Brain network study during resting states

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Group # 12

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Contents

Abstract:

In this project we focus on understanding brain functionality related to the Eye Movement. More precisely, we analyze Brain Signals recorded by EEG for two different Eye states i.e. open and close respectively. The analysis involves different methodologies including Power spectral density to find frequency, Graph Connectivity, Graph theory indices, Motif Analysis and community detection. We make a brief comparison of two Eye States for each of these methodologies. Finally, we discuss the overall results, understanding and learning outcome of the project

Introduction:

Understanding brain functionality has been a main concern among the computational neuroscientists. Over the year, different methodologies have been introduced and implemented to accomplish that. In this project, we study the brain functionality related to Eye Movement. We receive Data Set from the following URL https://physionet.org/physiobank/database/eegmmidb/. The Data set contains the EEG brain signals for a subject in two states as mentioned above. We combine methodologies from Signal processing and Graph Theory to understand the brain signal and connectivity pattern in the brain. The list of the specific tasks is present in Table 0. Analysis comprises of the brief comparison of two eye states involving each methodology.

Dataset:

The EEG data are available from PhysioNet website, “EEG Motor Movement/Imagery Dataset”. The whole dataset contains data acquired from 109 subjects, each containing 14 runs (files) of acquisition. Only the first two runs (S076R01 and S076R02) are relevant for this project: R01 is recorded during eyes-open (EO) resting state; R02 is recorded during eyes-closed (EC) resting state. Data was given in EDF files (European Data Format). This format includes metadata, among which the sampling frequency and the channel labels.

Objective:

Main objective of this analysis was to build a comparison between EEG datasets of two different Eye states i.e. open and close respectively. This EEG data are recorded from 64 electrodes with subject at rest in following states

1. Eyes-open
2. Eyes-closed

Strategies:

For our analysis we downloaded the two EDF (European Data Format) files corresponding to two 64-channels EEG signals from a single subject S076 namely S076R01.edf and S076R02.edf Each edf file has 64 columns and in order to read this data we use python library PyEDFlib. That is a free Open Source wavelet toolbox for reading / writing EDF/BDF files. We perform following analysis on this data:

1. Connectivity graphs (using spectral density)
2. Graph theory indices
3. Motif analysis
4. Community detection

Connectivity graphs:

Mandatory

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.

We select a relevant frequency value using power spectral density and we applied the threshold so that only the value above that threshold are used to form the edges. We choose these values statically as we can see the resulting matrix gives us the Network Density equal to 20 percent.

Class A - Perform the task for different values of Density:

We applied the threshold in a way such that the resulting binary matrix gives us the result for Network density equal to 1 percent, 5 percent, 10 percent, 20 percent, 30 percent and 50 percent. This is done using best alpha (threshold) finding with respect to densities.

Class D – Perform the task with subset channels:

We performed the connectivity using DTF for 19 subset channels.

Graph theory indices:

Mandatory:

Using networkx python package, 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

Class C - Study the behavior of global graph indices in function of network density:

We consider two cases, Clustering Coefficient and Average Shortest path length with respect to network density: 1 percent, 5 percent, 10 percent, 20 percent, 30 percent and 50 percent.

Class D - Small word network:

A small word network in mathematical graph defines networks in which most nodes are not neighbors among themselves but at the same time most nodes are reachable from every other node by a small number of steps. This kind of organization lets a rapid integration of information between different specified brain areas even when they are distant

Motif analysis

Mandatory

We examine the occurrences of 3 node sub graphs in the graph obtained by using density = 20 percent for both eyes open and eyes close. We discovered that the frequency of occurrence for both eyes open and eyes close and find the statistical significance based on Z score. As we know Z score formula for a sample is:

$$z = (x - \mu) / \sigma$$

Where μ is mean and σ stands for standard deviation
Results of our analysis are discussed in results section of this report

Class E perform Motif Analysis for 4 Node configurations

We implement the Motif analysis for 4 nodes. This is comparatively very time consuming as now we have more chance of finding such motifs. The behaviour of Motifs and Anti Motifs for 4 nodes is exactly the same as for 3 nodes configuration. However, the Z score for 4 nodes configuration is much, much higher than for 3 nodes. This is intuitive since we're more likely to find out the motifs involving 4 nodes than for 3 nodes. The Z score increases almost exponentially. The table containing the Z score for 4 nodes configuration is present in Table 4.

Community Detection

Mandatory

We perform community detection based on a Python routine which implements the Louvain algorithm for community detection. We consider two cases

Case 1: Case 1 corresponds to the Eyes Open Data set. We find out that the number of communities are two. The number of elements of each community is 28 and 20 respectively.

Case 2: Case 2 is for Eyes close data set. We find three communities here having 19, 30 and 15 number of elements.

Class C Compare community structure obtained by two different methods

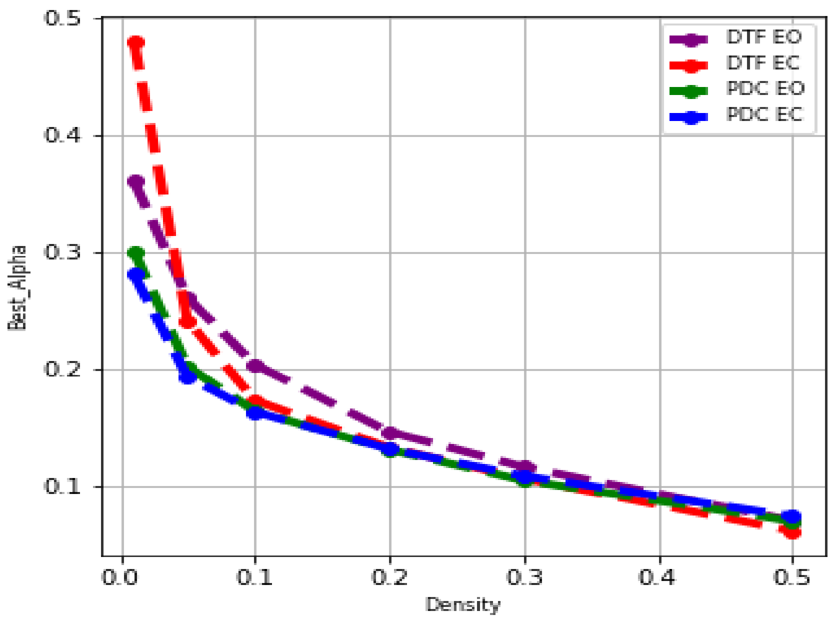
We use the tool Cystoscope to implement MCL clustering. We find out that there's only one community for both cases i.e. eyes open and eyes close and thus there's no significant comparison basis for both approaches. We however make a table listing the number of communities obtained by both Algorithms i.e.
Louvain and MCL and corresponding number of entries. This information is saved in Table 3.

