Brain Oscillatory and Network Activity during Resting state

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Abstract

Neural oscillations are repetitive patterns of neural activity in the central nervous system. In this paper, we analyzed two datasets of EEG data for a single subject at rest in (i) eyes-open and (ii) eyes-closed conditions, respectively. On those datasets, we established the connectivity of the brain signals using two different MVAR Estimators before computing various graph theory indices. Additionally, we performed motif analysis to investigate the presence of 3/4-node configurations in the network. Finally, we studied the various communities present in the network using the Louvain algorithm.

I. Introduction

Motor imagery (MI) brain-computer interface (BCI), MI-BCI uses the user's endogenous brain activity in the absence of any external stimuli. [1] MI BCI uses in other words "induced" brain activity from the cortex, rather than 'evoked' brain activity [3]. The power of BCI resides in their ability to translate the brain activity patterns of a user into messages for an interactive application.

The brain activity processed by the BCI systems is usually measured using Electroencephalography (EEG). EEG is a technique that measures in real time small electrical currents reflecting brain activity [**?**] with a device placed on the scalp.

In the following paper, we will be studying the differences in the brain activity of a single at rest for two states: eyes open and eyes closed both at baseline. The EEG data is made of 64 channels, on which we will perform connectivity graphs analysis, determine graph theory indices, perform motif analysis before detecting communities within our dataset.

*A thank you or further information

II. Methods

i. Data

The dataset was downloaded from the PhysioNet Bank [4] and consists of over 1500 one- and two-minute EEG recordings, obtained from 109 volunteers. Our work is focused on subject 3 from which two EDF files contained recordings of 64 channels of EEG signals. 2 set of signals were present: one with the subject at rest having their Eyes Open and the other set with the subject at rest having their Eyes Closed.

ii. Connectivity Analysis

ii.1 Graph Connectivity

We use graph connectivity analysis to visualize dynamic functional connectivity (DFC) amongst spatially different brain regions. DFC analysis identiïňĄes causal relationship amongst brain regions that exhibits temporal causality in neural activations. There exist numerous estimation models in literature, linear and nonlinear, bivariate and multi-variate, that quantiïňĄes such causality. Here we use

Granger causality principle based estimators i) Directed TransferFunction(DTF) and ii) PartialDirected Coherence (PDC) to perform the connectivity estimation. We use two-channel multivariate autoregression (MVAR) model to estimate the connectivity in frequency domain and compute pairwise causality index amongst all 64 channels.

ii.2 Multivariate Autoregressive Model

An autoregressive model assumes that a signal sample X(t) can be expressed in terms of linear sum of p previous values of the samples weighted by some model coefiňĄcients A and a random error $E(t)$. [9]

$$X(t) = \sum_{j=1}^{p} A(j)X(t-j) + E(t) \tag{1}$$

Here, p is called *modelorder*. The equivalent expression of the model in frequency domain is:

$$\begin{aligned} &E(f) = A(f)X(f) \\ &X(f) = A^{-1}(f)E(f) = H(f)E(f) \end{aligned} \tag{2}$$

$H(f)$ is called transfer matrix of the system that represents pairwise causality relationship between the signals and their spectral characteristics.

ii.3 Directed Transfer Function

Directed Transfer Function (DTF) is a frequency domain estimator introduced by [10], that describes causal influence of a channel on another channel at some frequency. The equation that defines normalized version of DTF measure is.

$$\mathrm{DTF}^2_{j\to i}(f) = \frac{|H_{ij}(f)|^2}{\sum_{m=1}^{k} |H_{im}(f)|^2} \tag{3}$$

ii.4 Partial Directed Coherence

Partial Directed Coherence is another spectral measure of directed influence between pairs of signals in a multivariate data set [11]. PDC estimator has been shown as frequency version of the Granger causality. It is defined as

$$P_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{\mathbf{a}_j^*(f)\mathbf{a}_j(f)}} \tag{4}$$

