Characterization of brain networks subtending movement execution and movement imagination

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***Abstract*—This paper contains the experiment procedure for analysis of EEG signals to obtain a functional brain connectivity matrix that is used to distinguish between the right/left-hand movement and imagination. The method used to perform this experiment is, to compute a partial directed coherence using time-invariant Multivariate Auto-Regression (MVAR). The results from this test used to obtain degrees, density, and other global and local indices to analyze if or not a certain hand movement is performed. The experiment is done using MATLAB platform.**

***Index Terms*—EEG, distinguish, MVAR, partial directed coherence, density, degree, local indices, MATLAB,**

I. Introduction

Advancement in technology produced a striking increase in interest for electroencephalography (EEG). This analysis can construct brain connectivities from the scalp. A lot of applications are possible using brain networks such as diagnosis, motor rehabilitation, prosthesis and orthesis, assistive technology, and so on. This paper deals with the use of brain networks to recognize whether a hand is actually moved or just imagined.

The goal of the project is to obtain functional brain connectivity using the datasets containing the samples of EEG analysis of left and right-hand actual movement and imagination. The functional brain connectivity is produced by computing time-invariant Multivariate Auto-Regression (MVAR) parameter estimation. This is used to obtain partial directed coherence (PDC) with some normalization which in turn is used to obtain a binary functional brain connectivity matrix. This matrix is used to compare and characterize if a hand movement is performed or imagined.

This paper is divided into three sections after the introduction. The next section deals with methodologies that contains a detailed explanation regarding the procedure and some theoretical aspects behind the experiment. And the later section deals with experiments and results that contain the details of the dataset used, the routine followed to perform the test, the set parameters, and the results obtained from the experiment. And finally, the paper is concluded.

II. Methodology

This section is divided into four parts, each explaining the steps taken to perform the analysis. First is the computation of MVAR parameter estimation, later PDC, and further local and global indices that include computation of degrees, density, and efficiency. Each step is elaborated in this section.

A. Multivariate Autoregressive Model

The AR model assumes a sample of data at a time and expresses it as a sum of previous values of the samples from the set of signals weighted by model coefficients and a random value. Coefficients are determined to minimize the error so an AR model is used like linear predictor, in this problem due to the fact that a bivariate model is not able to correctly represent common correlations to third parties, due to the multiple time series, a Multivariate approach has been used, so the connectivity pattern is obtained on the entire data-set.

This produces estimates of the parameters of a multivariate AR model of a certain order. The toolbox used to compute this is ARFIT which returns least squares estimates of coefficient matrices $A = [A_1 ... A_p]$ and the noise covariance matrix C. A optimal order for the MVAR model is chosen based on approximations to Schwarz's Bayesian Criterion [1].

B. Partial Directed Coherence

The coefficient matrix and covariance matrix computed before are used to compute the partial directed coherence. PDC is defined as the ratio between the outflow from one channel to another and all outflows from the source channel [2]. The values lie between 0 to 1. Different normalization is used which is defined as the ratio of the square of the coefficient matrix and the sum of the square of all the outflows from the source channel [3]. The normalization equation is as shown below.

$$\pi_{ij}(f) = \frac{|A_{ij}(f)|^2}{\sum_{m=1}^{N} |A_{im}(f)|^2} \tag{1}$$

where $\pi_{ij}(f)$ is the PDC and $|A_{ij}(f)|$ is the coefficient matrix. Note that, with this normalization,

$$\sum_{n=1}^{N} |\pi_{in}(f) = 1 \tag{2}$$

Finally, a 3-dimensional matrix is obtained which is the PDC with values ranging from $[0, 1]$ out of which one slice is considered which means the PDC values are considered for only one frequency. For this experiment, since we are dealing with hand movements which is part of the motor cortex, the range of frequency considered is $12 - 30Hz$ [4]. This gives a 2-dimensional matrix with size $CH \times CH$ where CH being the number of channels. For further analysis, a binary matrix is required, so the obtained 2-D PDC matrix is converted to a binary matrix by setting a threshold such that the density of the matrix will be 20%. The obtained binary matrix will be used to compute local and global indices.