Results and observations:

Connectivity graph:

In order to estimate functional brain connectivity among the 64 channels, we used both MVAR estimators PDC and DTF. We dynamically calculated threshold (best alpha) for all densities mentioned in the problem statement i.e.., 1%, 5%, 10%, 20%, 30% and 50%.

The estimations of connectivity between signals is executed first with the implementation of the MVAR. Since this method requires the selection of the order for the model, we used the Akaike information criterion for MVAR order estimation. We obtained best order for model for EO and EC states the frequency we selected is based on the range between 8-13 Hz, Below figure shows the best alpha representation for the densities.



Figures 1.1,1.2,1.3,1.4 in figure section represents the topological representation for all 64 channels with respect to EO and EC state using DTF and PDC for different densities.

For adjacency matrix representations please refer to Figures 2.1,2.2,2.3,2.4 in figure section

We can observe more connections in the network on the Figure 1.1 and 1.2 for DTF than topologies based on PDC in 1.3 and 1.4. Here, we see even more obvious concentration around central parietal channels than before.

With respect to PDC (refer the figure 1.4) for the EC state, we can observe that approximately 50% of the connection remain for density levels 30% and 20% and the rest is changing. It seems like the network is becoming more concentrated around parietal central channels.

Graph theory indices:

To analyze patterns in the graphs created in the previous step we did both microscopic and macroscopic analysis using host of indices both at the graph level (global)

For global indices, we tried to compare both clustering coefficient and average shortest path from both PDC and DTF at all densities. Please refer figure 3.1 and 3.2

We find out that the clustering coefficient for eyes open is relatively higher than for eyes close. We also find out that the Average Shortest path length is relatively lower for eyes open than for eyes close.

Motif Analysis:

We find out that the statistical significance for motifs in eyes close is higher than the motifs in eyes open case. For Anti Motifs, we however observe the opposite behaviour.
The results for Motifs and Anti Motifs for both node 3 and 4 and their corresponding Z score can be found in Table 1 and table 2 respectively. Please note that we used the Code extracted from Internet with few modifications. The proper reference is present in reference section.

Community Detection:

We perform community detection based on a Python routine which implements the Louvain algorithm for community detection. The result of analysis can be found in table 3 in references section.

References and Acknowledgments

1. Network Motifs, University of Helsinki https://www.cs.helsinki.fi/u/lmsalmel/biomodels/NetworkMotifs.html
2. ‘Connectivipy’, a Python package http://connectivipy.readthedocs.io/en/latest/tutorial.html
3. ‘Cytoscape’, an open source solution to visualize complex Networks http://www.cytoscape.org/
4. Python Signal Processing toolbox, https://docs.scipy.org/doc/scipy/reference/signal.html
5. Networkx, Python package to create, manipulate and visualize complex networks https://networkx.github.io/documentation/networkx-1.10/overview.html
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7. Pyedflib library: read/write EDF+/BDF+ files based on EDFlib
8. Github repository: https://github.com/holgern/pyedflib
9. Network motifs https://www.cs.helsinki.fi/u/lmsalmel/bio-models/NetworkMotifs.html
10. Scipy signal processing Version 1.0.0 https://docs.scipy.org/doc/scipy/reference/signal.html

Tables

List of tasks completed:

This Table shows the Tasks implemented.

Task	Category	Class
1.1	Mandatory	-
1.2	Optional	A
1.3	Optional	A
1.4	Extra	D
1.5	Extra	C
2.1	Mandatory	-
2.2	Extra	D
2.3	Extra	C
3.1	Mandatory	-
3.4	Extra	C
4.1	Mandatory	-
4.3	Extra	C

Table 0

This table shows the Motifs and Anti Motifs (for 3 nodes configuration only) and their corresponding Z scores.

Datasets	**Type**	**Z-Score**
Eyes Open	Motif	20675.800
Eyes Open	Anti-Motif	4333.5211
Eyes Close	Motif	16595.800
Eyes Close	Anti-Motif	8413.5211

Table 1

This table shows the Motifs and Anti Motifs (for 4 nodes configuration) and corresponding Z Scores.

Datasets	**Type**	**Z-Score**
Eyes Open	Motif	351133.332
Eyes Open	Anti-Motif	4479.708
Eyes Close	Motif	279720.332
Eyes Close	Anti-Motif	75892.708

Table 2

This table shows the communities and their structure for the task 'Community Detection'

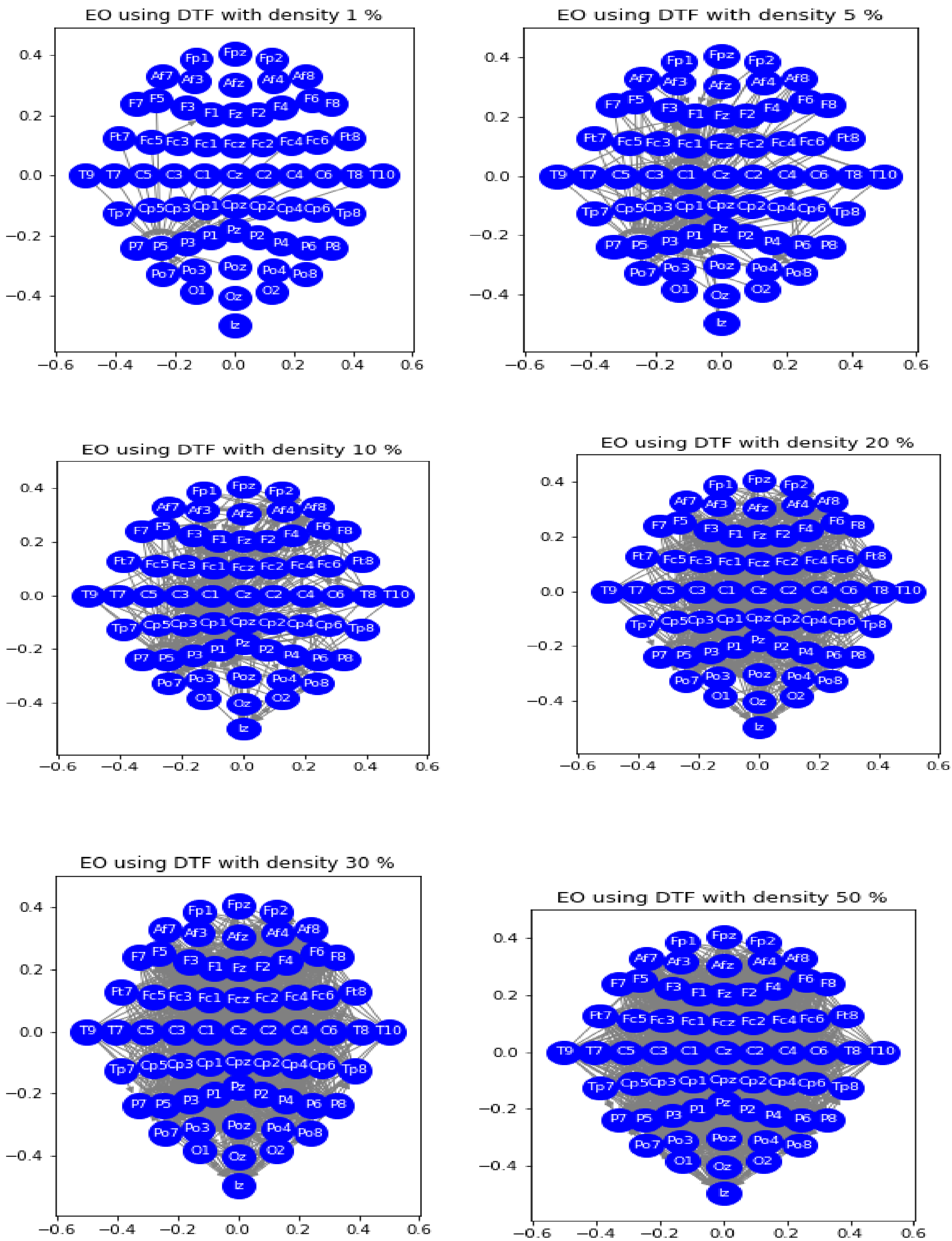
Dataset	Algorithm used	Number of Communities Structure	Number of entries
Eyes open	Louvain	3	(28, 20)
Eyes Open	MCL	1	64
Eyes Close	Louvain	3	(18, 32, 14)
Eyes Close	MCL	1	64