iii. Graph Theory Indices

iv. Motif Analysis

In order to perform motif analysis, we investigated the presence on 3 and 4 node configuration in the network. We have used the 'brain connectivity toolbox' python package to help us process the various motifs. [5] In order to process the motifs, we first extracted both the frequency of each category of motifs and the detailed motif frequency vector, from the binary directed connection matrix obtained from the previous parts. The resulting motif frequency matrix contains functional motifs which are defined as a subset of connection patterns embedded within anatomical/structural motifs [6]. We decided to study which motifs were over-represented and to determine their anti motifs which the help of the following formula:

$$Prob(f_{random}(G_K) > f_{original}(G_K)) <= P \tag{5}$$

$$f_{random}(G_K) - f_{original}(G_K) > D * f_{random}(G_k) \tag{6}$$

where $f_{original}$ correspond to the frequency matrix previously calculated, f_{random} to the frequency motif matrix in a random network, and D to the proportional threshold that ensures the minimum difference between $f_{original}$ and f_{random}. [7] Based on the above formulas, we first built a function that would generate random graphs, that would mimic the general structure of our real connectivity matrix. Finally, we built a function that would derive the overrepresented motifs with a probability of P = 95%, and a function that would derive the anti-motifs with a threshold D = 5%. The same idea was applied to a 4-node configuration representation too.

From that, we built another function that would extract and create a topological representation of connections belonging to only one category. To do that, we took our original graph and removed the edges of nodes not belonging to the detailed frequency vector for a particular motif. In addition, we built a final function that would return the motifs involved in a particular node (channel). In order to do that, we checked in which category of motif a given channel X is present, in our detailed frequency vector.

We applied the same exact method described above to do the same analysis considering this time only structural motifs.

v. Community Detection

The idea behind community detection is to find a way to extract the community structure of a large network. We will do that using a heuristic method that is based on modularity optimization. [8] We built a function that would compute the partition of the graph nodes which maximizes the modularity using the Louvain heuristics. This result was obtained with the help of a python package called community-louvain. The resulting communities will then be graphed on topological order with nodes of same color belonging to the same community.

III. Results and Discussion

i. Connectivity Analysis

i.1 Frequency Selection)

Power spectral density (PSD) analysis was performed on all channels to compare the strength of different frequency bands. As from the ïňĄgure below, most active signals were observed in the $\delta(1-4Hz)$ band for EO state and $\alpha(8-12Hz)$ for EC state.

i.2 Statistical test for connectivity index

In order to rule out the fact that causality may have been discovered between any two signals induced by environmental noise or by

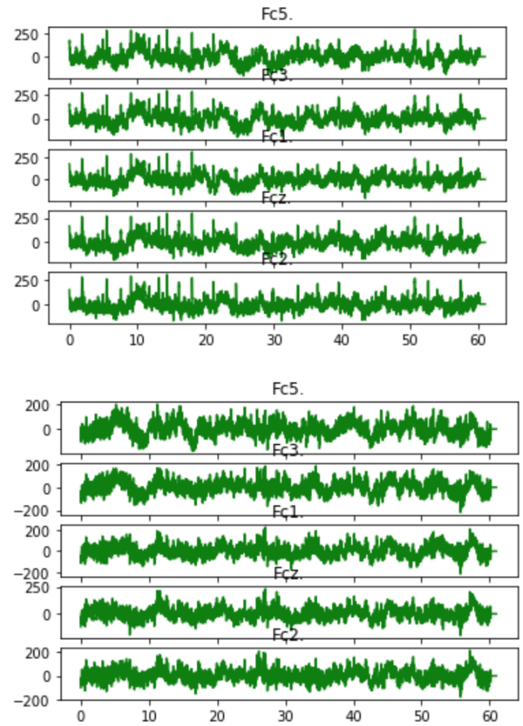

Figure 1: *Time series signal of brain signals (5 channels - Open / Closed eye))*

chance, we applied statistical p-value test using shufiňĆing method. ShufiňĆing method is based upon the generation of distribution of estimators using surrogate data from original datasets. The distribution of estimators were evaluated for each pair of channels for each frequency. Empirical value with signiïňĄcance level greater than 0.05 were considered as true values and rest of the values were set to 0. We produced connectivity graphs for varying network density at 1%, 5%, 10% and so on for both DTF and PDC connectivity estimators.