C. Local Indices

1) In / Out / Total Degrees: In directed graphs, it is possible to define three kind of degrees indices. Let $m_{i,j}$ be the element of graph's binary matrix M, at row i and column j:

- **In-degree** of a node i ($i \in [1, N]$) as the number of edges directed to node i

$$g_i^{in} = \sum_{j=1, i \neq j}^{N} m_{j,i} \quad , \ g_i^{in} \in [0, N-1] \tag{3}$$

- **Out-degree** of a node i ($i \in [1, N]$) as the number of edges originated from node i

$$g_i^{out} = \sum_{j=1, i \neq j}^{N} m_{i,j} \quad , \ g_i^{out} \in [0, N-1] \tag{4}$$

- **Degree** of a node i ($i \in [1, N]$) as the total number of edges originated from and directed to the node i

$$g_i = g_i^{in} + g_i^{out} \quad , \ g_i \in [0, 2 \cdot (N-1)] \tag{5}$$

For the computation of the degree indices the function `graph_nodes_degrees` is defined, taking as input arguments the binary PDC matrix M of the selected graph and the number of recording channels of the collected data (64 or 21). The subroutine `compute_degrees` is then called which, according to the definitions of *in-degree* and *out-degree* indices, count in a double-nested loop the number of connection among nodes i and j, keeping the value $M(i, j)$ of the corresponding element in the binary graph matrix.

Thus, the *out-degree* index of node i is updeted by the count of *1s* in correspondence with the node j, and in turn the in-degree index of node j is updated by the count of *1s* in correspondence with the node i. In the end, the *total degree* index for each node is computed in a single loop iterating over all the nodes of the binary matrix M.

2) Left and Right Hemisphere Densities: Density k of a binary graph is the ratio between the number L of edges in the graph anf the maximum possible of edges L_{tot}

$$k = \frac{L}{L_{tot}} \quad , \ k \in [0, 1] \begin{cases} \text{0: no edges in the network} \\ \text{1: fully connected network} \end{cases} \tag{6}$$

For directed graphs, $L_{tot} = N(N-1)$, where N is the number of nodes in the graph.

The computations of the density indices for both the left and right brain network hemispheres is computed by using the `get_density_val` function, which takes as input arguments the binary PDC matrix M and the list of the recording channels for the selected data, giving the position of nodes for each channel in the graph.

A support graph matrix $matrix$ is computed by iterating over the elements of the input graph M and assigning to the element at location $matrix(ind_i, ind_j)$ of support graph $matrix$ the value of the element $M(channels(i), channels(j))$ of input graph M in position $(channels(i), channels(j))$, where $channels(i)$ (and $channels(j)$ respectively) is the i-th (j-th) element in the channels indices list.

The indices ind_i , ind_j are updated during the nested loops iterating over the input graph M, respectively in the outer loop, iterating over matrix rows, and in the inner loop, iterating over the matrix columns.

Finally, the density value for the selected hemisphere is computed by calling the `density_dir` function (Olaf Sporns, Indiana University), implementing the expression of k defined in equation (6).

D. Global Indices

Information exchange is an important measure in the neural network. Efficiency is an indicator of how well the network exchange information. This general idea of efficiency can be applied to both global and local scales in a network. The global efficiency quantifies the exchange of information across the entire network, while local efficiency quantifies a network's resistance to the failure of a node on a small scale, or in other words, is how information is exchanged by its neighbors when the node itself is removed and only its neighbors are considered.