Table 3

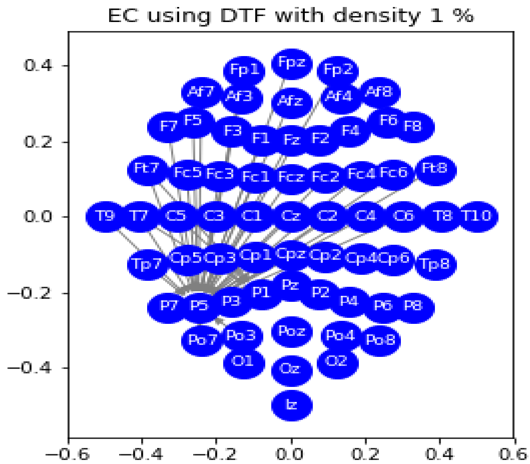
Figures

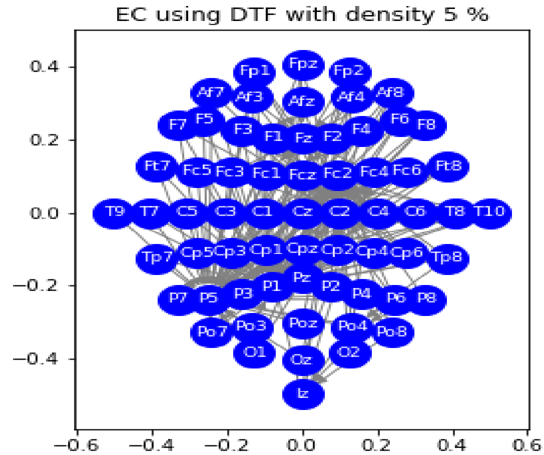
Figure 1: Connectivity graph: - Topology

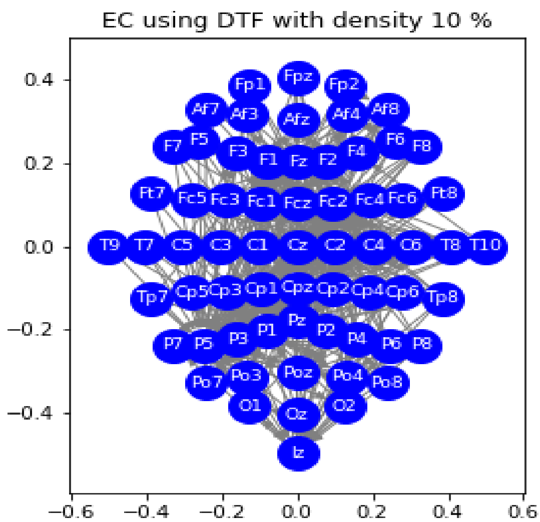
1.1 DTF – Topology diagrams for EO at different density levels

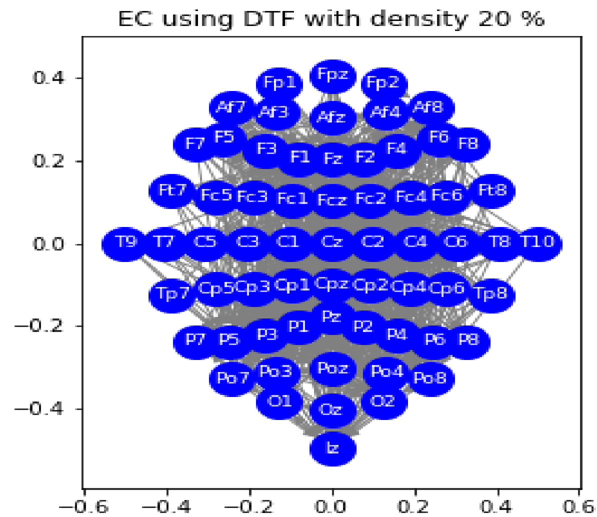


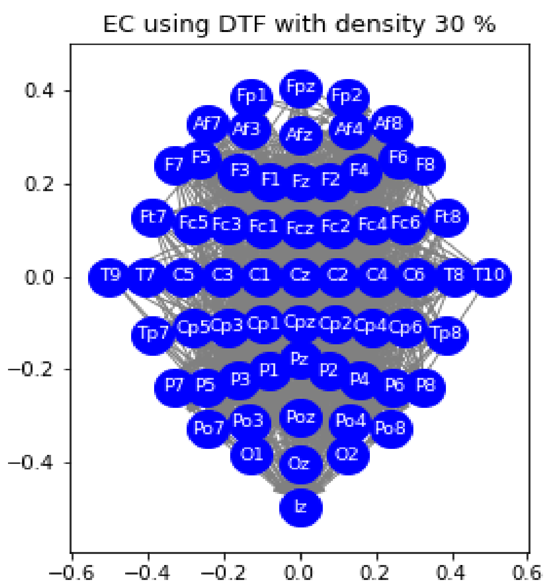
1.2 DTF – Topology diagrams for EC at different density levels:

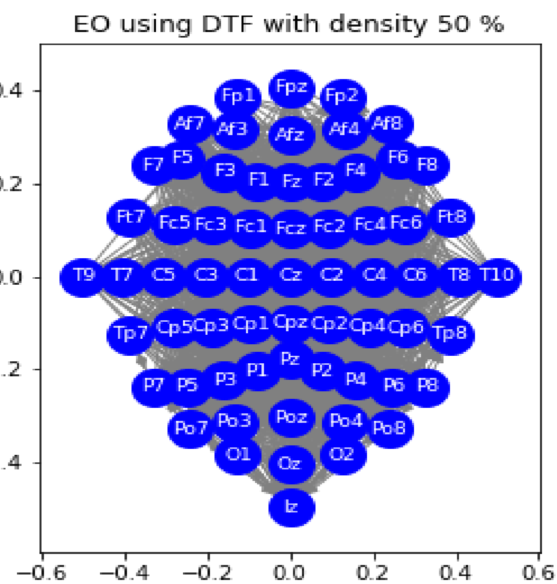




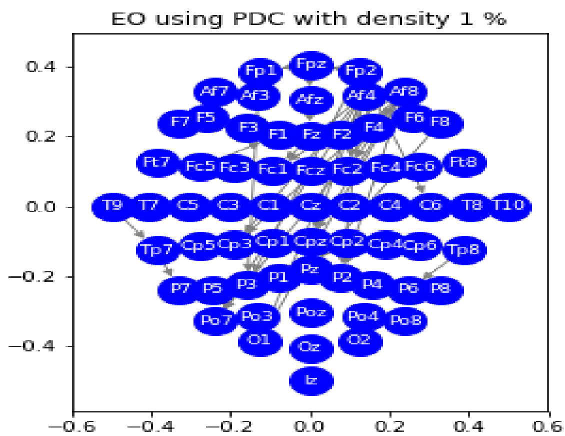


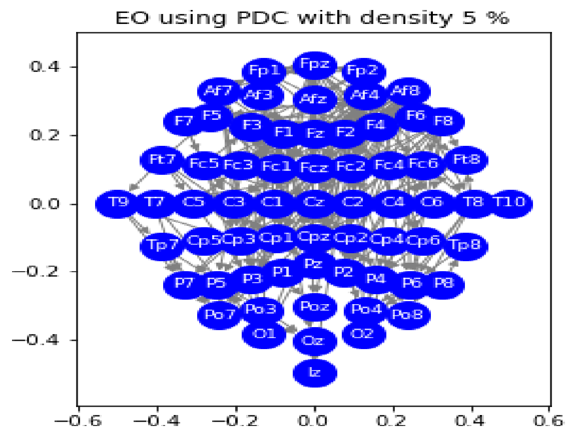


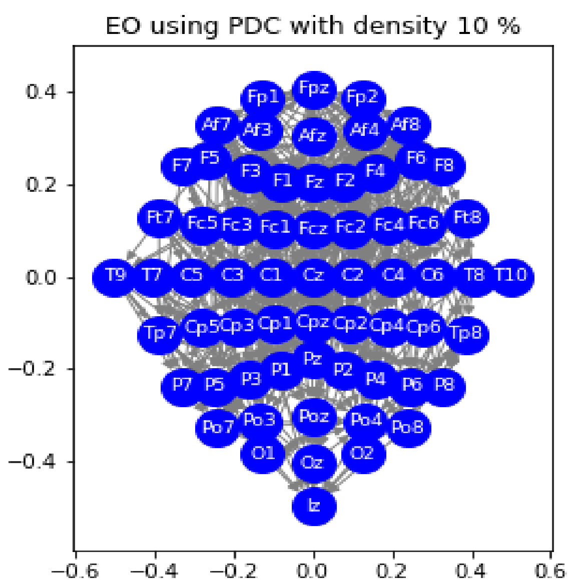


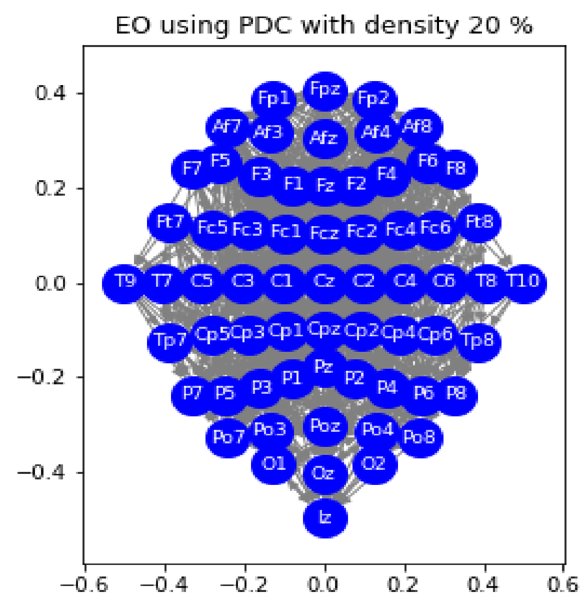


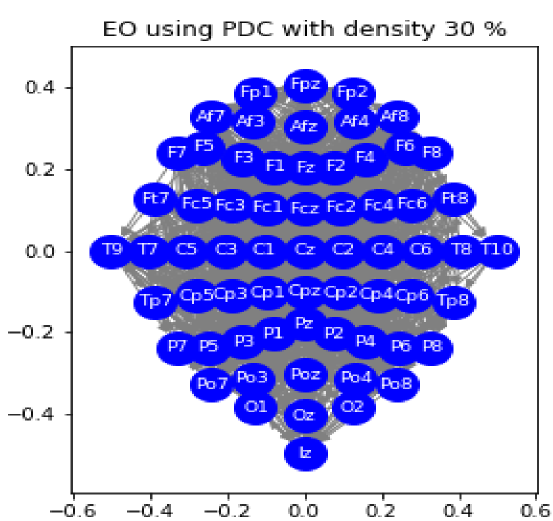
1.3 PDC : Topology diagrams for EO at different density levels

