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Selective auditory attention using phase synchronization

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1. Theory

This research aimed to evaluate the possibility of recognition of attended ear using functional connectivity features extracted from EEG signals. To achieve this goal, the phase lock index (PLV), phase lag index (PLI), and Rho index features of every channel and Bidirectional-Long Short-term Memory (Bi-LSTM) algorithm were used.

1-1. Phase-lock value (PLV)

The most commonly used phase interaction measure is the Phase Locking Value (PLV), the absolute value of the mean phase difference between the two signals expressed as a complex unit-length vector (Lachaux et al., 1999; Mormann et al., 2000). If the marginal distributions for the two signals are uniform and the signals are independent then the relative phase will also have a uniform distribution and the PLV will be zero. Conversely, if the phases of the two signals are strongly coupled then the PLV will approach unity. For event-related studies, we would expect the marginal to be uniform across trials unless the phase is locked to a stimulus. In that case, we may have nonuniform marginals which could in principle lead to false indications of phase-locking.

$$PLV = \left|\left\langle e^{i\Delta\varphi_{rel}(t)}\right\rangle\right| = \left|\frac{1}{N}\sum_{n=1}^{N} e^{i\Delta\varphi_{rel}(t_n)}\right| = \sqrt{\left\langle \cos\Delta\varphi_{rel}(t)\right\rangle^2 + \left\langle \sin\Delta\varphi_{rel}(t)\right\rangle^2} \quad 1\text{-}1)$$

When comparing electrode pairs that share a common reference or overlapping lead field sensitivities, or when investigating cortical current density maps of limited resolution, the PLV suffers from sensitivity to linear mixing in which the same source can contribute to both channels. In these cases, the PLV can indicate an apparent phase-locking with the relative phases concentrated around zero.

1-2. Phase-lag index (PLI)

the phase lag index was calculated for all combinations of each two channels. This index can determine the functional connectivity of two time-series with less sensitivity to the volume conduction effect. This is based on the principle that a constant nonzero phase lag between two time-series cannot be the effect of volume conduction from a single source, so it renders true interactions between sources. Therefore this index can be an appropriate estimate of phase synchronization in EEG studies.

Asymmetry of the phase difference distribution can be explained as the difference of the likelihood of the phase difference $\Delta\emptyset$ being in the interval [-π,0] with the likelihood of it being in the interval [0,π]. This asymmetry shows the presence of a constant nonzero phase lag between two time-series. This distribution is symmetric when there is no synchronization between the two time-series. This index can be obtained using equation 1.

$$PLI = \left|\left\langle sign\left[\Delta\varphi\left(t_k\right)\right]\right\rangle\right| \qquad 1\text{-}2)$$

The PLI is limited to the interval [0,1] in which zero shows either no coupling or coupling with a phase lag centered around 0 mod Π and one shows a perfect phase locking at a value of $\Delta\emptyset$ different from 0 mod Π.

1-3. Rho index

To characterize the strength of synchronization, we have to quantify the deviation of the actual distribution of the relative phase from a uniform one. For this purpose, we propose two measures, or *n:m synchronization indices*. (i) *Index based on the Shannon entropy* is defined as,

$$\rho_{nm} = \frac{S_{\max} - S}{S_{\max}} \qquad 1\text{-}3)$$

where $S=-\sum_{k=1}^{N} p_k \ln p_k$ is the entropy of the distribution of $\varphi_{n,m}$, and $S_{\max}=\ln N$, where N is the number of bins. Normalized in this way, $0 \le \rho_{n,m} \le 1$, where $\rho_{n,m}=0$ corresponds to a uniform distribution (no synchronization) and $\rho_{n,m}=1$ corresponds to a Dirac-like distribution (perfect synchronization).

Stage 1: Loading Data

In the first stage, EEG data have to be loaded into the workspace.

Stage 2: Choosing needed index

Next, you are asked which index you want to be calculated.

Stage 3: Saving Outputs

When the procedure is finished, the output matrix and its plot will be saved in the Results subfolder.