To compute these indices the distance matrix is computed which is nothing but the shortest path from one node to another. This is computed using the Dijkstra algorithm which is available in the Graph toolbox in MATLAB. This algorithm takes is fed with an adjacency matrix of the binary directed graph, which is the network representation itself. The global efficiency is obtained by reciprocating the distance between each pair of nodes [5] as shown in the equation below.

$$E_g = \frac{1}{N(N-1)} \sum_{i,j=1,i}^{N} \frac{1}{d_{ij}} \tag{7}$$

$$E_g \in [0, 1] \tag{8}$$

where, $E_g = 1$ being graph fully connected and $E + g = 0$ being void graph.

The local efficiency is computed by finding the adjacency matrix for each sub-networks. Where a subnetwork S_i is a network that has all the nodes directly connected to i without including i itself and then computing global efficiency of it. The above steps are done to all the nodes, checking in each node, all the nodes that are not directly connected. The equation to compute this is shown below.

$$E_l = \frac{1}{N} \sum_{i=1}^{N} E_g(S_i) \tag{9}$$

To do this for the i^{th} node is necessary access on the elements in position (i,j) and (j,i), both are 0 being that neither in or out arc is present, or that i^{th} and j^{th} are not directly connected. Indeed in next, is necessary removing correspondingly rows an columns and adjusting matrix indices. The average of all the nodes is called the local efficiency [5]. Any possible consideration on the obtained results is discussed in the next section.

III. Experimental Results

The experiment is composed of a series of operations which are, computation of estimated MVAR parameters, PDC, Degrees, Density, Local and Global Indices, and Graphs representation. The samples obtained from the dataset is read into a file and split into left and right-hand samples. The MVAR model is defined with the following input parameters, the sampling frequency is set to 160Hz, which means the cut-off frequency that should be smaller than half of the sampling frequency i.e., 50Hz and the frequency points N_f ranging from 1-64Hz. The routine mentioned above is done 16 times by changing the dataset (LHM, KHI, RHM, RHI), frequency, and the number of channels. The analysis of the *Local Indices*, shows interesting results expecially focusing on the comparisons between *execution* and *imagination* movements, for both the left and right hand experiments. For both the cases of study, histogram plots are generated to show how the *total degrees* index for each node varies in relation to the changing of the sampling frequency and the number of channels from which the data are recorded.

1) Nodes' total degrees: For the Right hand experiments, it is possible to notice a sensible difference in the degree values between execution and imagination movements, expecially when a frequency band $f1 = 13$ is considered. In this case, we can highlight the following results:

- for 21-channels data, nodes with low indices show higher degree values for the execution movement experiment, while high indexed nodes have huge degree index for the imagination movements task.
- for 64-channels data, nodes'degree values distribution is similar, on average, for both execution and imagination movements tasks, but with a majority of nodes exhibiting higher degrees for the execution movement task with respect to the imagination movement experiments.

The left hand experiments are characterized by a quite similar distributions of degree values in all the cases of study, with some interesting exceptions.

- 21-channels data: few but sensible higher degree values of a subset of nodes for the execution movement task.
- 64-channels data: many nodes reach higher degrees for the imagination movement experiments.

The result can be see in Figure 4.

2) Left and Right Hemispheres' densities: The analysis of the density indices for left and right network hemispheres appears interesting when considering a frequency band $f1 = 13$ and 21-channels data. In the first case, for the left-hand execution and imagination movement tasks, it is got an higher value for the left hemisphere's density and in the case of 21-channels data, the density value is even double with respect to the density of the right hemisphere.

When considering all 21-channels data, with different frequency bands $f1 = 13$ and $f2 = 16$, we can notice larger density values for the execution movement task, and the largest double for the $f2 = 16$ frequency band. Densities are instead the same for the left-hand imagination movement task, with frequency band $f2 = 16$. The result can be see in Figure 3

3) Local and Global Efficiency: From the experiments related to the *Local* and *Global* efficiency, especially the ones involving the 21-channels data samples, it is possible to ascertain the expected behavior for the left and right hemispheres during the left and right-hand movement, i.e. the left hemisphere appears to be more engaged in the left-hand movement and the reverse holds for the right hemisphere during the right-hand movement.

