A Data Exploration into the Brains of Monkeys

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Abstract

This project is a data exploration on the paper "Cortical Network Architecture for Context Processing in Primate Brain" [1]. The original paper focuses on the brain data the three monkey who are shown six different types of stimulus videos. We explore how Independent Component Analyis (ICA) can distinguish activity between cortical areas and use connectivity measurements to provide insight into the connectivity between these regions. The other avenue of data exploration is an implementation of a machine learning classification model in order to see if there is enough of a difference between the waiting, context, and response segments of stimulus videos to allow a model to classify them correctly.

1 Introduction

Context is Everything. How we respond to a situation and our resulting behavior depends on the context. Different contexts can drastically alter perception, cognition, emotional reactions and decision-making. Within the brain's cortical networks, contextual information is present in the form of sensory encoding or mnemonic retrieval. There is a lack of knowledge on how experiences are encoded and communicated across those networks due to the limitations of current technology; it is not currently possible to create high-resolution brain-wide recordings capable of capturing every detail in this process. However, electrocorticography (ECoG) can provide large-scale measurements of neuronal activity by recording local field potentials in the cerebral cortex.

1.1 Extensions to the original work

The paper we are basing our data exploration and replication off of provides insight into current methods in which contextual information processing has been studied such as visual perception, emotion, language and social cognition [1]. The researchers were able to measure cortical activity from 3 Japanese macaques observing videos of agents interacting with a monkey. The clips that were presented to the monkeys were divided into three segments. The first part of the video shows a blank screen, which is followed by an action performed by one of these agents. The agents include a monkey, a human and an empty wall. The last part of the clip displays a response from the video monkey.

We first did an exploration on the metadata and our dataset to make sure we understood how the information was organized, what components were related and how we could parse sections of the data in order to understand the process the authors of the original went through. Once we had more of an understand on the data and the information it contained, we started out with an Independent Component Analysis (ICA) and compared the process of using a Python library versus the Matlab library the authors used[2]. After that, we used several classification methods to demonstrate the benefits to ICA. Our final analysis was to build a model of coherence for the cortical regions associated with each component.

2 Materials and Methods

Our exploratory analysis was performed on the data used by the original paper [1]. The entire dataset is composed of ECoG, event and brain map data for three test subjects identified as Chibi, K2, and Kin2. Since we also have access to the eye tracking data for K2, we will be focusing our data exploration on this monkey. We started by exploring the process on implementing ICA on K2's ECoG data with both the scikit/python library's [3] and with Matlabs EEGLab software[4]. The Matlab EEGLab software is also dependent on the Signal Processing toolbox[5], the Statistics toolbox[6], the Source Information Flow Toolbox[7], the Optimization toolbox[8], and the Image processing toolbox[9]. It also draws on methods from the ICASSO software[10] and scripts from the FastICA library[11]. For python-based independent component analysis and connectivity measurement, we employed the MNE-Python library for ECoG visualization and analysis [12].

2.1 ICA

We followed several pre-processing steps for the raw ECoG signal that were outlined in the the original paper. The time-series are first filtered to remove 50Hz line noise using the MATLAB Chronux Toolbox[13]. The filter provided by Chronux uses an alternative to Fourier analysis known as multi-tapering. Parameters for the filter were determined from a source referenced in the original paper [14]. The channels were then down-sampled from 1kHz to 250Hz. Principal Component Analysis (PCA) was performed to determine the number of components needed to explain 90% of the variance.

Alternative ICA processing was performed using the Scikit-learn Python library in order to validate results and extend testing. Due to computational restrictions, the pre-processing steps had to be skipped in this case. This could explain the discrepancy in ICA results between the MATLAB and Python implementations, as noted in the Results section.

2.2 Classification in Modeling

One of the largest aspects of how these video clips are set up is that each clip can be broken into three segments, a waiting period for 2.5 seconds, a context period of 1.5 seconds, and a response period of 3 seconds. Since there is an abundance of these clips and segments as well as the ECoG data associated with these clips, one method of exploration is seeing how well classification models can classify the category a segment of video is most likely to belong to. In order to get an idea about how this would be set up, we processed our event data, which is composed of the times of starting clips, and break that down into subsections based on the length of each type of video segment. These segments are then given new labels of zero for waiting, one for context, and two for response. all of these are created equally so there is an even number of video segments in each class. The three models that we explored are the Random Forest classifier, the Ada Boost classifier, and the XGBoost classifier.

