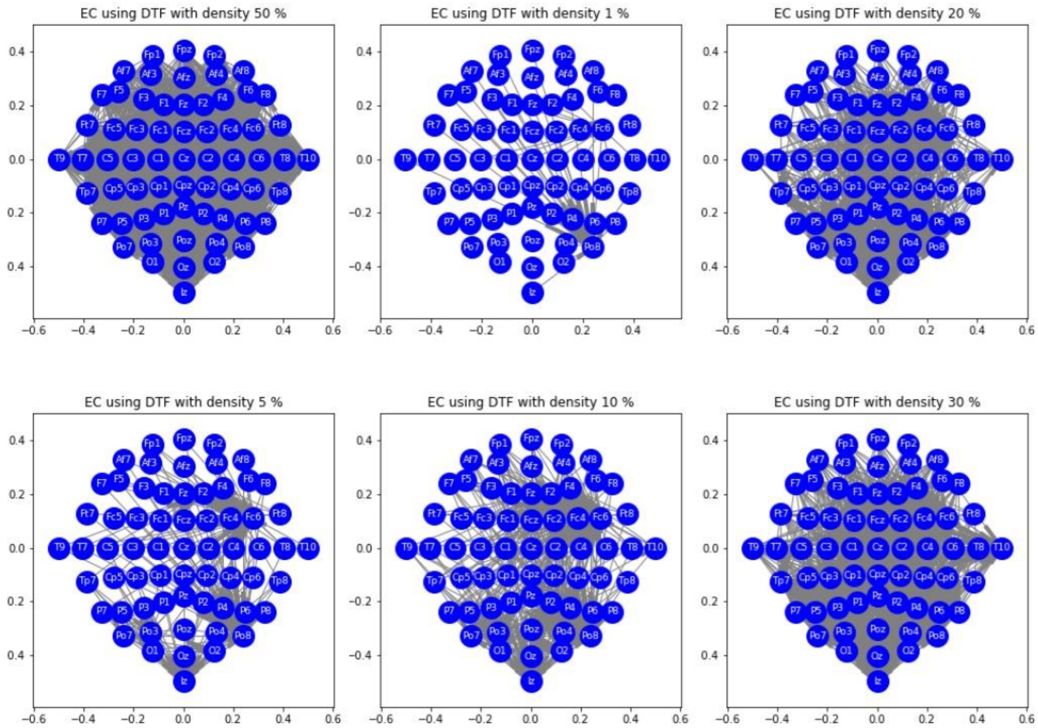

Fig 5.1: Topology representation for DTF EC at different densities

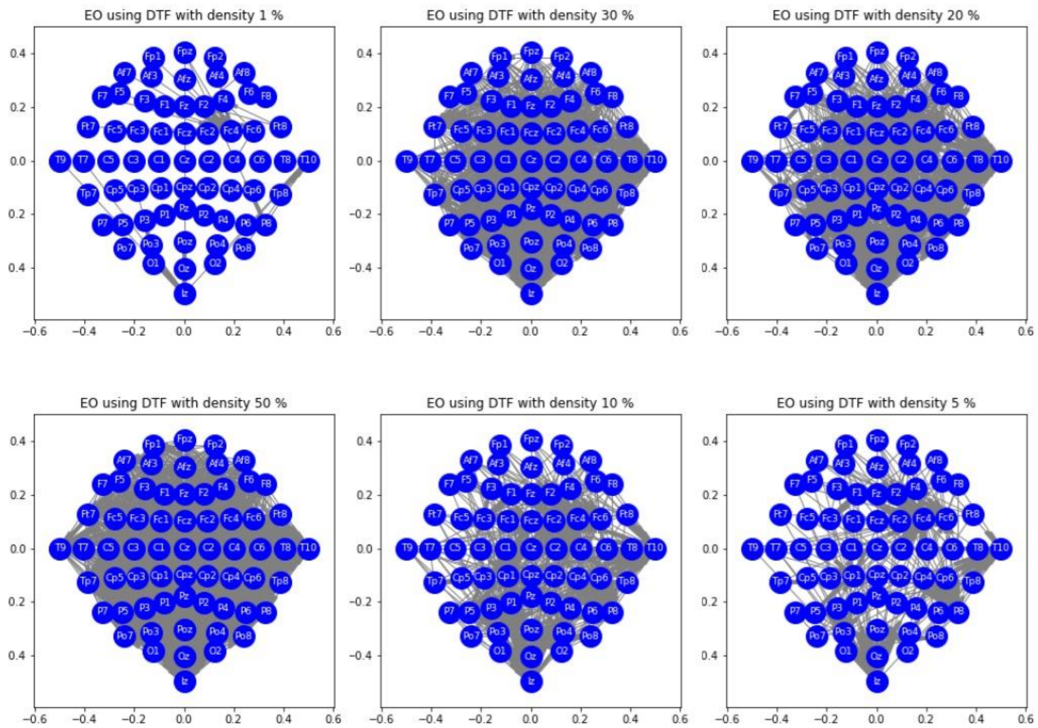

Fig 5.2: Topology representation for DTF EO at different densities

Topology diagrams using PDC:

