Functional Communities in EEG Data from a Face Recognition Task

Z.Weng and D. Damiano

Department of Mathematics and Computer Science, College of the Holy Cross

Introduction

In this project, we analysed electroencephalogram (EEG) data from a face recognition experiment.[1] Our goals are

- Identify functional communities in the brain activated by the face recognition tasks
- Analyze how the communities vary under different conditions and in different frequency bands.

EEG data:

Recordings of electrical brain activity captured through the use of an electroencephalogram (EEG). It comprises voltage measurements obtained from scalp electrodes, detecting and amplifying electrical signals generated by neuronal firing.

Functional Communities:

Groups of brain regions that exhibit synchronized and coordinated activity when an individual is engaged in a specific cognitive task or resting state.

Experimental Data [1]

- The data encompasses EEG data obtained from 16 healthy adults engaged in a simple task while viewing images of different type of faces. The data has been stored in BIDS (Brain Imaging Data Structure) format which is a standard format for organizing neuroimaging data.
- **Conditions:** viewing (i) familiar faces, (ii) unfamiliar faces, and (iii) scrambled faces.
- **Trial:** In a single trial, the participant focuses on a fixation cross for a randomly selected duration between 400-600 ms. Following this, a stimulus is presented for a randomly chosen period between 800-1000 ms. Finally, a central white circle is displayed for 1700 ms to prevent any pre-stimulus phase resting and the interference of ongoing neural oscillations.
- **Runs:** A run consist of approximately 150 trials evenly divided between conditions. Each participant completed 6 runs.

Stimuli[1]

- The face stimuli comprised two sets of 300 greyscale photographs, half from famous people and half from nonfamous people (unknown to participants), compiled from previous sources

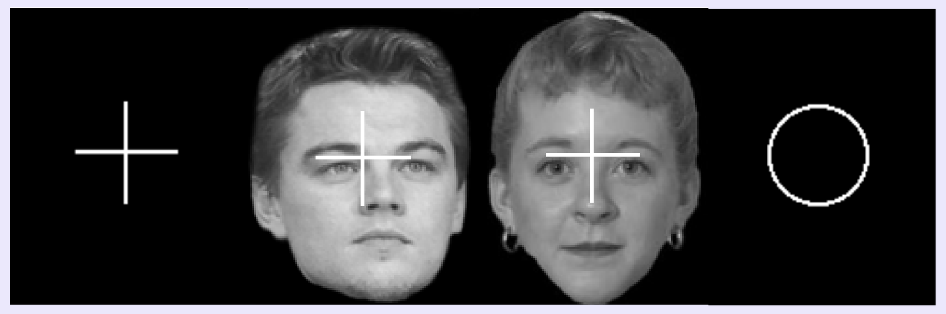

Figure 1: The fixation cross crosshair.bmp

Figure 2: Sample of a famous face. f022.bmp

Figure 3: Sample of a nonfamous face. u123.bmp

Figure 4: The white circle for relaxation Circle.bmp

Methods

We use MATLAB as the primary programming platform. In Particular, we use:

- SPM12 (Statistical Parametric Mapping 12) package for preprocessing the data.This included:
  a. Converting BIDS format to SPM12 format.
  b. Labeling the event conditon for each trial. This allows us to select data by conditions (i.e. famous, non-famous and scrambled).
  c. Epoching the visual stimuli to span 800ms for each trial.
  d. Applying band pass filter with cutoff frequencies 5Hz and 18Hz(Alpha and Beta Bands).
- FieldTrip toolbox for:
  a. Converting SPM12 format to FieldTrip format.
  b. Segmenting the data by condition for each run.
  c. Computing the fourier transform of the segmented data.
  d. Calculating the Debiased Weighted Phase Lag Index (dWPLI) matrix for each condition in each run.
- MATLAB for:
  a. Constructing a multilayer network from the dWPLI matrices.
  b. Computing a consensus community structure on the network.

dWPLI Matrices

dWPLI

- **dWPLI** is a statistical measure of the in-phase correlation between signals from a pair of electrodes during all repetitions of a single condition.
- **Debiased:** Incorporating a bias correction procedure, making it more reliable in estimating phase synchronization, especially when dealing with limited or noisy data in neuroscience research.
- **Weighted:** WPLI considers the magnitude of phase differences between brain regions making WPLI more sensitive to the strength of phase synchronization than PLI.
- dWPLI takes value between 0 and 1,where 0 represents no correlation between signals from 2 electrodes and 1 represent a perfect correlation.

Networks Basics

Community

- **A community** is a set of nodes that are densely interconnected among themselves while having fewer connections to nodes outside the set.

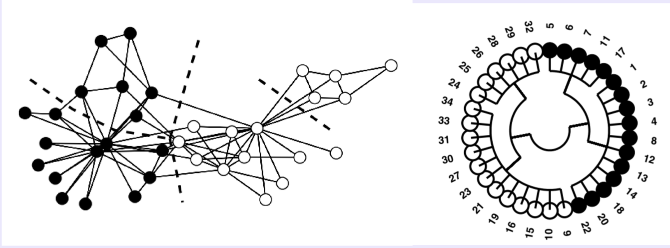

Figure 5: The Zachary Karate Club network.
A classic example of community within a network[4]

Multilayer Networks

- **Nodes:** Each dWPLI matrix is interpreted as the adjacency matrix of a weighted network whose nodes correspond to the electrodes.
- **Edges:** The weight of the edge between nodes i and j is the (i,j) entry of the dWPLI matrix.
- **Layer:** There is one network for each condition of each run for 16 participants.
- Total number of layers = 3 condtions x 6 runs x 16 participants = 288