2. The Structure of Programs

In this project we have the main function and several sub-functions, as follows:

Main Function:

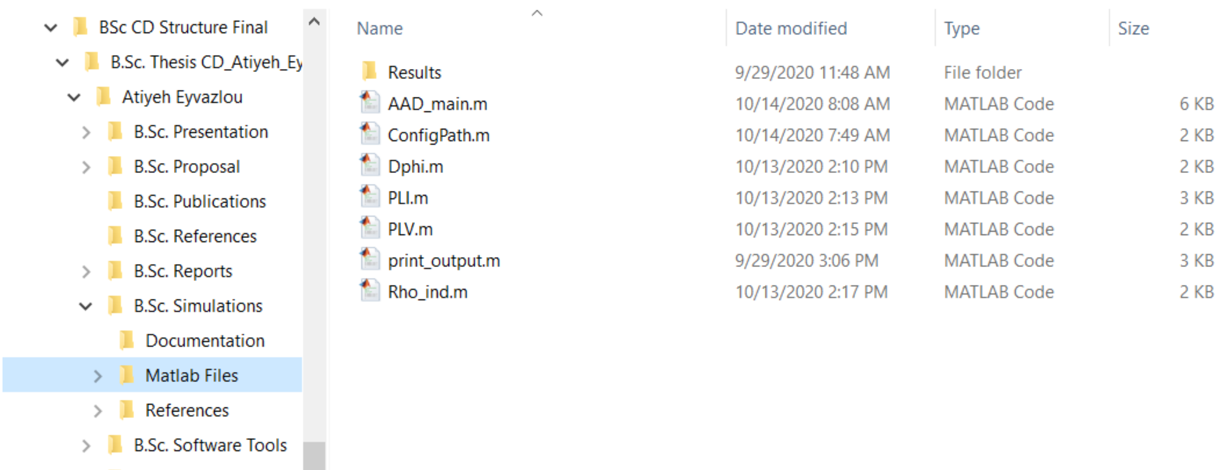

Figure (2-1): The main function folder.

- **AAD_main.m**

Description:

This program contains the main structures of the system based on phase synchronization indexes and, includes the following stages.

Stage 1: Loading input EEG data.

Stage 2: Computing connectivity indexes.

Stage 3: Saving results.

Usage:

```
Rho_ind(dataMatrix(:,:),chNum,fs,tLeng,i);

PLI(dataMatrix(:,:),chNum,fs,tLeng,i);
```

```
PLV(dataMatrix(:,:),chNum,fs,tLeng,i);
```

Inputs:

dataMatrix(:,:): load EEG signal to Matlab and put it into the dataMatrix

chNum : number of electrodes used when recording EEG

fs : Sampling Frequency

tLeng : processing time length (seconds)

Outputs:

The connectivity curves and their .mat matrix files.

3. Simulations Results

3.1. Running the Programs

To run this program, write a command such as shown below, in the Command Window of MATLAB:

```
Command Window
fx >> AAD_main
```

Figure (3-1): Running in the command window.

Running 'Main' you will be asked a question about the index you want to be calculated.

```
Command Window
   ConfigPath: Paths added
fx Which index do you want to be calculated? (plv=1, pli=2 ,rho=3 ,break = 0)
```

Figure 3-2): Choosing the desired index.

3.2. Results

The simulation results are shown in Figure (3-3), (3-4), and (3-5). They would be saved in the results subfolder.