About the comparisons between *imagination* and *execution* an interesting results is observable in the plot shown below. There, we could notice that the $CP5$ node has high intensity, suggesting that this channel's activity is of particular interest for the analysis of right-hand movement allowing the distinction between movement imagination and movement execution, showing higher efficiency values in the latter case rather that in the former. The result can be seen in Figures 1 , 2.

IV. Conclusion

Recent developments in this area have turned an ever-increasing interest towards EEG electroencephalography. In this sense, from the results obtained it was possible to confirm the already known result on the control of the right hemisphere on the motor control on the left and vice versa, although the number of runs examined was sufficient, greater safety could derive from the extension of this study to a much larger case history of subjects and records.

While for the main discussion distinction between real and imaginary movement, the results of the efficiencies show

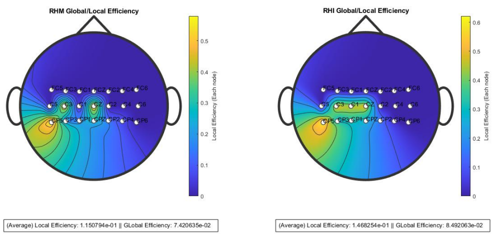

Fig. 1. Efficiency - Execution and Imagination Movement of Right Hand

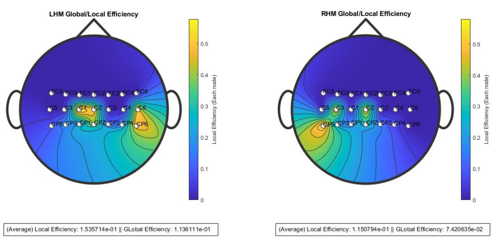

Fig. 2. Efficiency - Left-Hand Imagination Movement

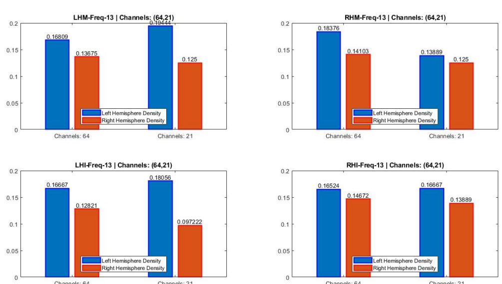

Fig. 3. Density - Movement Imagination and Execution for 64 / 21 channels

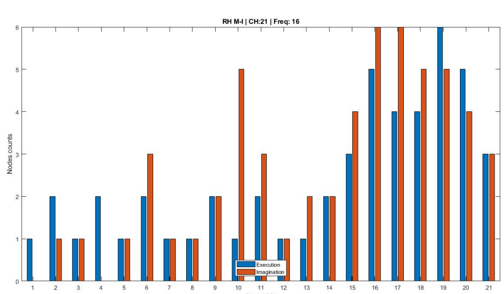

Fig. 4. Degree - Right-Hand Movement Execution and Imagination 21 channels

that if we take 21 channels from 64 original channels, the differences are more marked, and even only graphically it is possible to make a distinction between the two cases, in the tested frequency range. On the other hand, if all 64 channels are considered in full, it is much more difficult to find differences between real and imaginary, perhaps because each electrode is partly influenced also by others. The efficiency was particularly useful for our purpose, but degrees showed no particular differences, another important local index is density, this is in general slightly lower for the imaginary part and can be used to improve the detection of real and imaginary movement.

V. Individual Contributions

Each member of the team has contributed to a part of the code that is listed below.

- Akshay Dhonthi: Data load, MVAR, and PDC computation, PDC normalization, threshold computation, Topographical representation, Code structuring, and routine setup.
- Francesco Vincelli: Data split for left and right-hand samples, local indices (in/out degrees, left and right hemisphere density) computation. Degree, density, and efficiency graph plot.
- Francesco Peracchia: Data merge from multiple runs, global indices (global and local efficiency)

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