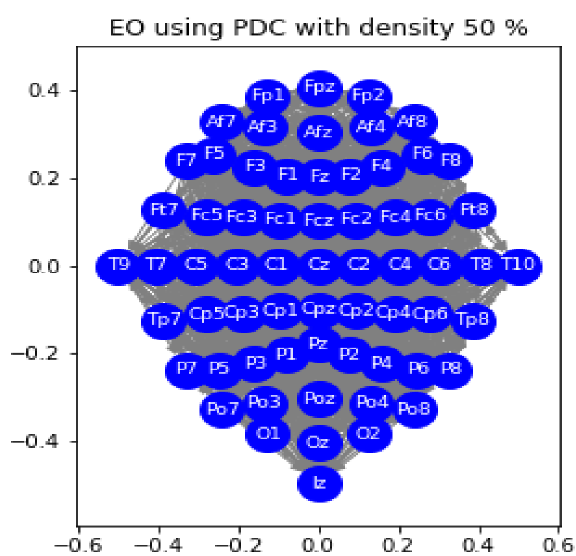




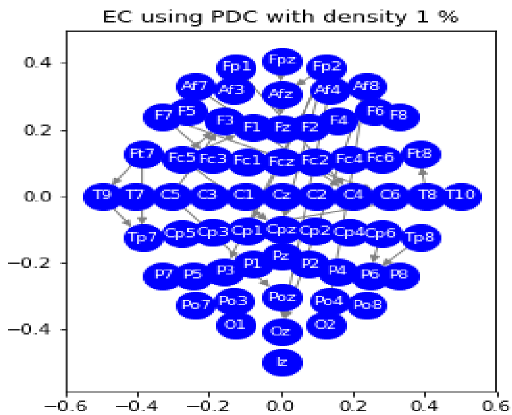


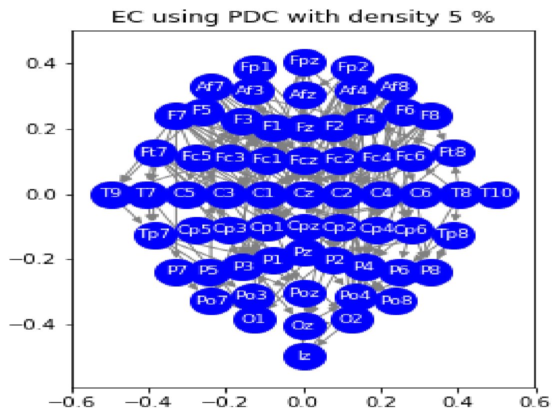


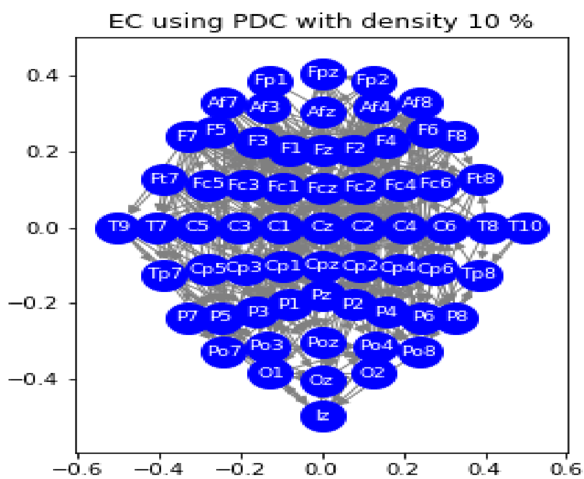


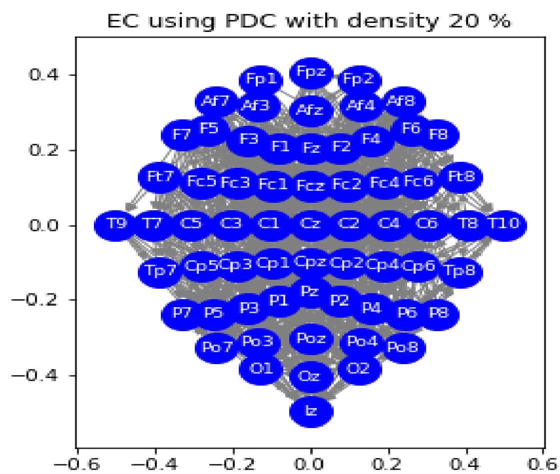


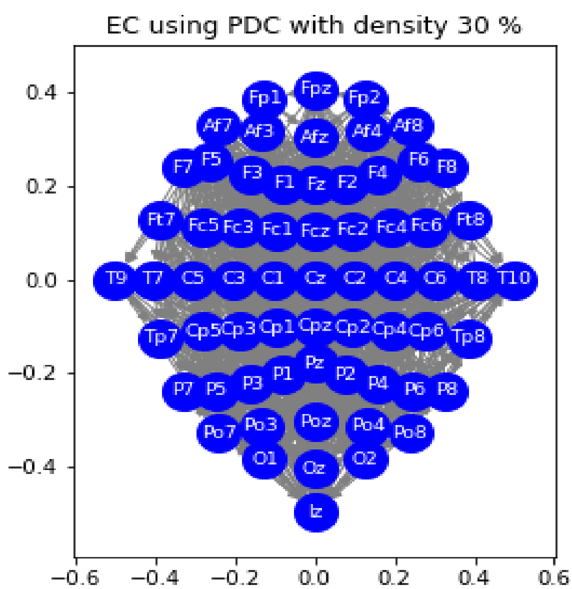
1.4 PDC : Topology diagrams for EC at different density levels