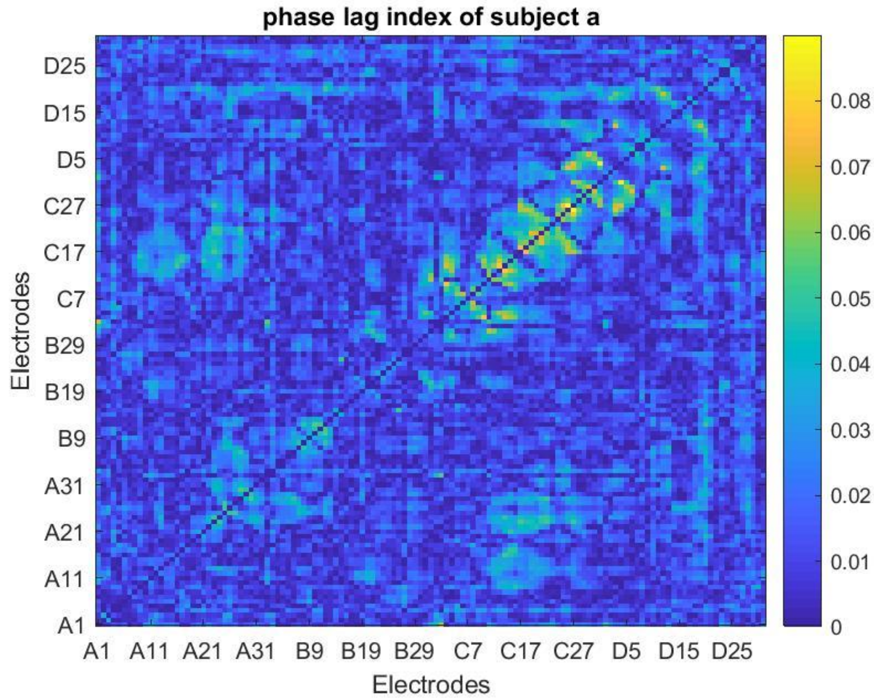

Figure 3-3): PLI connectivity matrix show.

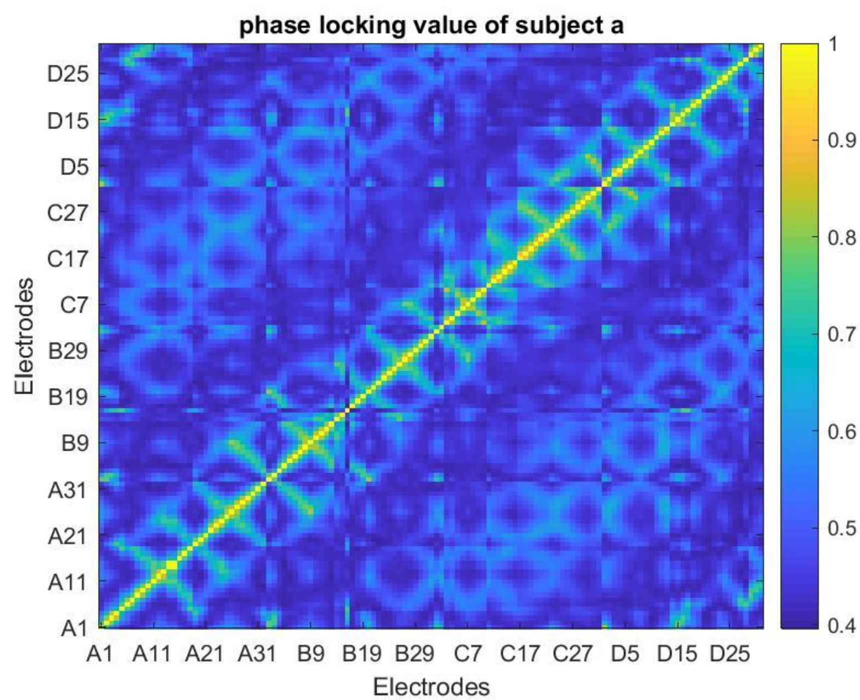

Figure 3-4): PLV connectivity matrix show.