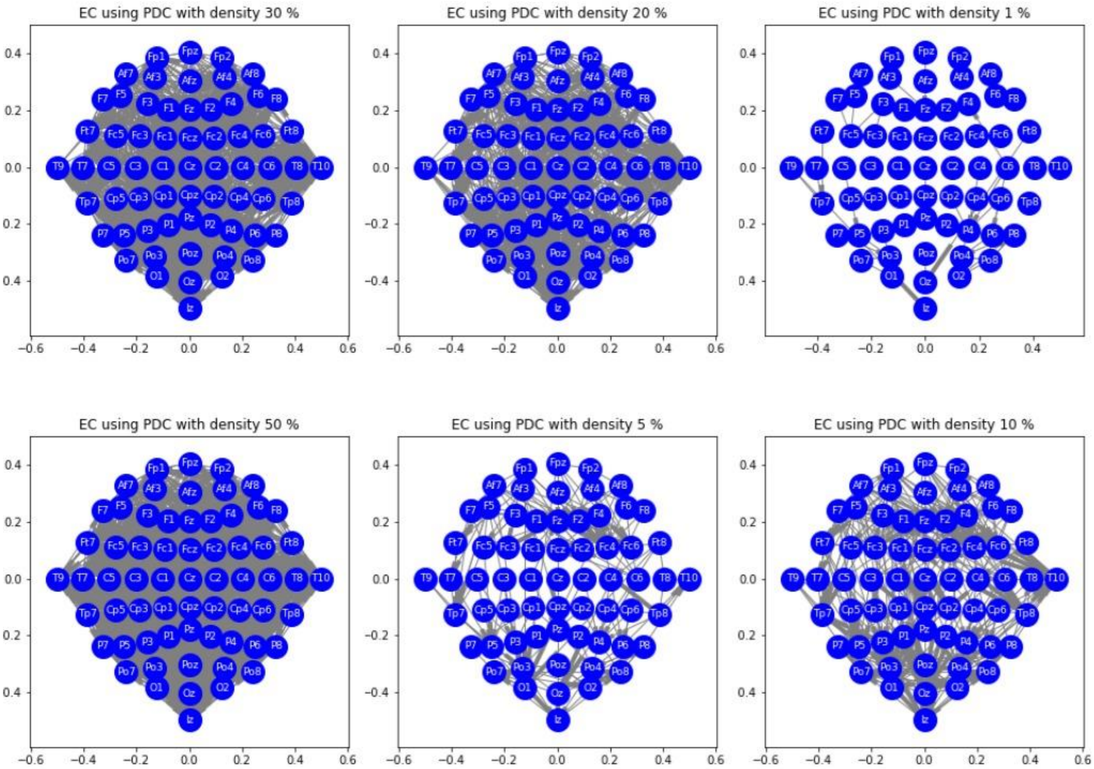

Fig 5.3: Topology representation for PDC EC at different densities

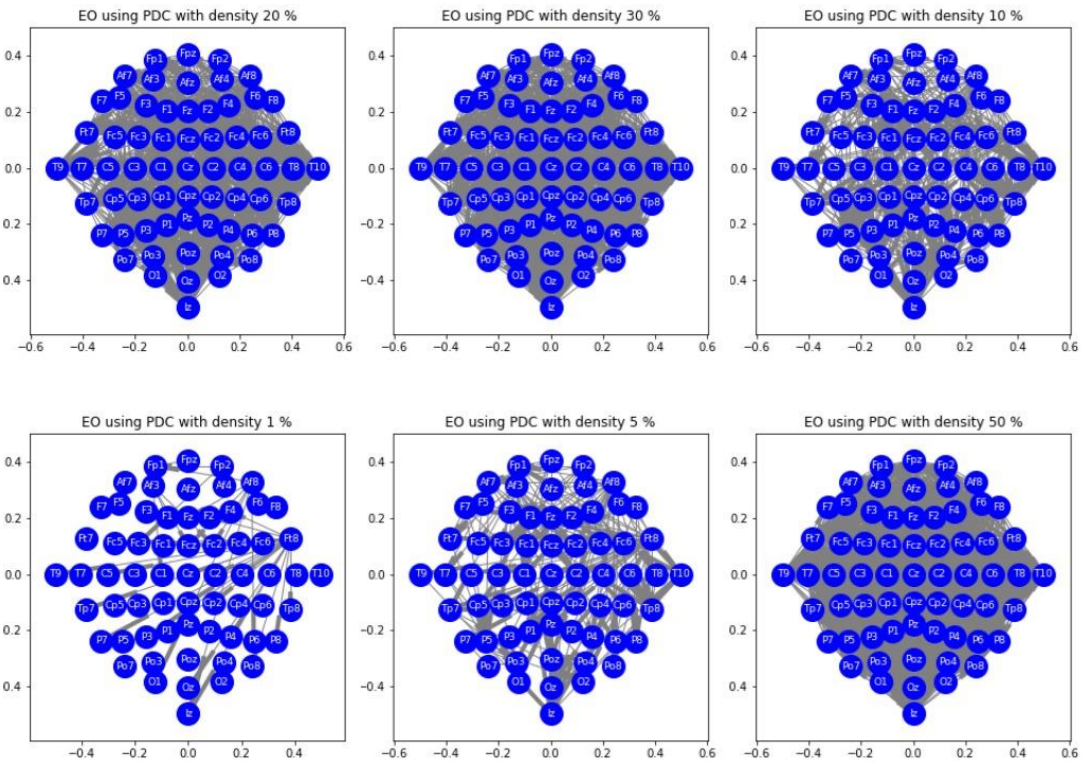

Fig 5.4: Topology representation for PDC EO at different densities

Adjacency matrix diagrams using DTF:

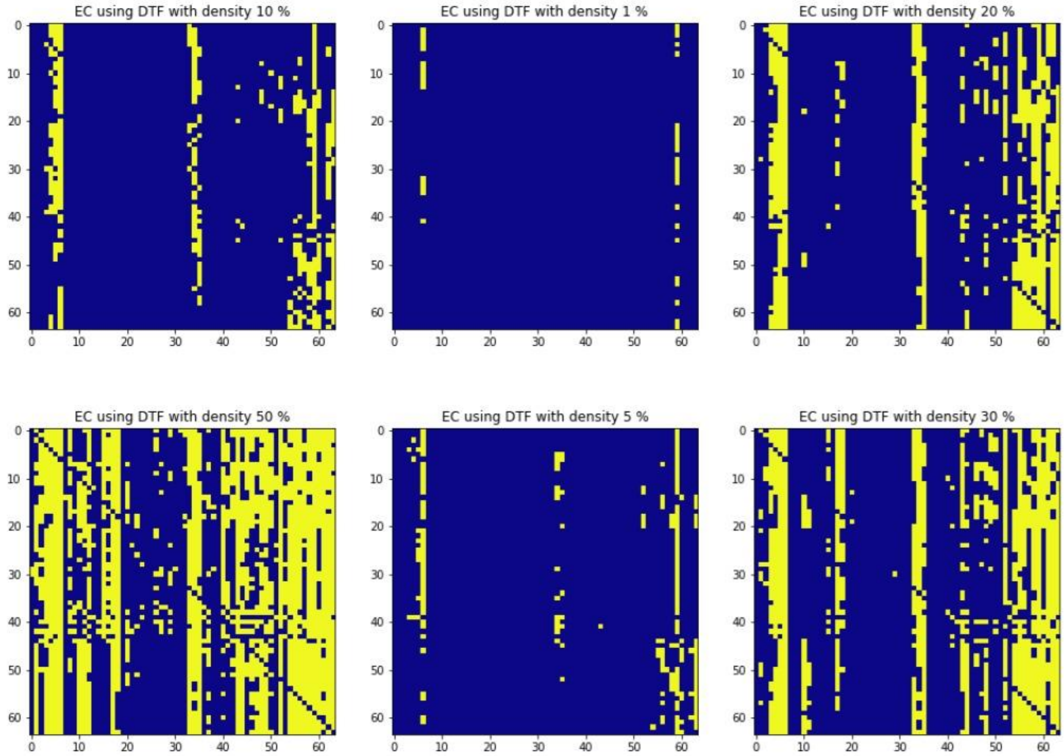

Fig 5.5: Adjacency matrix representation for DTF EC at different densities

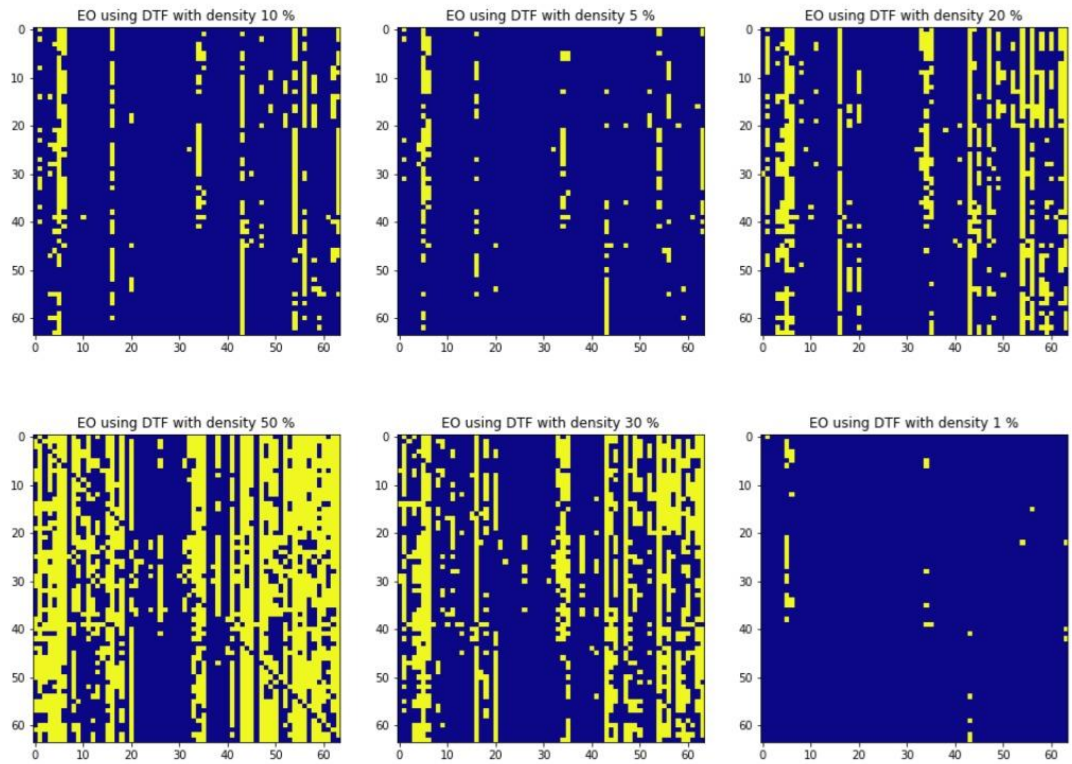

Fig 5.6: Adjacency matrix representation for DTF EO at different densities

Adjacency matrix diagrams using PDC:

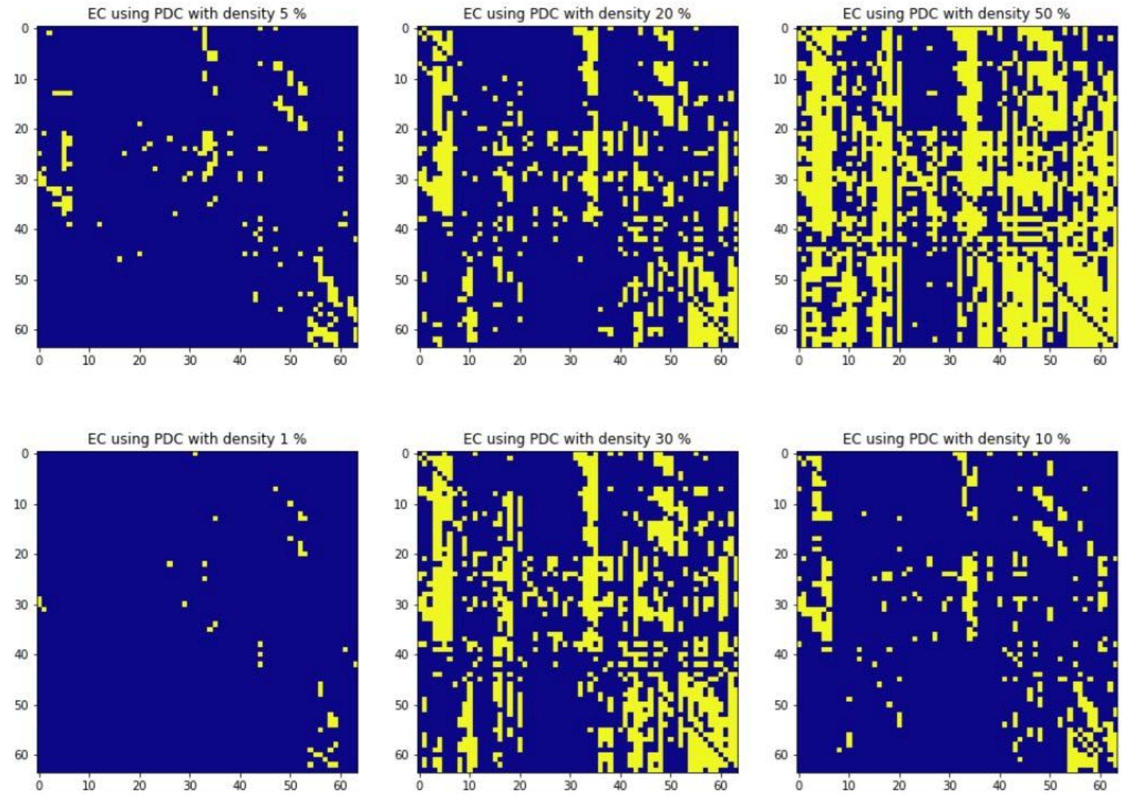

Fig 5.7: Adjacency matrix representation for PDC EC at different densities

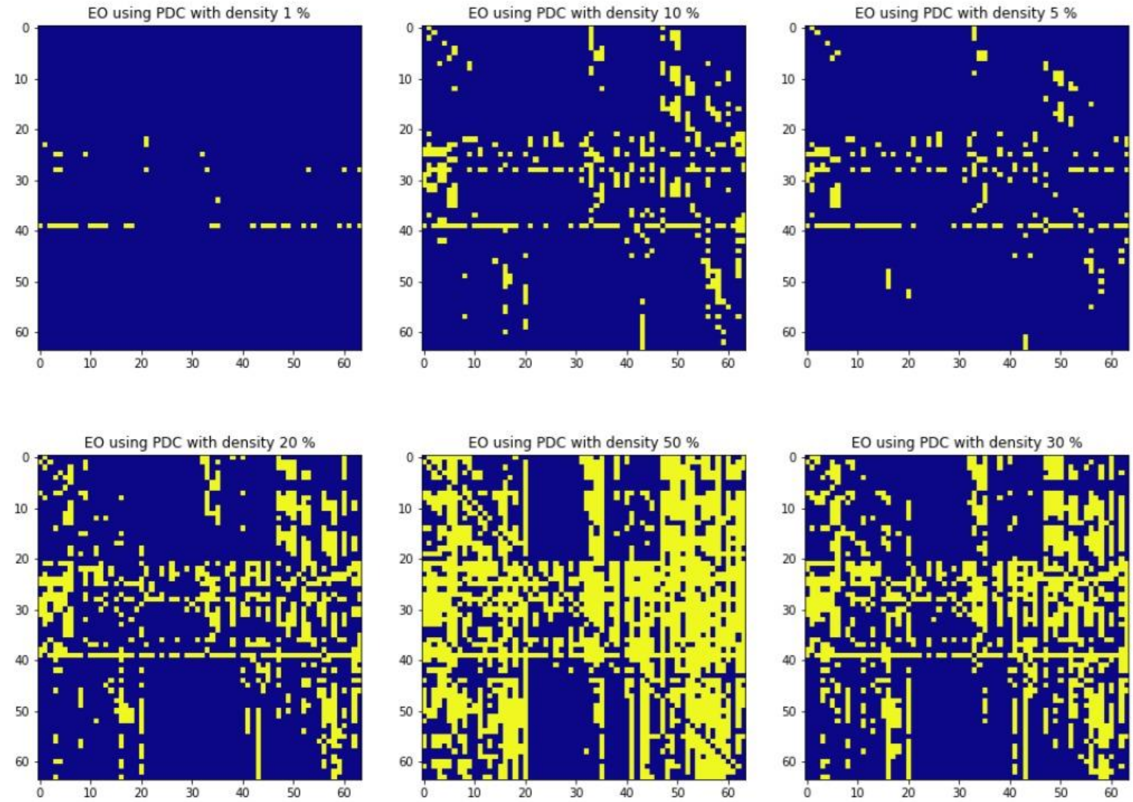

Fig 5.8: Adjacency matrix representation for PDC EO at different densities

Appendix B: Graph Indices

Degree topology diagrams using DTF:

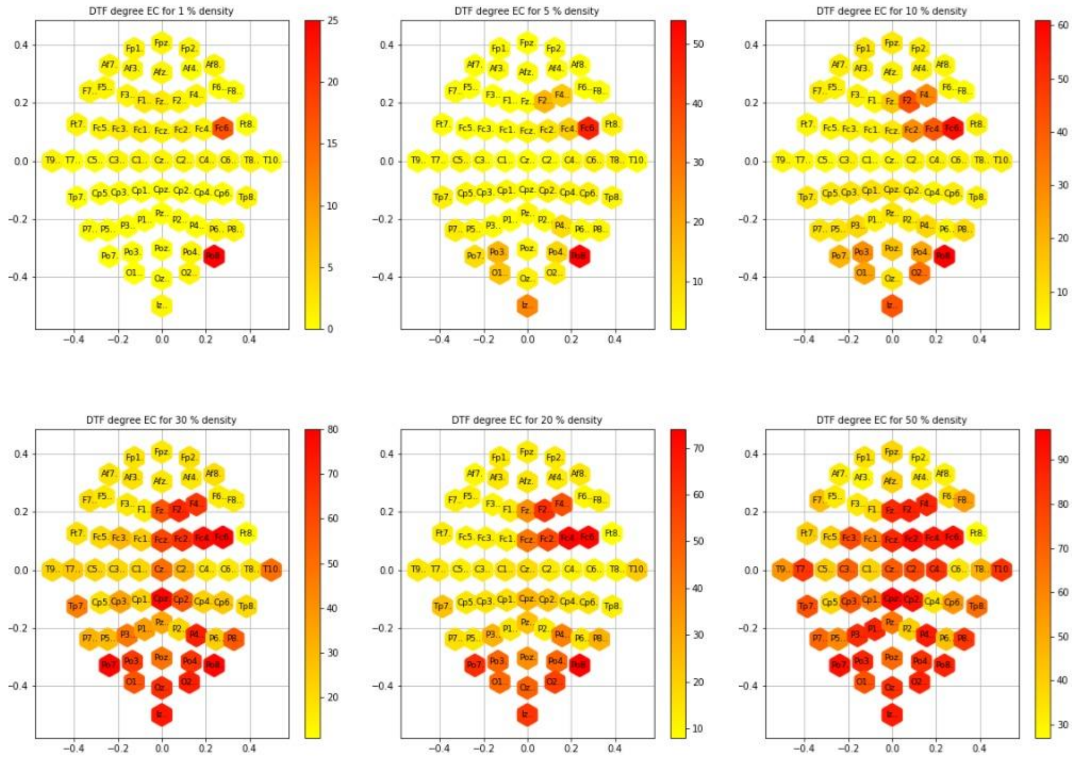

Fig 5.9: Topology representation of degree for DTF EC at different densities

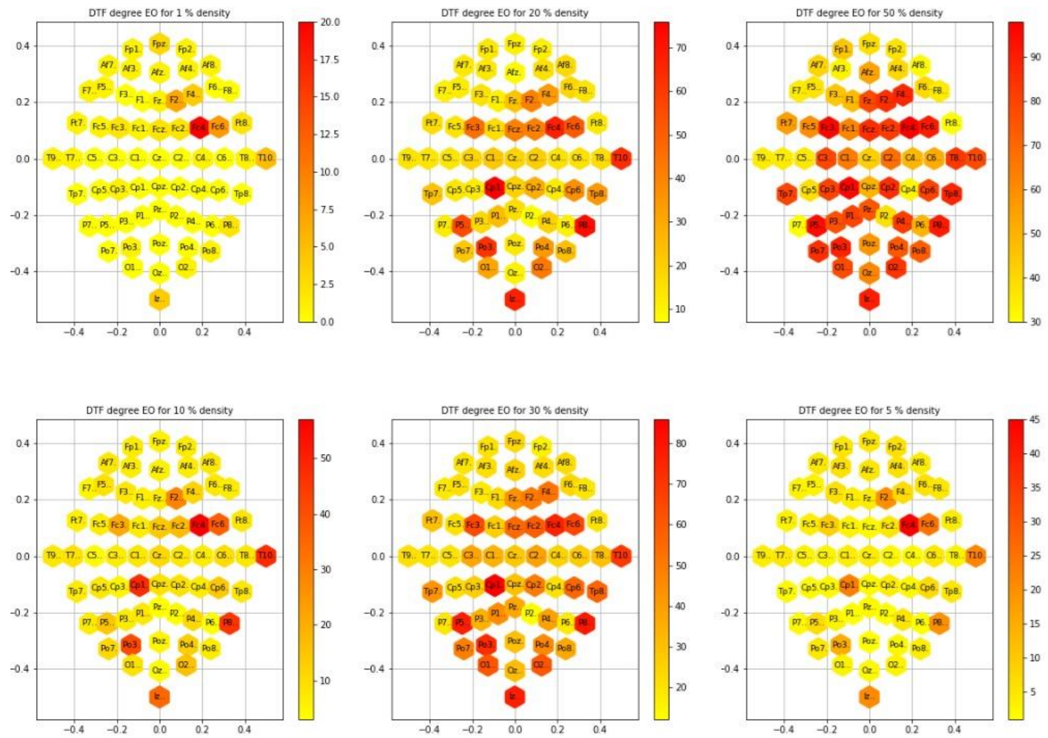

Fig 5.10: Topology representation of degree for DTF EO at different densities

Degree topology diagrams using PDC:

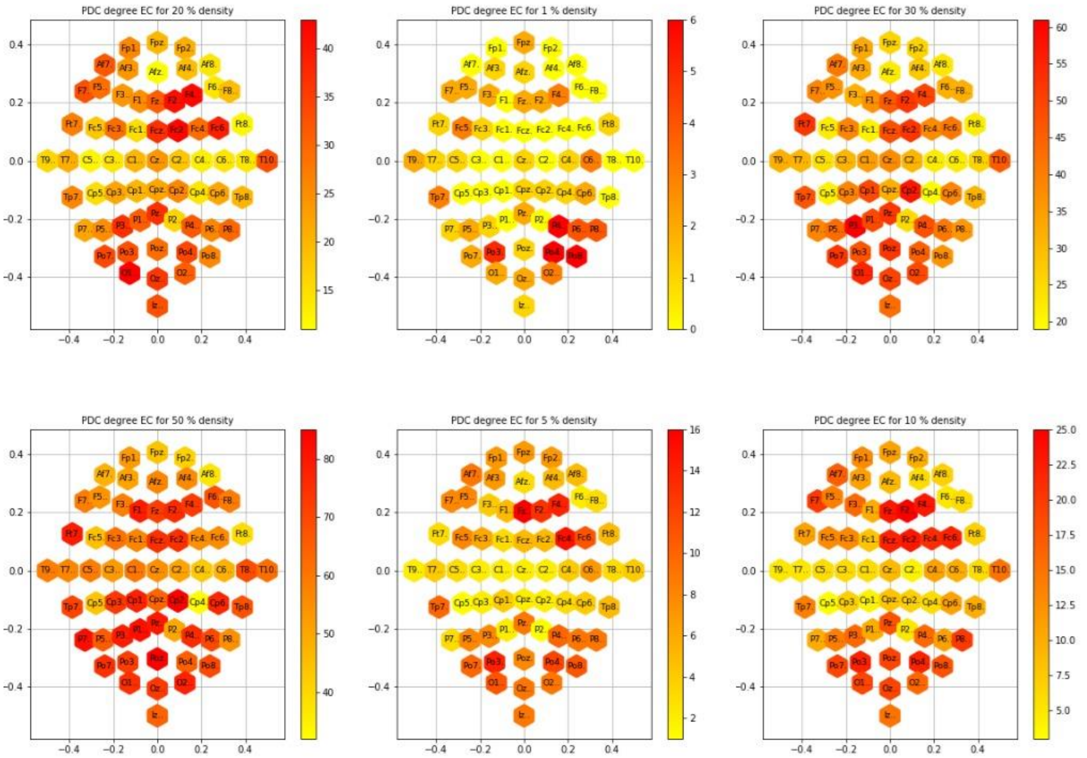

Fig 5.11: Topology representation of degree for PDC EC at different densities

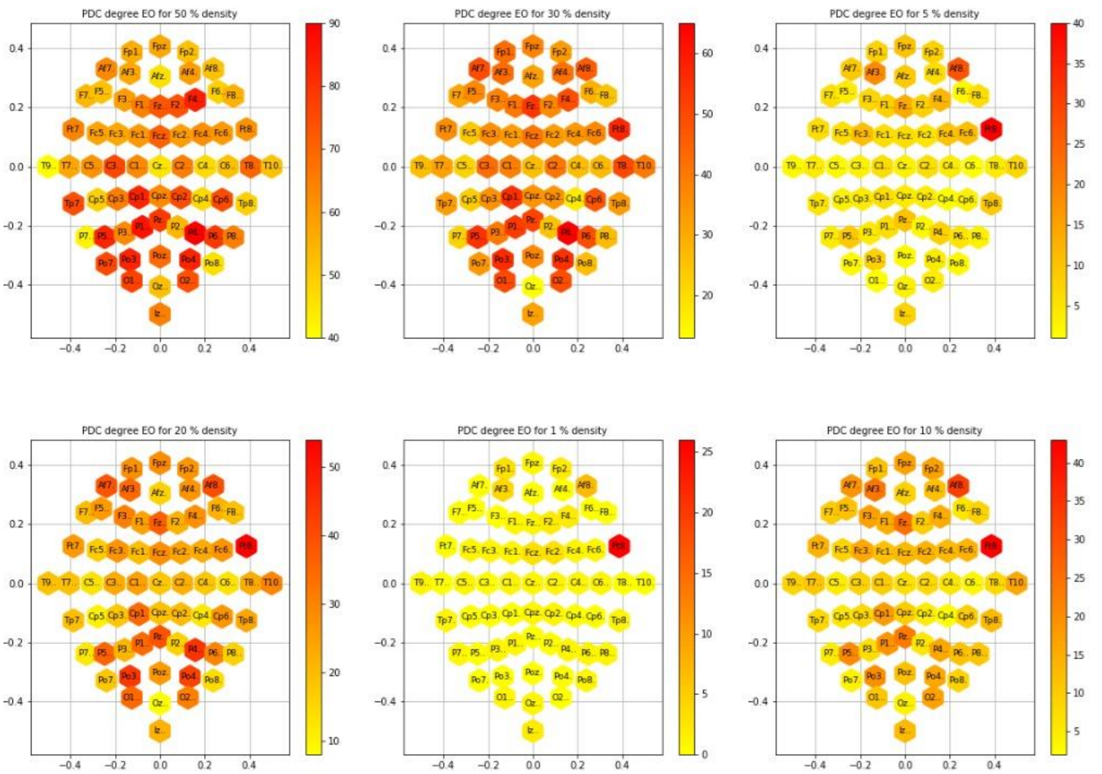

Fig 5.12: Topology representation of degree for PDC EO at different densities

In-Degree topology diagrams using DTF:

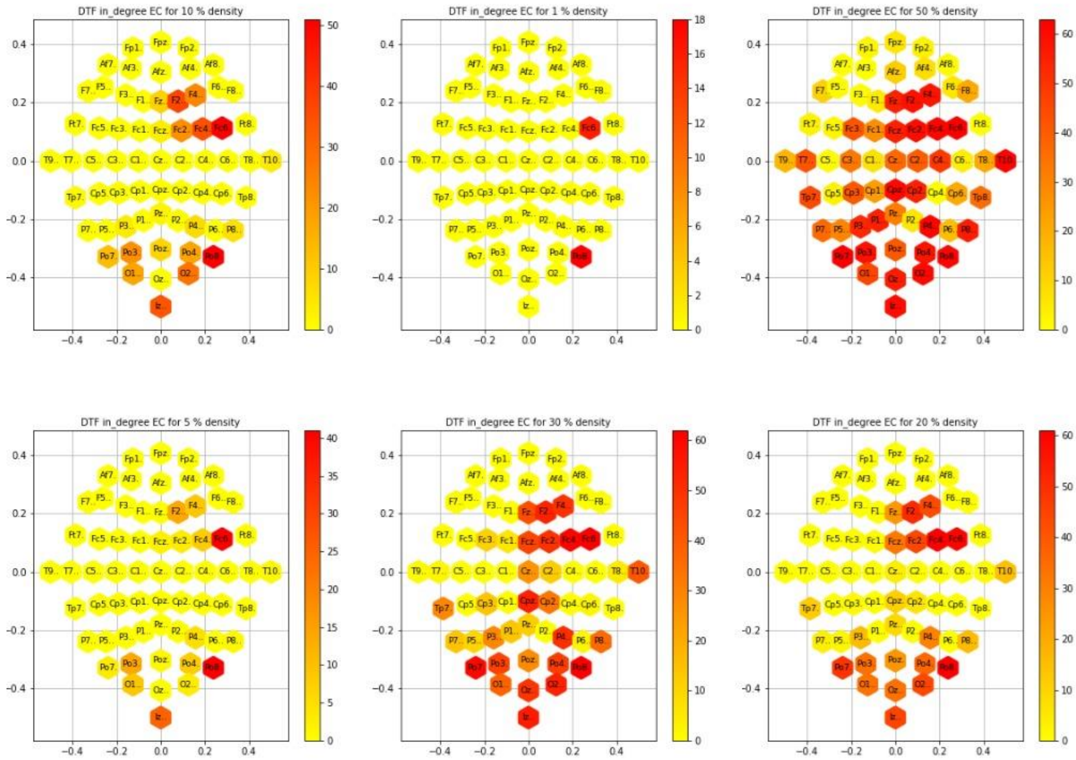

Fig 5.13: Topology representation of in-degree for DTF EC at different densities

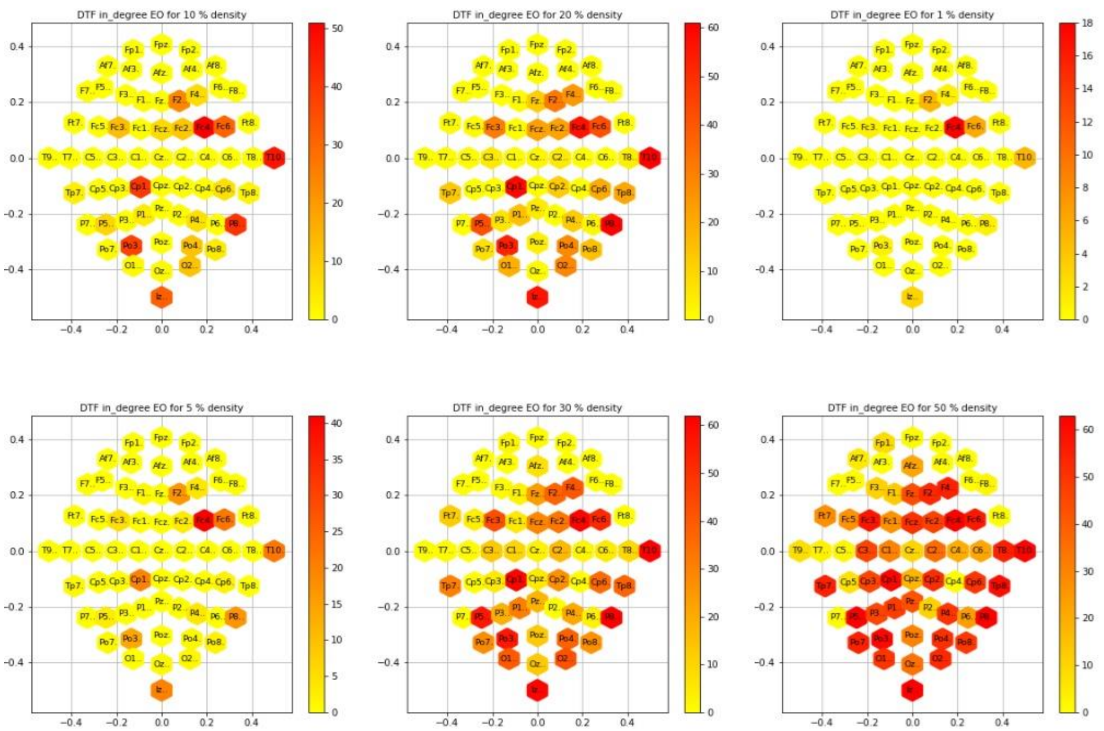

Fig 5.14: Topology representation of in-degree for DTF EO at different densities

In-Degree topology diagrams using PDC:

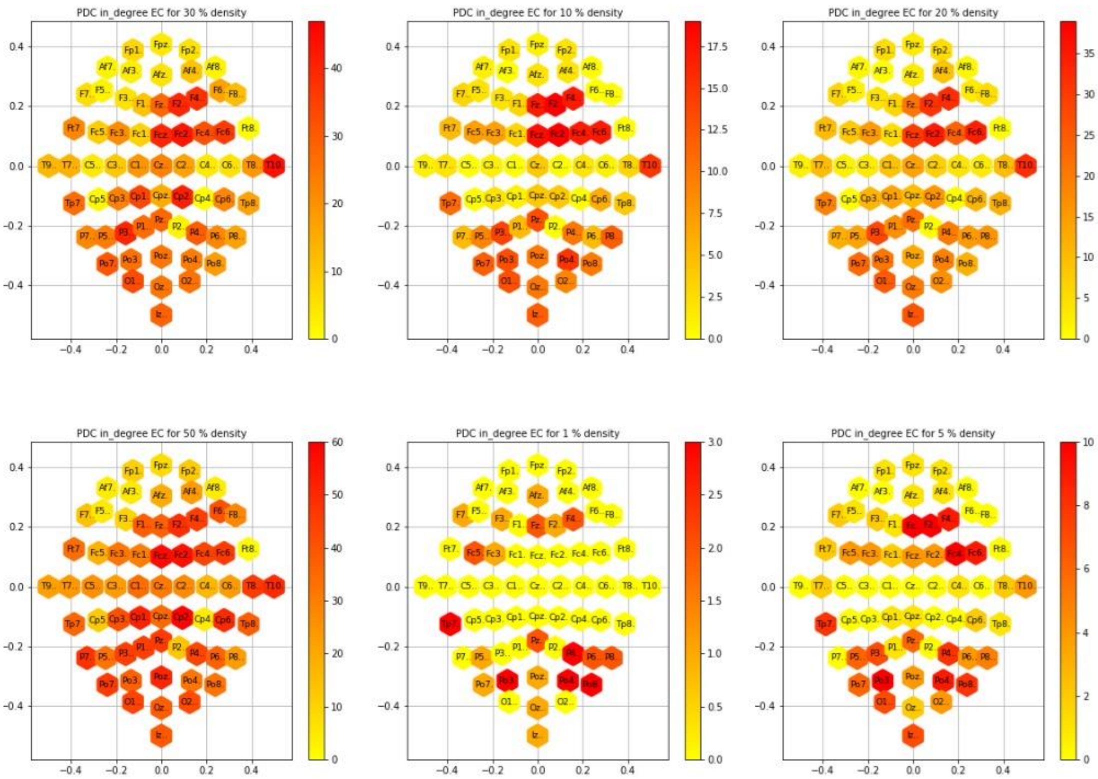

Fig 5.15: Topology representation of in-degree for PDC EC at different densities

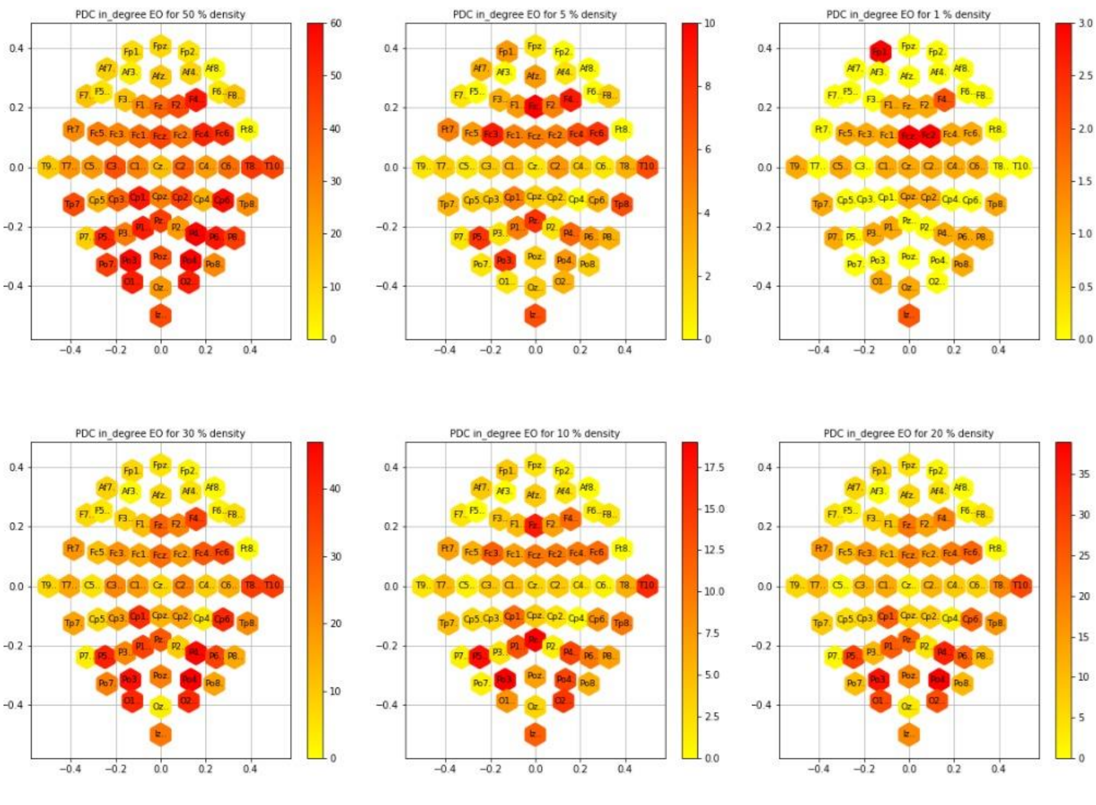

Fig 5.16: Topology representation of in-degree for PDC EO at different densities

Out-Degree topology diagrams using DTF:

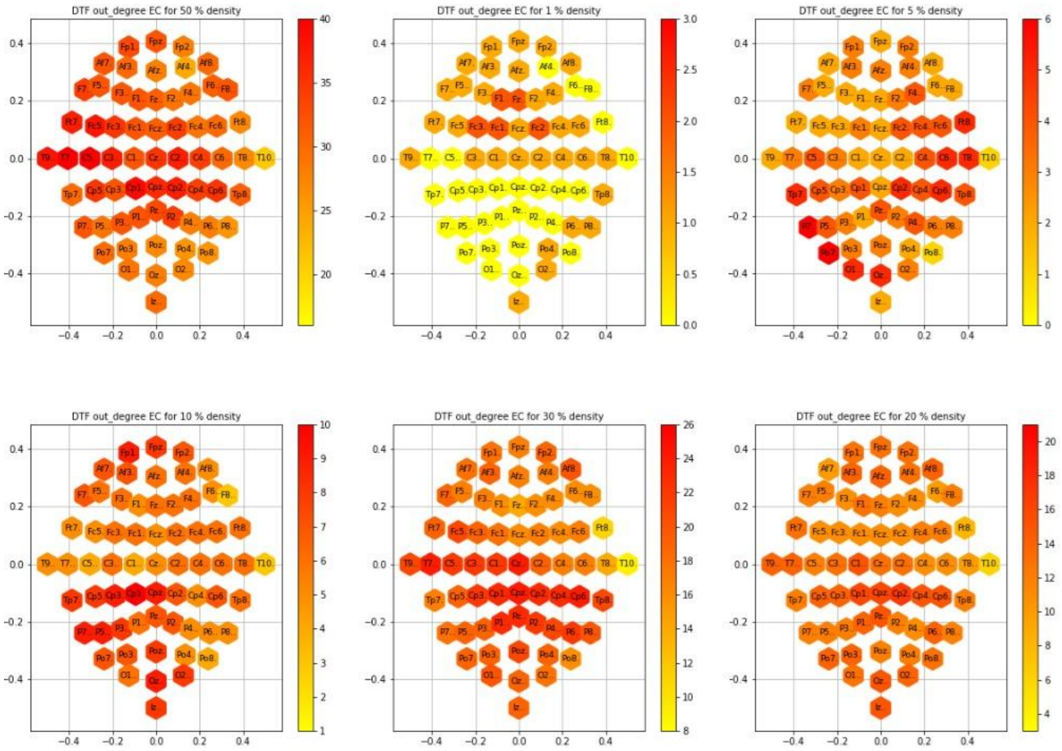

Fig 5.17: Topology representation of out-degree for DTF EC at different densities

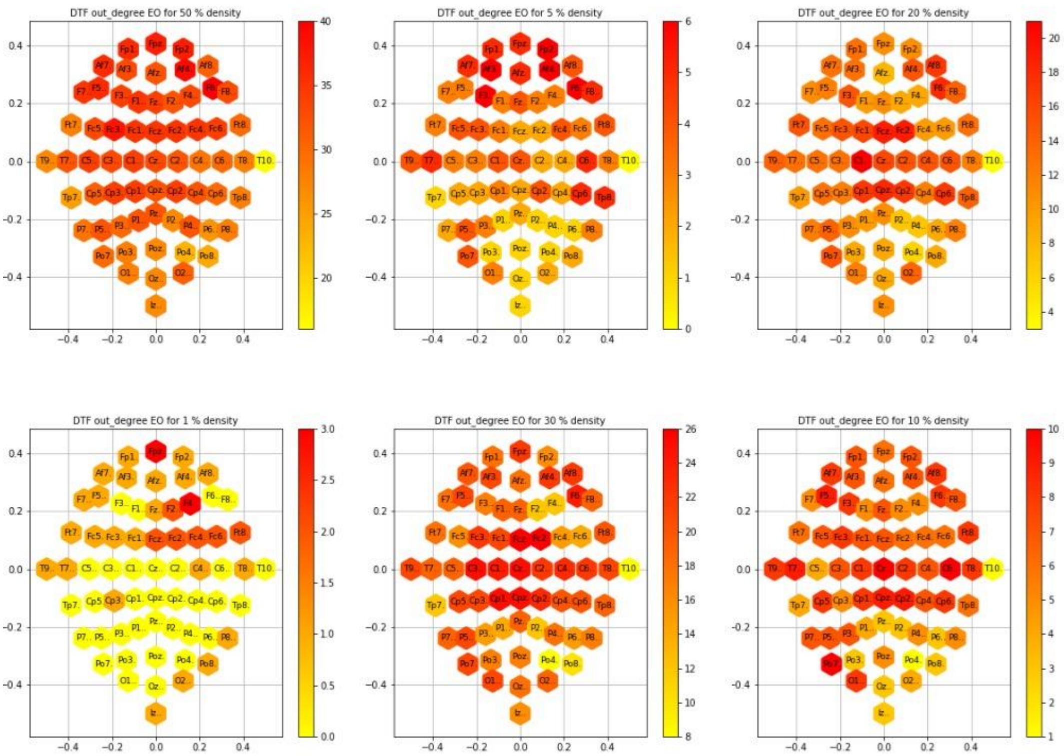

Fig 5.18: Topology representation of out-degree for DTF EO at different densities

Out-Degree topology diagrams using PDC:

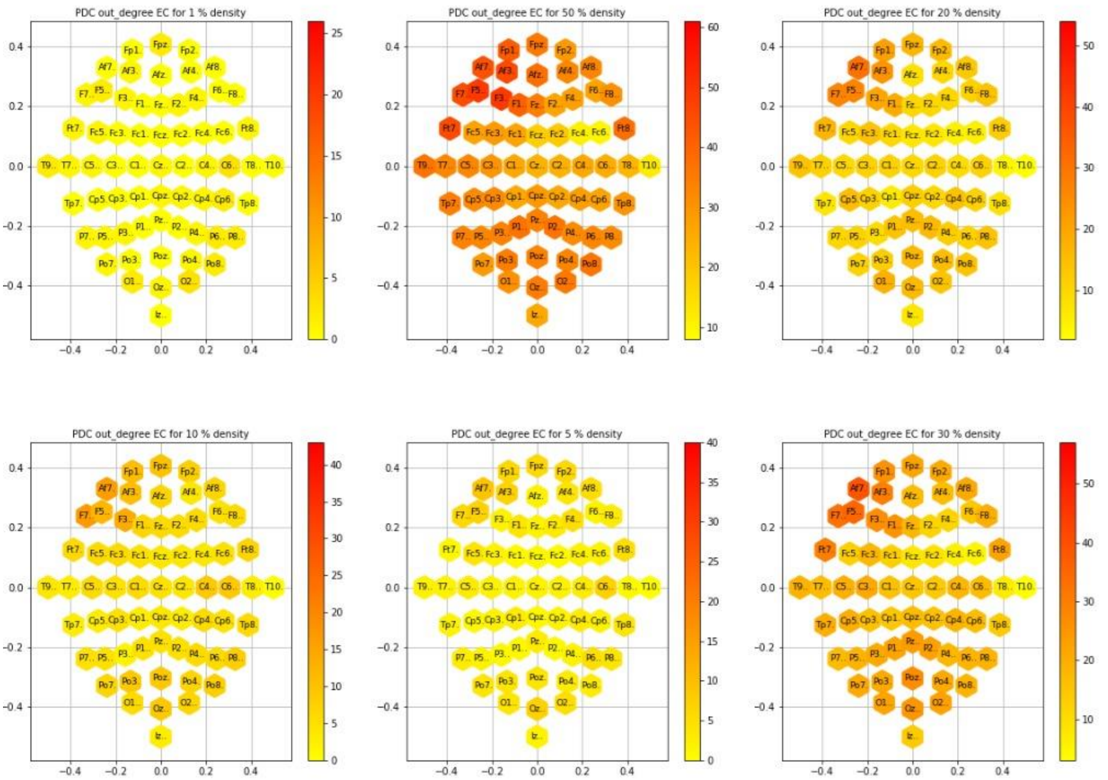

Fig 5.19: Topology representation of out-degree for PDC EC at different densities

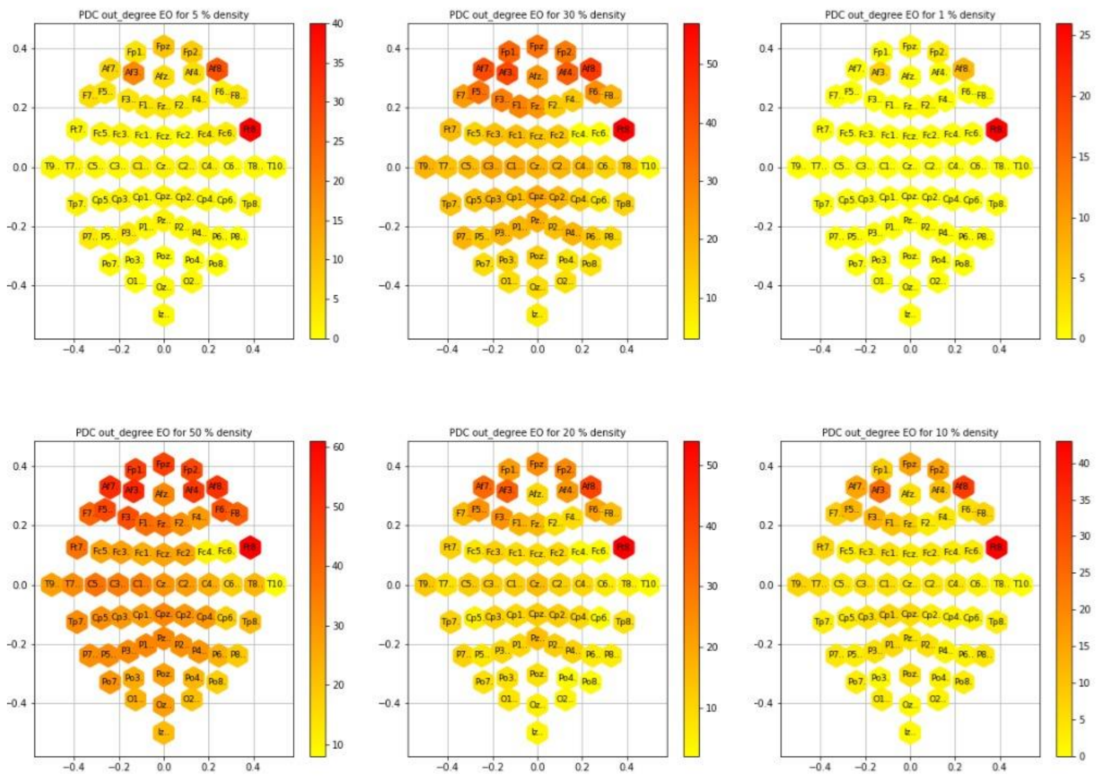

Fig 5.20: Topology representation of out-degree for PDC EO at different densities

Correlation of Degree, In-Degree-Out-degree across PDC and DTF (both EO and EC)

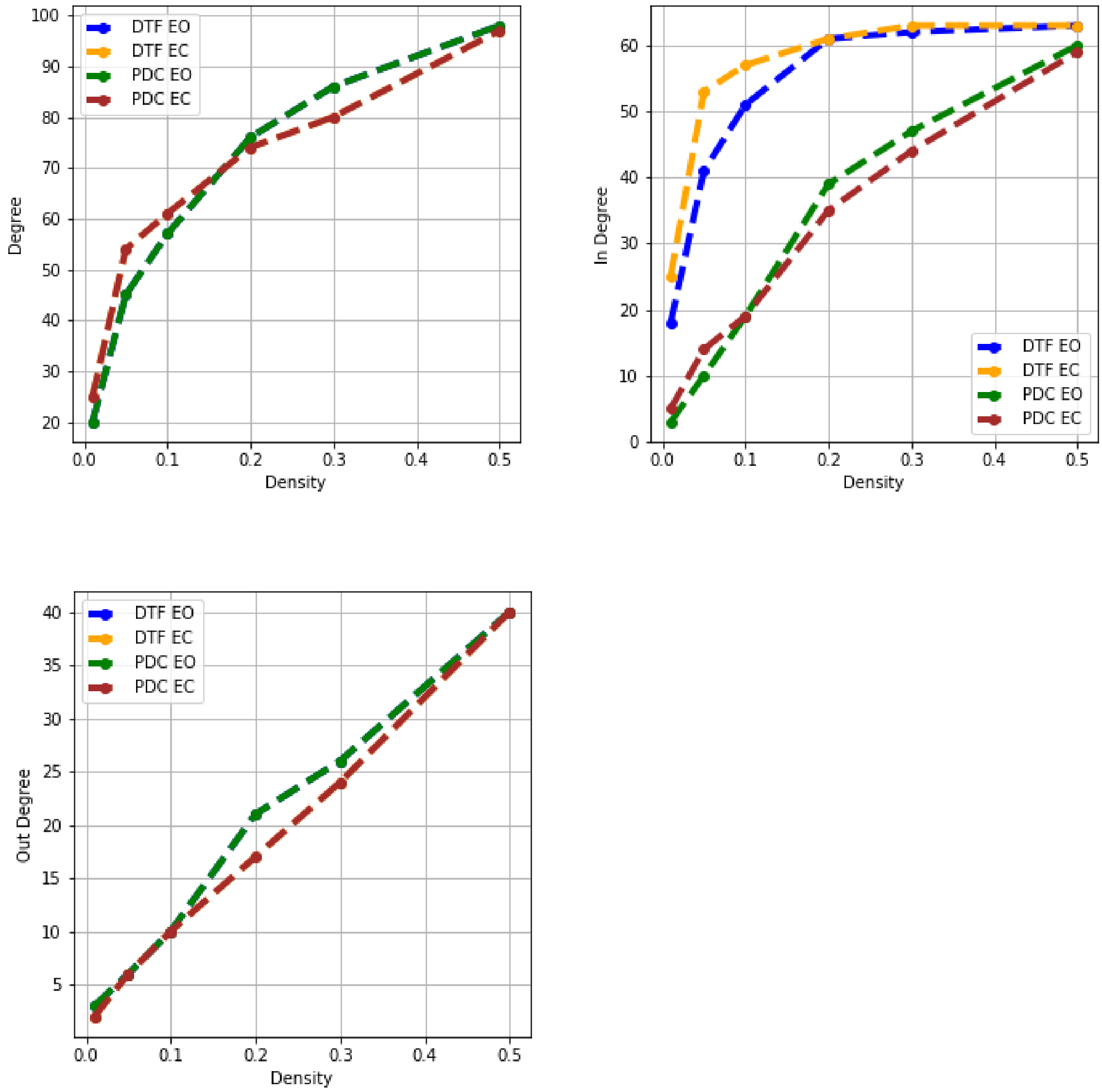

Fig 5.21: Correlation of local indices for both PDC and DTF at different densities