For connectivity analysis in case I (delta band) analysis, using DTF estimator we observed high degree of connectivity around right-frontal lobe in both open and closed eye state while PDC estimator approximates even distribution of connectivity across whole brain region. We do not observe considerable discrepancy in connectivity patterns between open and closed eye state for delta band. Delta

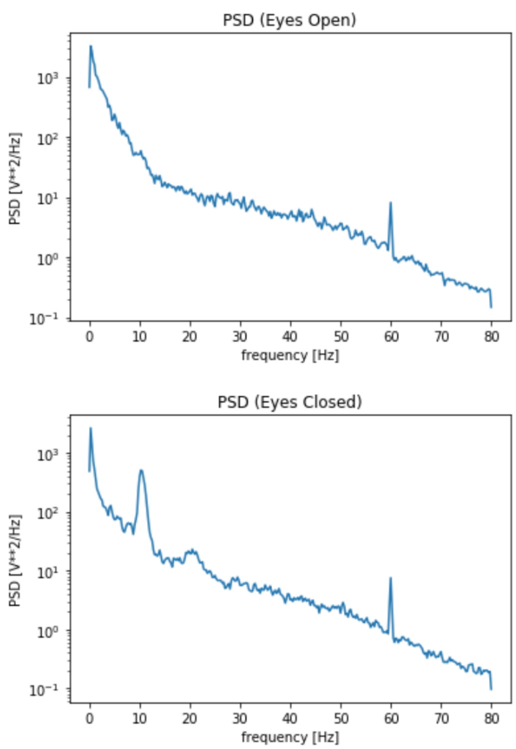

Figure 2: *Average Power Spectral Density of brain signals*

wave form are associated to relaxed state of brain. Since the subject is at rest, in absence of any external stimuli in both eyes open and closed state, we see no considerable changes in terms of connectivity in two states.

In case II (alpha band), DTF estimation projects connectivity of the nodes highly localized in right-frontal lobes in eyes-open state but in case of eyes closed state the connectivity is localized more in parietal and occipital regions. This form of slight perturbation in localization of connectivity can also be observed using PDC estimators. The increased power in alpha band, as seen in PSD diagram, can be attributed to the phenomenon called 'alpha blockage', the process in which alpha waves decreases and beta wave increases as a subject open their eyes.