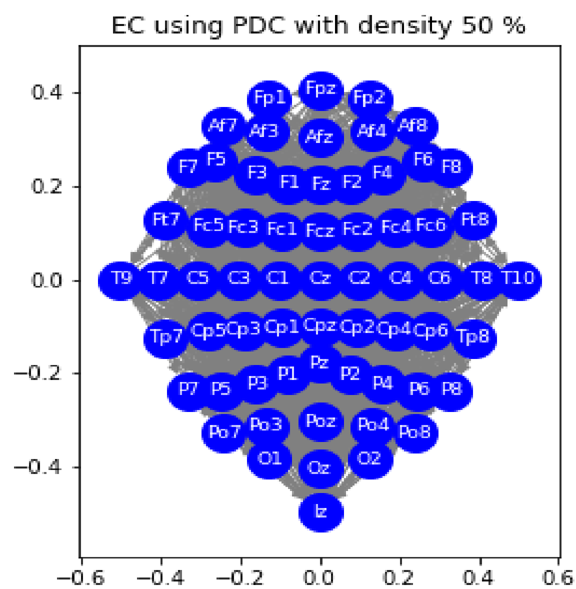
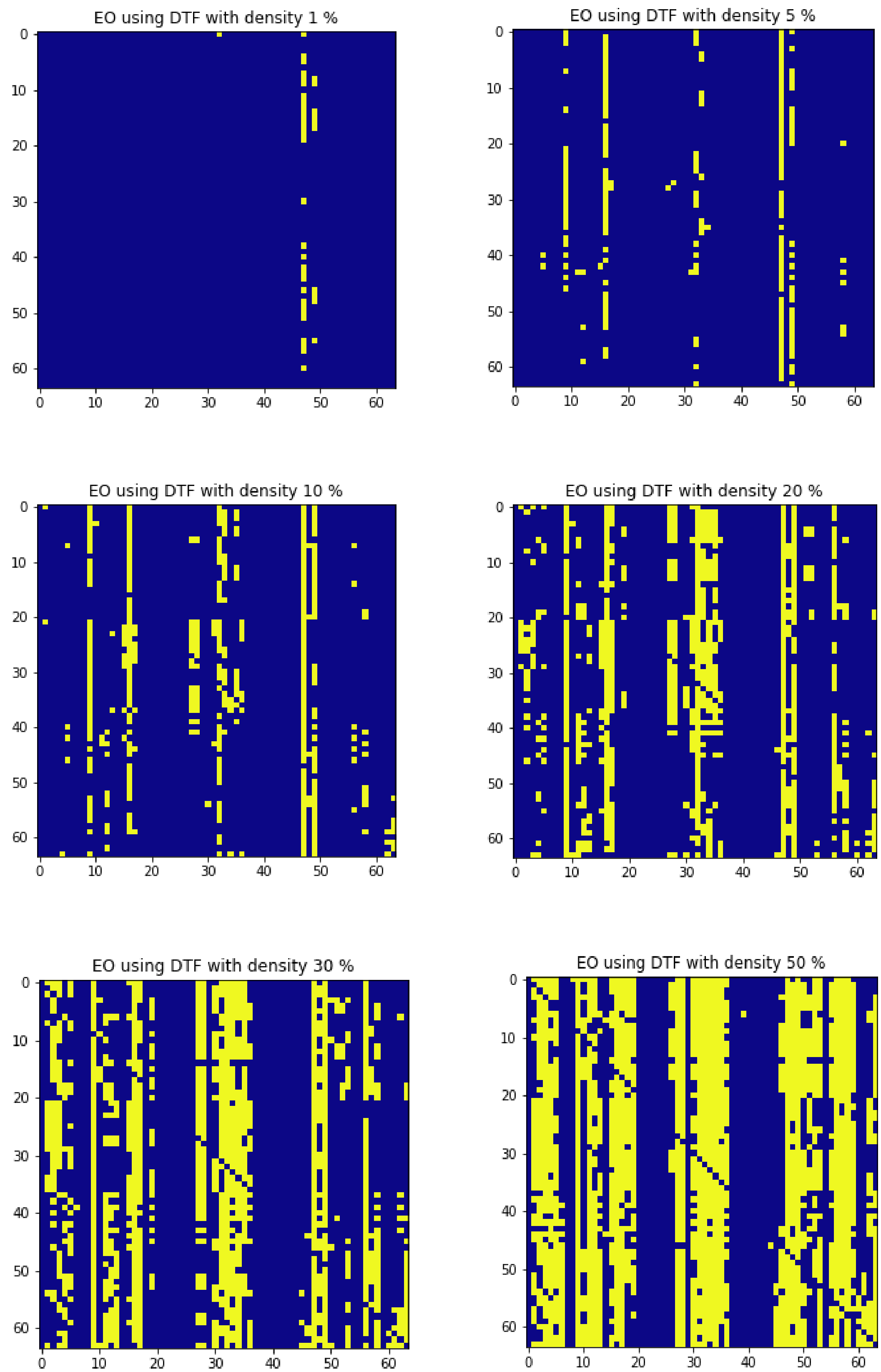
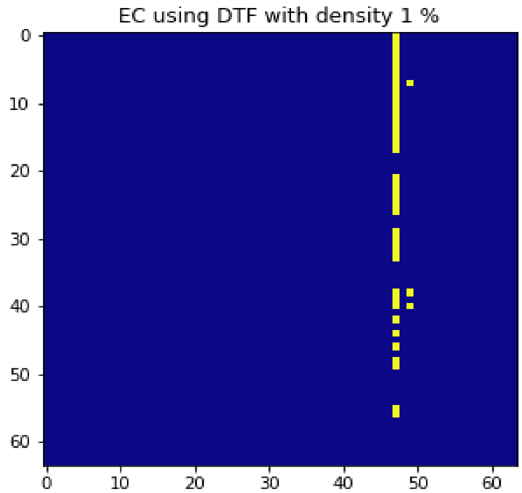


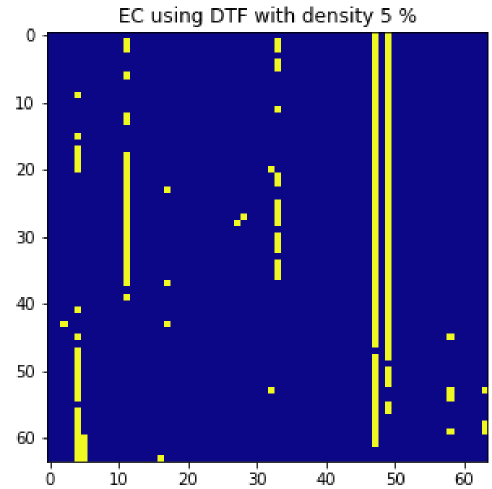
Figure 2 Connectivity graph: - Adjacency matrix

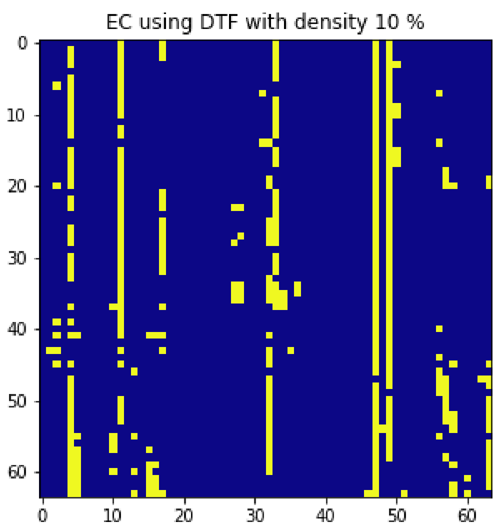
2.1 DTF – Adjacency matrix for EO at different density levels:

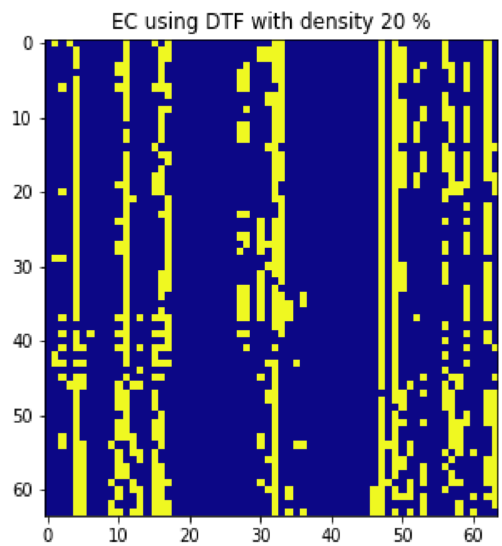


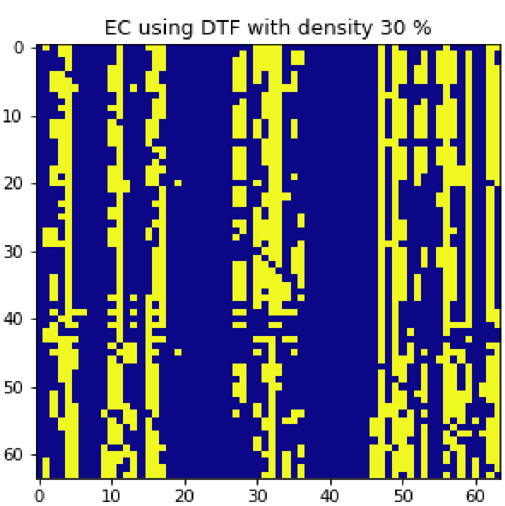
2.2 DTF - Adjacency matrix for EC at different density levels:

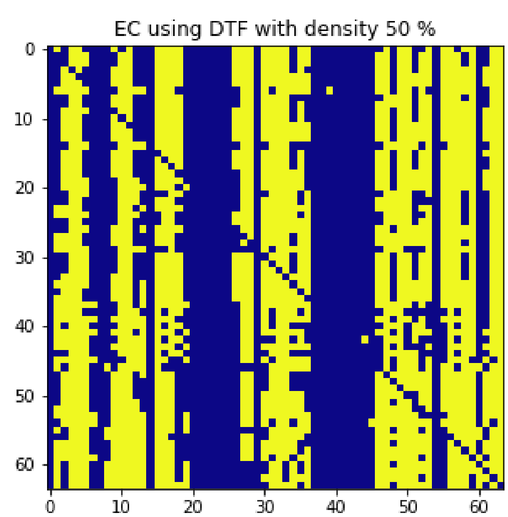




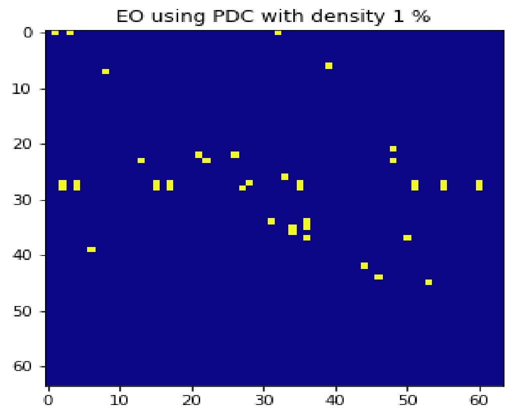


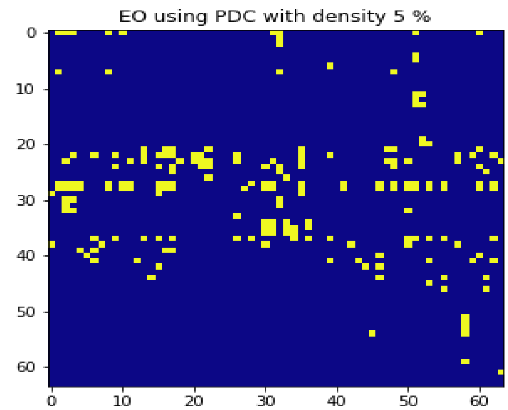


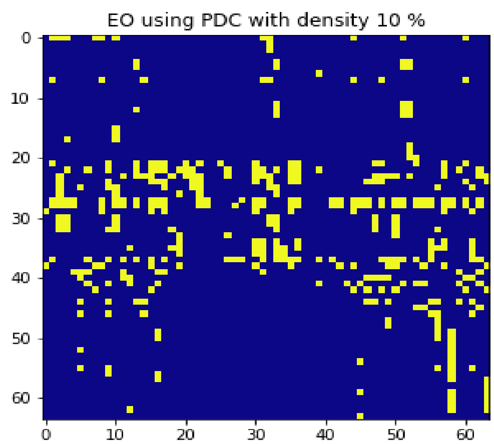


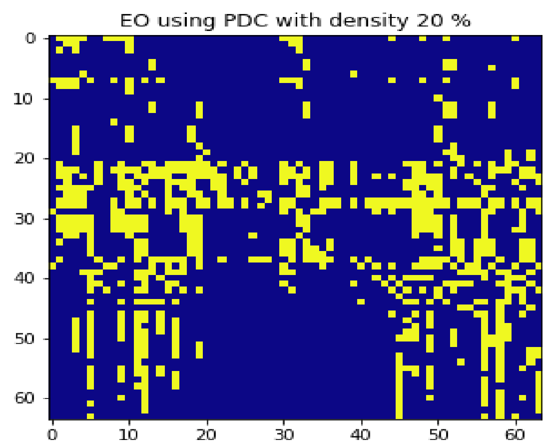


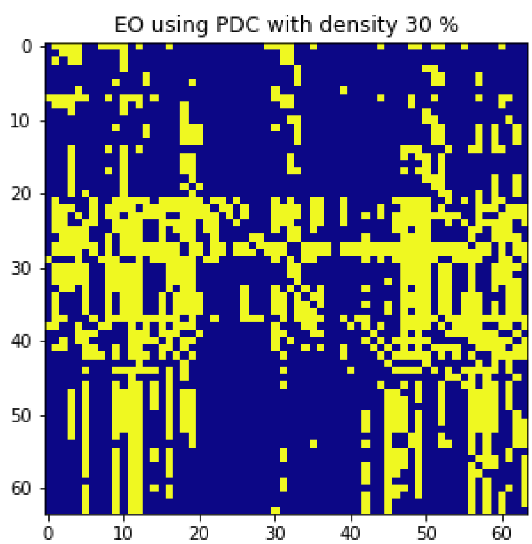
2.3 PDC - Adjacency matrix for EO at different density levels:

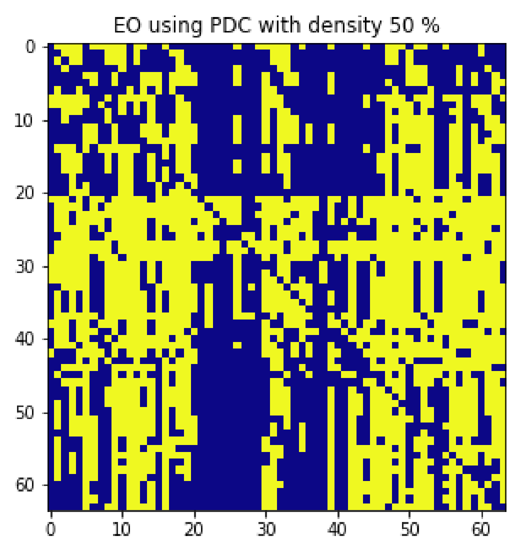




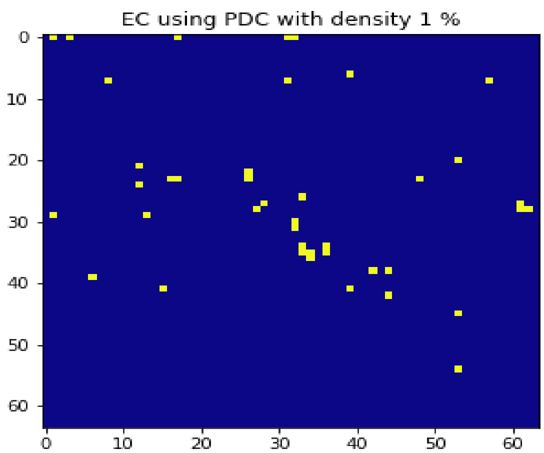


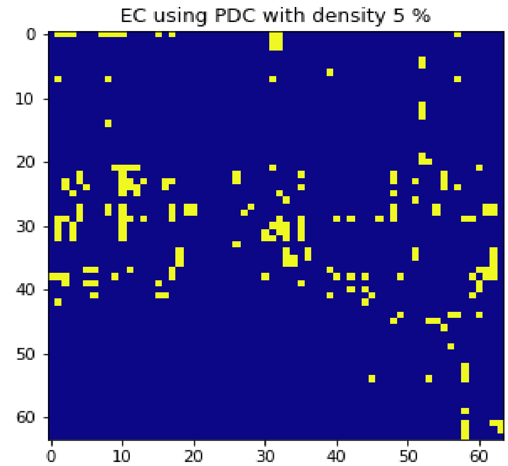


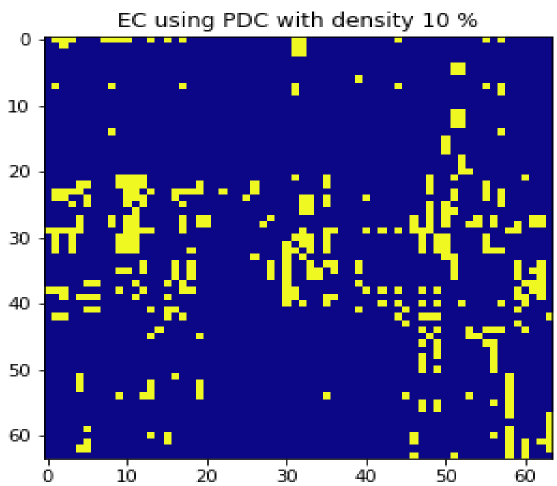


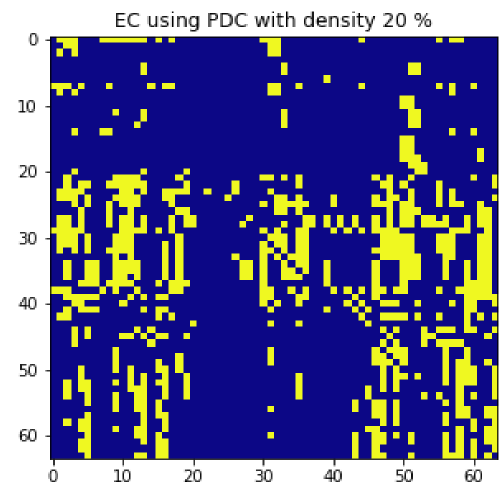


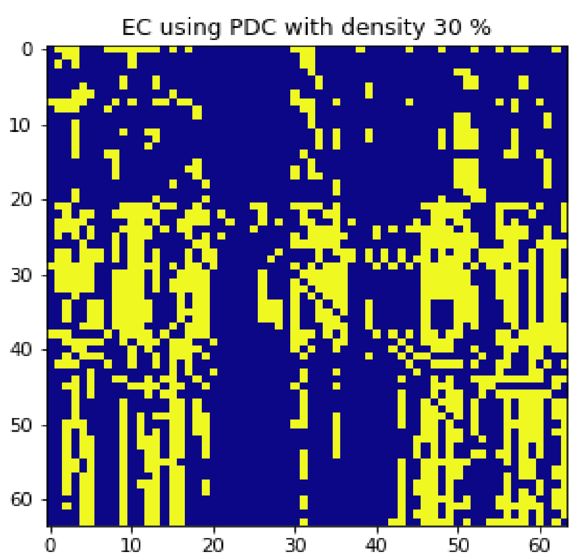
2.4 PDC - Adjacency matrix for EC at different density levels:











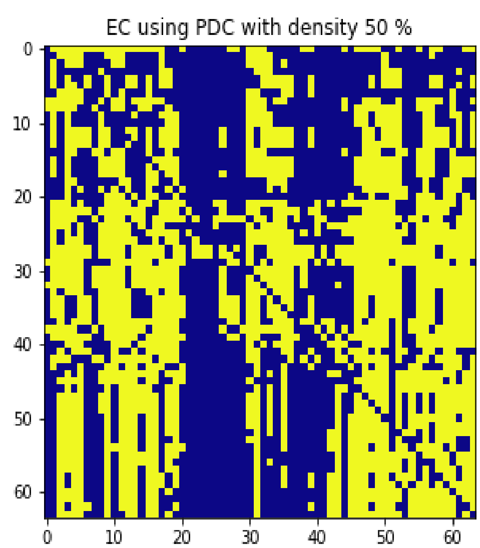
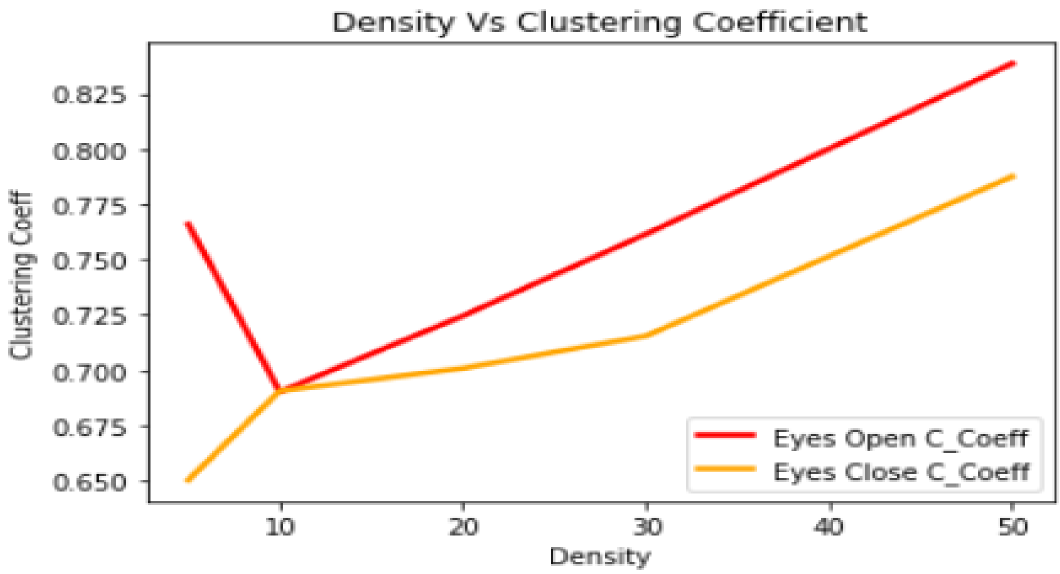


Figure 3 : Graph theory indices:

3.1 : Clustering coefficient – Global indices



3.2 Shortest path length - Global indices