Appendix C: Motif Analysis

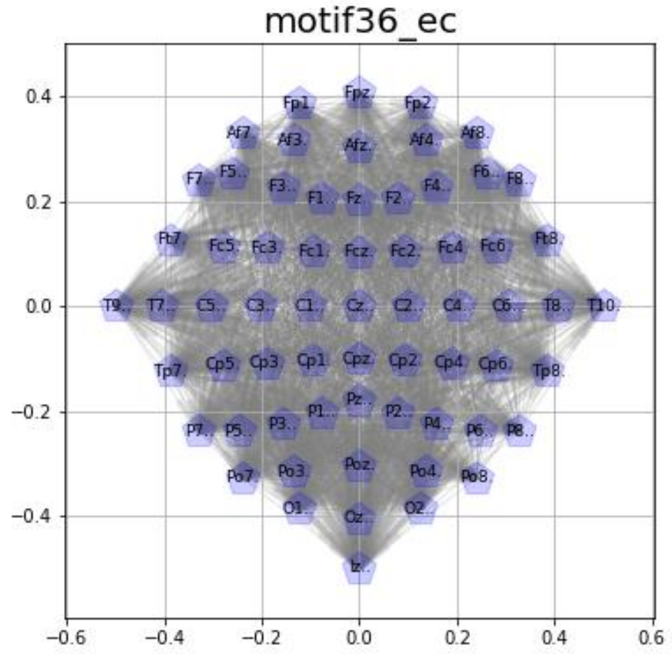

Figure 21: 3-nodes motif analysis of type A → B ← C. Eyes Closed(EC) using DTF

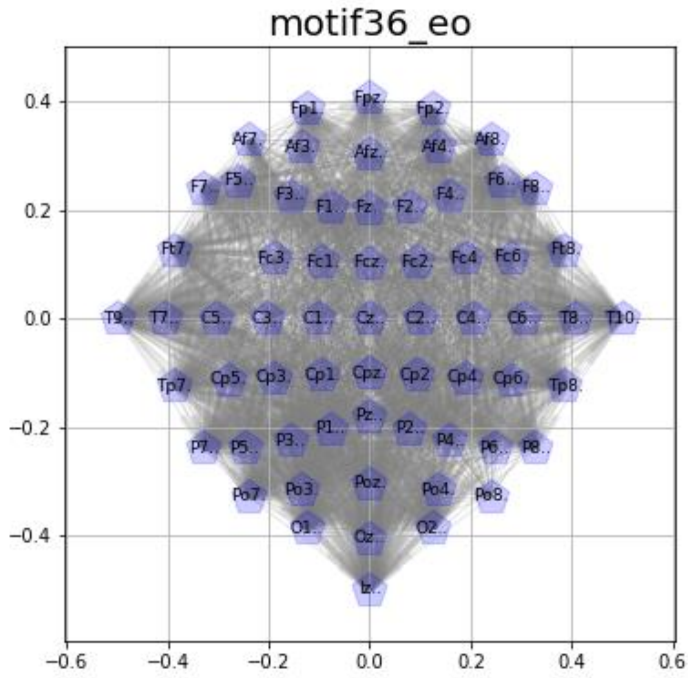

Figure 21: 3-nodes motif analysis of type A → B ← C. Eyes Open(EO) using DTF

3-node motif analysis

For EC(Eyes-Closed) -

Motif ID	Frequency	Statistical Significance
6	434	anti-motif
12	718	not significant
14	60	anti-motif
36	7974	anti-motif
38	1715	motif
46	131	motif
74	1462	not significant
78	53	anti-motif
98	10	not significant
102	81	anti-motif
108	1098	not significant
110	181	not significant
238	65	motif

Table 1: 3-node motif analysis EC

For EO(Eyes-Open) –

Motif ID	Frequency	Statistical Significance
6	196	anti-motif
12	565	not significant
14	46	anti-motif
36	8251	anti-motif
38	1256	not significant
46	88	motif
74	1746	anti-motif
78	33	anti-motif
98	6	not significant
102	108	anti-motif
108	1479	motif
110	240	not significant
238	128	motif

Table 2: 3-node motif analysis EO

4-node motif analysis

For EO(Eyes-Open) -

Motif ID	Frequency	Statistical Significance
2184	85650	anti-motif
2186	25201	not significant
4436	22338	motif
4370	17777	anti-motif
6552	17421	not significant
2252	8408	not significant
392	6370	not significant
76	4105	anti-motif
408	3716	not significant
6554	3638	anti-motif

Table 3: 4-node motif analysis EO

For EC(Eyes-Closed) -

Motif ID	Frequency	Statistical Significance
2184	75485	anti-motif
2186	29300	not significant
4436	17746	not significant
2252	12279	anti-motif
2254	1876	motif
2458	1991	motif
4370	12019	not significant
2202	1489	motif
6552	11698	not significant
76	8665	anti-motif

Table 4: 4-node motif analysis EC

Appendix D: Community Detection

Community detection using Louvain:

Community ID	Elements	Channels
0	22	Fc6,C3,C2,C4,C6,Cp5,Cp1,Cpz,Cp2,Cp4,Cp6,Tp8,P3,P1,Pz,P2,P4,P6,P8,Po4,Po8,O2
1	17	Fc3,Fcz,Fc4,C1,Cz,Fp1,Fpz,Fp2,Afz,Af4,Af8,F3,Fz,F2,F4,F6,Ft8
2	17	Fc5,C5,Af7,Af3,F7,F5,F8,Ft7,T7,T9,Tp7,P7,P5,Po7,Po3,O1,Iz
3	8	Fc1,Fc2,Cp3,F1,T8,T10,Poz,Oz

Table 5: Communities using Louvain eyes-closed using DTF graph

Community ID	Elements	Channels
0	25	Fc1,C1,Cp5,Cp1,Cpz,Cp2,Cp4,Cp6,T10,Tp8,P7,P5,P1,Pz,P2,P4,P6,P8,Poz,Po4,Po8,O1,Oz,O2,Iz
1	23	Fc5,Fc3,Fcz,Fc2,Fc6,C3,Fp1,Fpz,Fp2,Af7,Af3,Afz,Af4,Af8,F7,F5,F3,F1,F2,F4,F6,F8,Ft7
2	8	Cz,C6,Cp3,Fz,Ft8,T7,T9,Po7
3	3	C5,Tp7,P3
4	2	C4,T8
5	2	C2,Po3
6	1	Fc4

Table 6: Communities using Louvain eyes-open using DTF graph

Community detection using Info map:

Community ID	Elements	Channels
0	55	Fc5,Fc3,Fcz,Fc2,Fc4,Fc6,C5,C3,C1,Cz,C2,C4,C6,Cp5,Cp3,Cp1,Cpz,Cp4,Cp6,Fpz,Fp2,Af7,Af3,Afz,Af4,F7,F5,F3,Fz,F2,F4,F8,Ft7,Ft8,T7,T8,T9,T10,Tp7,Tp8,P7,P5,P3,P1,Pz,P2,P4,P6,P8,Poz,Po4,Po8,Oz,O2,Iz
1	3	Po7,Po3,O1
2	2	Fc1,F1
3	2	Cp2,Fp1
4	2	Af8,F6

Table 7: Communities using Info map eyes-closed using DTF graph

Community ID	Elements	Channels
0	52	Fc1,Fcz,Fc2,Fc4,Fc6,C5,C3,C1,Cz,C4,C6,Cp5,Cp1,Cpz,Cp4,Cp6,Fp1,Fpz,Fp2,Af7,Af3,Afz,Af4,Af8,F1,Fz,F2,F4,F6,F8,Ft7,T8,T10,Tp7,Tp8,P7,P5,P3,P1,Pz,P2,P4,P6,P8,Po3,Poz,Po4,Po8,O1,Oz,O2,Iz
1	5	Fc5,Fc3,F7,F5,F3
2	8	Cz,C6,Cp3,Fz,Ft8,T7,T9,Po7
3	3	Cp3,Ft8,Po7
4	2	T7,T9
5	2	C2,Cp2

Table 8: Communities using Info map eyes-open using DTF graph