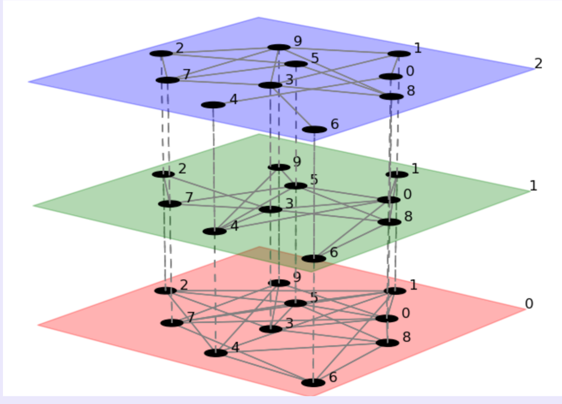

Figure 5: Sample of a Multilayer Network

Detecting Community

- **Generalized Louvain Algorithm** is a widely used algorithm in network analysis for detecting communities in large networks by maximizing a quality function:

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j),$$

  - **Aij** is the dWPLI value between electrode i and electrode j.
  - **ki** and **kj** are the sums of the weights of the edges attached to electrodes i and j.
  - **m** is the sum of all of the edge weights in the network.
  - **ci** is the community of node i
  - **δ (ci , cj)** = 1 when electrodes i and j are in the same community.
  - **δ (ci , cj)** = 0 when electrodes i and j are in the different community.

Detecting Community[5]

- We applied the Generalized Louvain (genLouvain) algorithm to the multilayer network given by the dWPLI matrices within layers and a constant weight omega connecting an electrode to itself in the next/previous layer.
- We ran genLouvain for 100 times (to account for the randomness of seed choices in the algorithm) for gamma values 1.0:0.1:2.0. The consensus connectivity matrix for each gamma value is the normalized frequency matrix of the 100 iterations.
- For each of the 11 consensus connectivity matrices, genLouvain is run for a second value of gamma in the range 0.1:0.05:3. The number of communities for each of the 59 of these gamma values and the quality function Q value as well as the community assignments are recorded.

Result

- We have identified 7 stable functional communities within the Alpha and Beta frequency bands using EEG data among all conditions. The appropriate community assignments to use is when the first gamma value equals to 1.7 and the second gamma values equals to 1.8

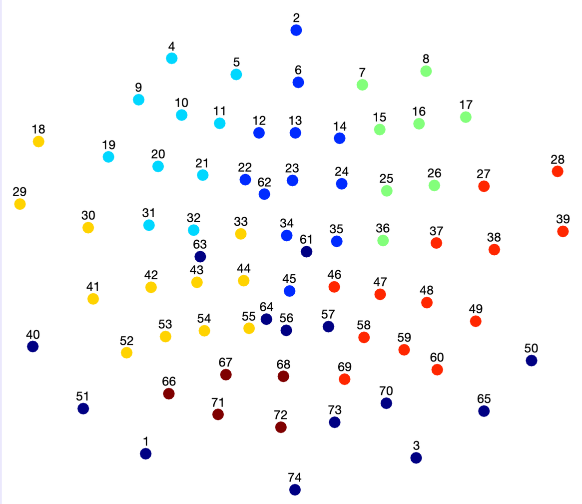

Figure 6: Community Stucture of the EEG Data

Further Research

- We have successfully detected functional communities among all trials.
- Our next step will be to explore how functional communities differ under different conditions (i.e. famous faces, non-famous faces, scrambled faces).
- Currently, our analysis has been limited to the Alpha and Beta frequency bands. It would be intriguing to compare these results with those from the Gamma bands, as different frequency bands correspond to different cognitive behaviors.
- The dataset we possess also includes MEG and fMRI data. It would also be interesting to conduct a similar analysis using both the MEG and fMRI datasets.

Selected References

- [1] Wakeman, D.G. & Henson, R.N. (2015). A multi-subject, multi-modal human neuroimaging dataset. Sci. Data 2:150001 doi: 10.1038/sdata.2015.1
- [2]Henson, R.N., Abdulrahman, H., Flandin, G. & Litvak, V. (2019). Multimodal integration of M/EEG and f/MRI data in SPM12. Frontiers in Neuroscience, Methods, 13, 300.
- [3]Imperatori LS, Betta M, Cecchetti L, Canales-Johnson A, Ricciardi E, Siclari F, Pietrini P, Chennu S, Bernardi G. EEG functional connectivity metrics wPLI and wSMI account for distinct types of brain functional interactions. Sci Rep. 2019 Jun 20;9(1):8894. doi: 10.1038/s41598-019-45289-7. PMID: 31222021; PMCID: PMC6586889.
- [4]Porter, Mason Alexander and Onnela, Jukka-Pekka and Mucha, Peter J. and Mucha, Peter J., Communities in Networks (February 22, 2009). Notices of the American Mathematical Society, Vol. 56, No. 9, 2009, Available at SSRN: https://ssrn.com/abstract=1357925
- [5]Lucy R. Chai, Ankit N. Khambhati, Rastko Ciric, Tyler M. Moore, Ruben C. Gur,Raquel E. Gur, Theodore D. Satterthwaite, and Danielle S. Bassett. Evolution of brain network dynamics in neurodevelopment, Network Neuroscience, 2017, 1(1), 14–30.doi:10.1162/netn_a_00001

Acknowledgements

- We thank Sarah McGuire ’19 and Emily Devine '21 for sparking the analysis of this project.
- We thank The Weiss Summer Research Program and Dan Kennedy '68 for their support.