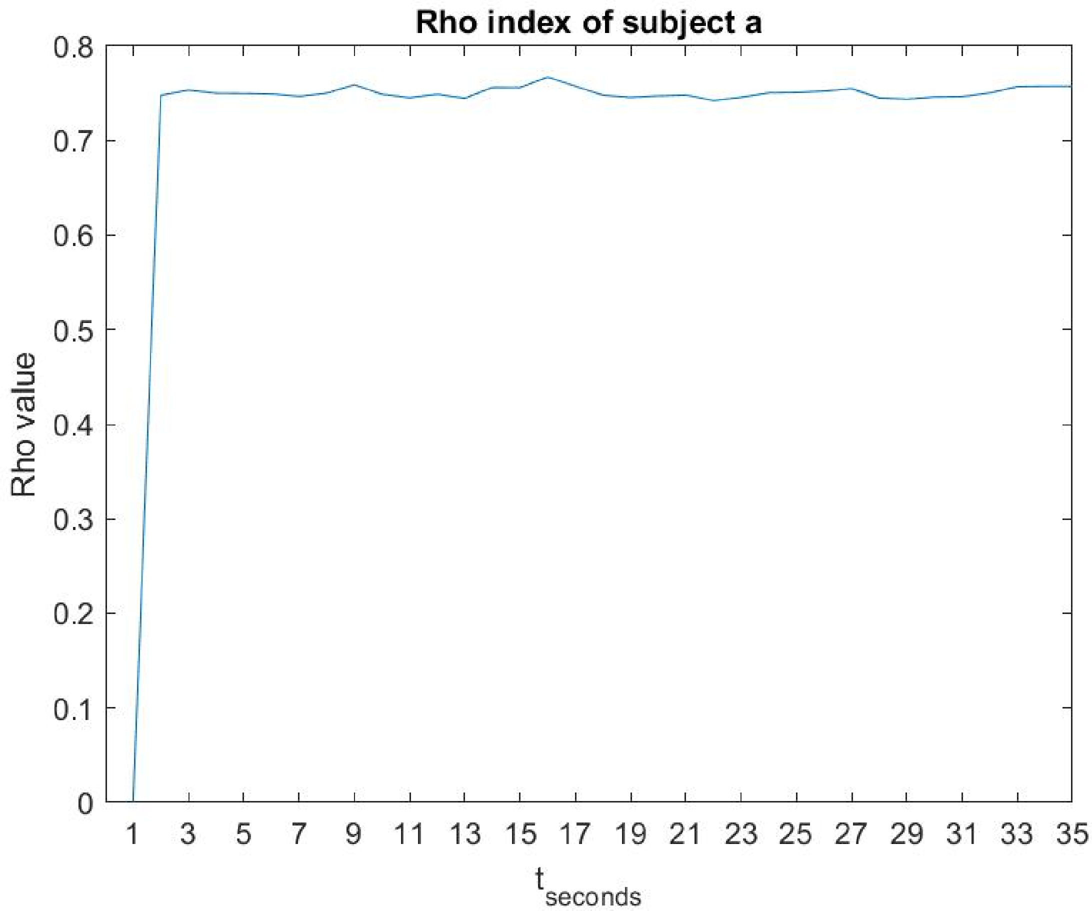

Figure 3-5): Rho output.

Extracted PLVs and PLIs are fed to the bi-directional long short-term memory (Bi-LSTM) classification model to detect the attended speaker. Bi-LSTM, as an extension of the traditional long-short term memory (LSTM), is trained on the input sequence with two LSTMs set up in reverse order. The LSTM layer reduces the vanishing gradient problem and allows the use of deeper networks as compared with the recurrent neural networks (RNNs). The advantage of Bi-LSTM to the convolutional neural networks (CNNs) is its dependency on the sequence of inputs by taking the forward and backward paths into account.

2-layers Bi-LSTM with 100 hidden units in each layer, Adam algorithm with the learning rate of 0.001 and 'cross-entropy' as loss function is used in the training procedure of Bi-LSTM. The total epochs are set to 100 and the criteria for early stopping of the training algorithm is no decrease of the loss function on validation.

Table 3-1): Bi-LSTM neural network results.

	Accuracy	Sensitivity	Specificity	PPV	NPV	Error rate
PLV	96.88	80.00	100	100	96.43	3.13
PLI	95.31	77.78	98.18	87.50	96.43	4.69
rho	93.75	66.67	98.18	85.71	33.95	6.25

References:

[1] G. Niso *et al.*, "HERMES: towards an integrated toolbox to characterize functional and effective brain connectivity," *Neuroinformatics,* vol. 11, no. 4, pp. 405-434, 2013.