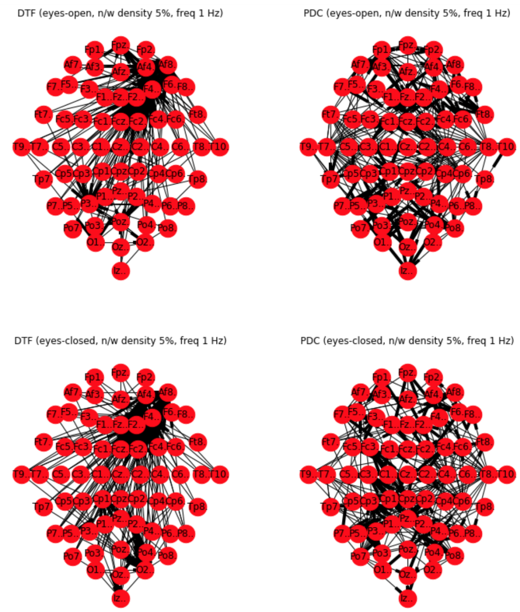

Figure 3: *Functional connectivity graph @ f = 1Hz (delta band)*

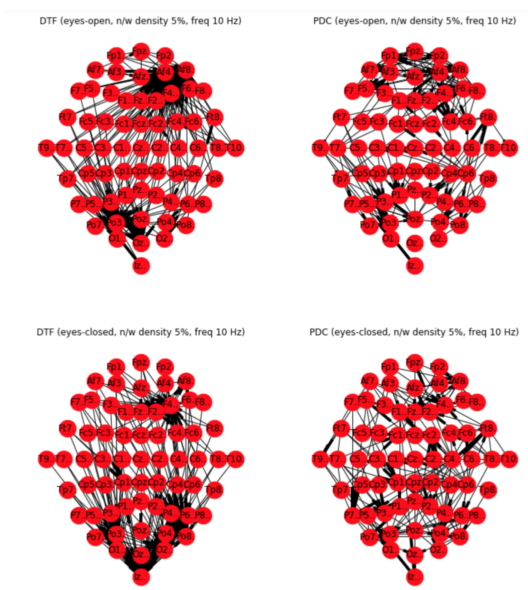

Figure 4: *Functional connectivity graph @ f = 10Hz (delta band)*

ii. Graph Theory Indices

iii. Motif Analysis

The resulting motif frequency matrix gives us an integer corresponding to the category of motifs and its corresponding frequency. The detailed frequency vector corresponds to the category of the motifs as an index and, as value, we have the motif frequency, which is the frequency of occurrence of motifs around a node (channel). The total number of motifs for a 3-node configuration representation can be summarized in figure **??** We did motifs analysis on both structural and functional motifs[1].

iii.1 Functional Motifs

Regarding the functional motifs, we did analysis on both the full graph and the reduced one. The most frequent motif is the one from category 1 for the full graph and category 3 for the reduced one for both eyes open and eyes closed. The most common motifs are located within the category 1 to category 6.

Regarding the Overrepresentation and antimotifs, we note that 12 out of 13 nodes are overrepresented in Eyes Closed and all of them are overrepresented in Eyes Open for the full graph whereas only motif of category 1 are overrepresented in the reduced graph. One interesting thing to note here is the fact that we do not discover anti-motifs for the open eye state; even if the threshold of confidence is dropped to .5. The fact that most motifs are overrepresented might be due to the high density of the full graph.

We created as well a topological representation of the connections of the network only involved in the pattern $A \rightarrow B \leftarrow C$. This corresponds to the category 4 which appears 64 times in the open state and 60 times in the closed state for the reduced graph, and appears 6483 for the opened eyes state and 3815 for the closed eye state of the full graph. Those networks can be visualized in section e 5 and 6 in the appendices.

We proceeded in choosing a channel in the pareto-occipital (PZ) scalp region in order to figure our the various motifs a specific channel is involved in. The result of this test can be found in **??**

[1] the motifs results table are available in the notebooks and excel file attached to this paper

Finally we did the exact same analysis for a 4-node configuration. You can find the full frequency table in the appendix section. One thing to note for the Eyes Opened state of the full graph, we found that all of the motifs were over represented but no anti motifs could be be found as for the closed state, it follows the exact same behavior having just motif 13 not overepresented. Once a gain, this might be due to he high amount of connections. Working on the reduced version. we found out that 2 motifs were overrepresented (motif of category 9 and 30) and 26 antimotifs for the open state and for the closed state we found 4 overrepresented motifs and 57 antimotifs.

The results show us how different the two network are in terms of connections. A full result table is available as a excel table in the files along this report.

iii.2 Structural Motifs

The structural motifs used the exact same methodology employed to obtain the results. The detailed results can be found in the annexes and files attach to this paper. To summarize, motifs are 50% less frequent in the structural motifs than in the functional motifs. This behavior is somehow expected since functional motifs by definition somehow include the structural motifs. Structural motifs tend to be less overrepresented. The trade-off is that more antimotifs were observed in the structural motifs than in the functional ones. More information is present in the notebooks attached to this presentation

iv. Community Detection

We discovered 4 communities for the PDC network for Eyes Opened, 3 communities for the PDC network for Eyes Closed, 3 communities for the DTF network for Eyes Opened and 5 communities for DTF Eyes Closed. The created the topological representation of those various community in 9fig. The table witch each labels matched with their respective community is available in tables 7, 8, 9 and 10

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IV. Appendices

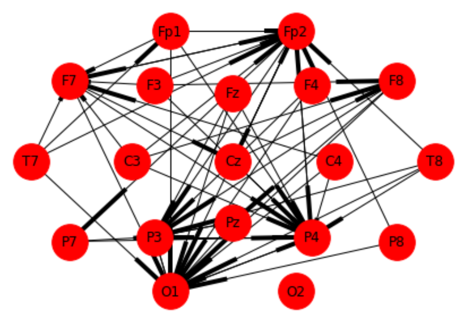


Figure 5: *Topological representation connections only involved with motif with pattern* $A \rightarrow B \leftarrow Cfortheeyesopenforfunctionalmotifs$

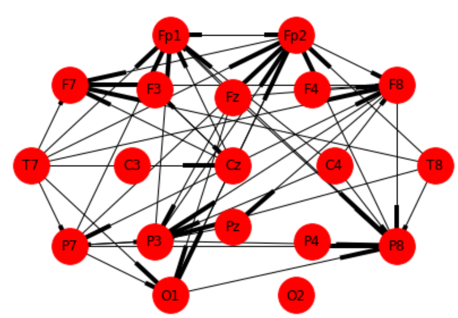


Figure 6: *Topological representation connections only involved with motif with pattern* $A \rightarrow B \leftarrow Cfortheeyesclosedforfunctionalmotifs$

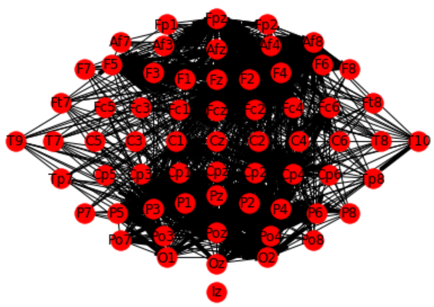
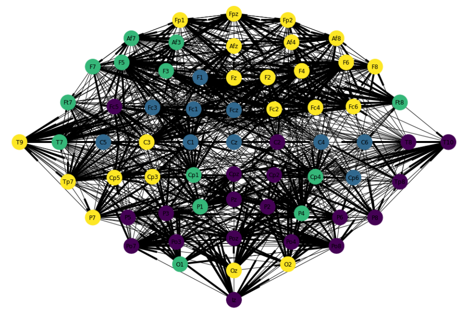
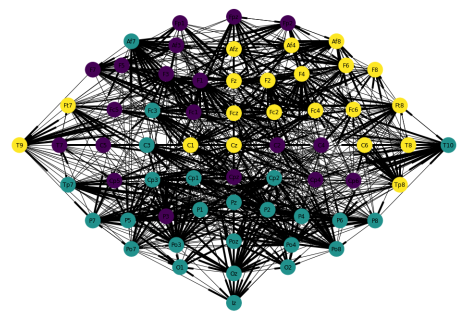


Figure 7: *Topological representation connections only involved with motif with pattern* $A \rightarrow B \leftarrow C fortheeyesopenedonafullgraphforfunctionaln$



(a) *PDC - Eyes Open*



(b) *PDC - Eyes Open Closed*

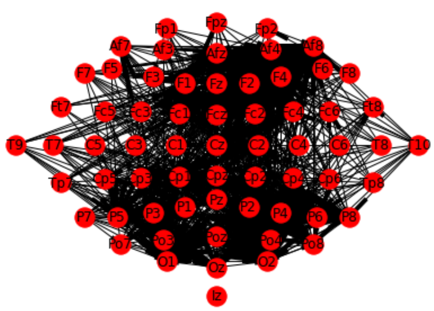
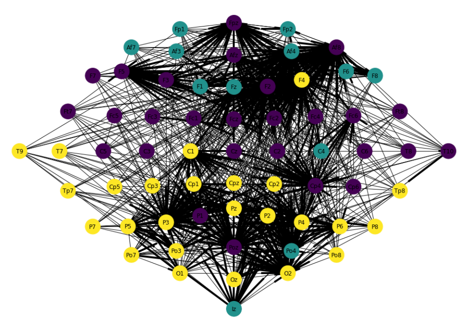
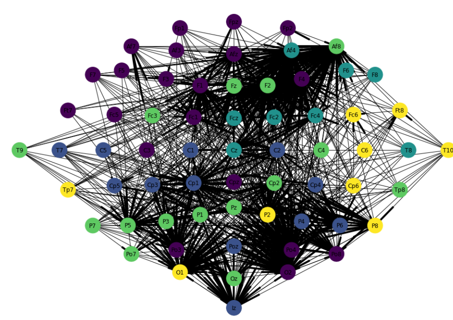


Figure 8: *Topological representation connections only involved with motif with pattern* $A \rightarrow B \leftarrow C fortheeyesclosedonafullgraphforfunctionalm$



(c) *DTF - Eyes Open*



(d) *DTF - Eyes Closed*

Figure 9: *Topological representation of communities*

Cat.	Freq.	Over Rep	Anti.Mot.
1	14247.0	YES	NO
2	16069.0	YES	NO
3	20747.0	YES	NO
4	6483.0	YES	NO
5	15609.0	YES	NO
6	8066.0	YES	NO
7	5765.0	YES	NO
8	4242.0	YES	NO
9	2145.0	YES	N0
10	2545.0	YES	NO
11	5036.0	YES	NO
12	1673.0	YES	NO
13	978.0	YES	NO

Table 1: *Frequencies, Overrepresentations and Antimotifs for Eyes Open Functional motifs*

Cat.	Freq.	Over Rep	Anti.Mot.
1	200.0	YES	No
2	188.0	NO	NO
3	206.0	NO	NO
4	64.0	NO	NO
5	111.0	NO	NO
6	47.0	NO	NO
7	18.0	NO	NO
8	39.0	NO	NO
9	17.0	NO	NO
10	8.0	NO	NO
11	16.0	NO	NO
12	5.0	NO	NO
13	0.0	NO	NO

Table 3: *Frequencies, Overrepresentations and Antimotifs for Eyes Open Reduced Functional motifs*

Cat.	Freq.	Over Rep	Anti.Mot.
1	13463.0	YES	YES
2	9529.0	YES	YES
3	8850.0	YES	YES
4	3815.0	YES	YES
5	6927.0	YES	YES
6	1497.0	YES	YES
7	939.0	YES	YES
8	2855.0	YES	YES
9	446.0	YES	YES
10	394.0	YES	YES
11	668.0	YES	YES
12	190.0	YES	YES
13	6.0	NO	NO

Table 2: *Frequencies, Overrepresentations and Antimotifs for Eyes Closed Functional motifs*

Cat.	Freq.	Over Rep	Anti.Mot.
1	165.0	YES	NO
2	182.0	NO	YES
3	243.0	NO	YES
4	60.0	NO	YES
5	125.0	NO	YES
6	78.0	NO	YES
7	39.0	NO	NO
8	24.0	NO	YES
9	30.0	NO	YES
10	17.0	NO	YES
11	24.0	NO	NO
12	8.0	NO	NO
13	0.0	NO	NO

Table 4: *Frequencies, Overrepresentations and Antimotifs for Eyes Closed Reduced Functional motifs*

State (channel PZ)	Motif Involved (in category)
Full Channel E.O (graph)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Full Channel E.C (graph)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Reduced Channels E.O	1, 2, 3, 4, 5, 8
Reduced Channels E.C	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12

Table 5: *Motifs involved in channel PZ for the functional motifs*

State (channel PZ)	Motif Involved (in category)
Full Channel E.O (graph)	1, 2, 3, 4, 5, 6, 7, 8, 10, 11
Full Channel E.C (graph)	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13
Reduced Channels E.O	1, 2, 3, 4, 5, 8
Reduced Channels E.C	1, 2, 3, 4, 5, 6, 8, 9, 10, 12

Table 6: *Motifs involved in channel PZ for the structural motifs*

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

Table 7: *Community PDC Eyes Open*

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

Table 8: *Community PDC Eyes Closed*

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

Table 9: *Community DTF Eyes Open*

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

Table 10: *Community DFT Eyes closed*