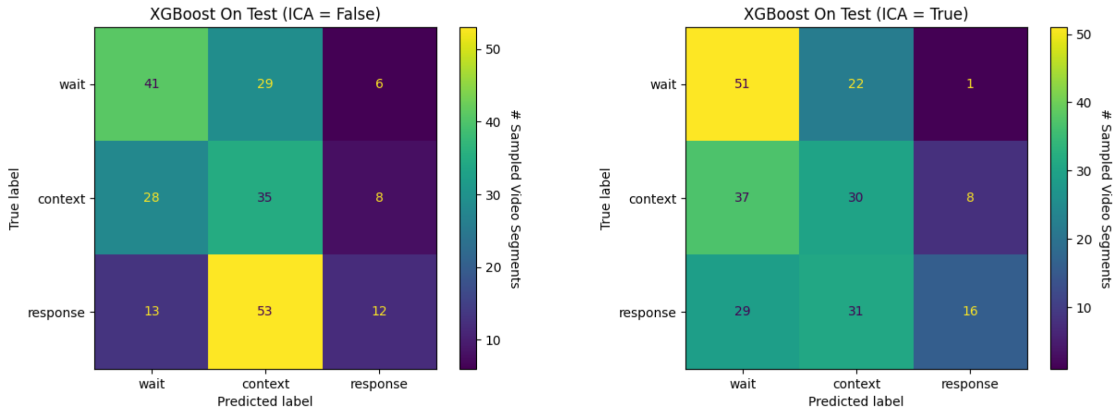
2.3 Connectivity Analysis

One of the core topics of the original paper is the spectral causality analysis of the ECoG data in the context of the six measured video clips. In order to fully explore the data, we performed preliminary connectivity analysis on the components produced by the ICA processing for four frequency bands for each video clip. As each ECoG sensor monitors signals from the brain, the statistically independent sources of these signals are, ideally, the physical cortical areas responsible for said signals' production. So, by performing connectivity analysis on the independent components, we can visualize the relationships between cortical areas. We used a simple, non-multivariate coherence measurement implemented in MNE to estimate connectivity between components. This measurement was performed at frequency bands of 0 to 4 Hz, 4 to 8 Hz, 8 to 12 Hz, and 13 to 30 Hz; corresponding to the delta, theta, alpha, and beta wave bands respectively.

3 Results

3.1 Component count

In our MATLAB implementation, we found that 59 components were needed to explain 90% of the variance of the recorded data for Subject 1. The original paper reports only 58 components are needed. Though comparable steps were taken, a different number of principle components were found to explain 90% variance: 53 instead of 59. This is the number of independent components considered for sections on connectivity measurement, as the tool used to compute connectivity extended the Python implementation. As mentioned previously, this discrepancy is likely caused by a difference



(a) Without ICA

(b) With ICA

Figure 1: Confusion matrices for XGBoost classifier

in pre-processing steps, as time and computational resource restrictions prevented us from properly filtering the Python data.

3.2 Classification

We found that an XGBoost classifier achieved the most accuracy for predicting trials not present in the training data. All models that were trained performed better after applying ICA to the ECoG time-series. We tested three different XGBoost models with different parameters (Table 1). The XGBoost classifier with 6 estimators, a max depth of 2 and a learning rate of .001 resulted in a train score of 0.539 and a test score of 0.431. We can see that the waiting segments and the context segments were consistently more likely to be chosen by the model than the response segments (Figure 1).

# Estimators	4	6	6
Max Depth	2	2	4
Accuracy	0.391	0.391	0.324
Accuracy (ICA)	0.431	0.431	0.333

Table 1: XGBoost Classifier Results

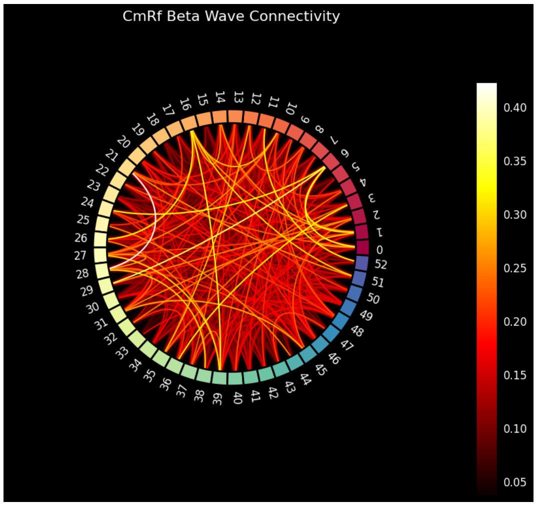
3.3 Connectivity

We successfully plotted the coherence measurements as a radial graph, one for each frequency band for each video clip. While no notable patterns can be seen in coherence between video clips, some patterns can be seen when considering different frequency bands. As seen in the connectivity estimate for beta waves (Figure 2), for any two video clips (CmRf and ChRn have been chosen at random) the same independent components display roughly the same degree of connectivity for a given frequency band. Given this information, we plotted the average connectivity for each frequency band between all six video clips (Figure 3). Notably, several IC's are highly connected in each band range. The implications of this are discussed in the Discussions section.

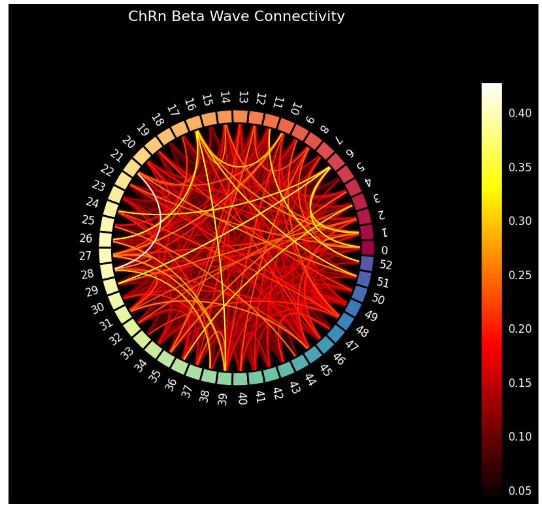
4 Discussion

4.1 Classification

The model we chose was decently capable of distinguishing waiting segments from the rest. This suggests there is a clear difference in cortical activity between a blank screen and visual stimulus.



(a) CmRf



(b) ChRn

Figure 2: Connectivity Estimate for Beta Waves Between Two Video Clips

ICA was shown to improve the accuracy of the model. ICA works to separate independent signals (i.e. cortical regions) and this could be beneficial for XGBoost, since the algorithm aims to minimize complexity to prevent overfitting. A number of problems could have negatively impacted the accuracy score. The first concerns issues with the dataset. There could be a lack of data distinct features, the classification goal is not what the model is actually classifying, the different types of segments are too similar in terms ECoG data, there is something about the data that is currently unknown, or a mistake was made in configuring the data in the first place. There could also be issues with the models we chose. Our exploration covers a couple different types of classifiers but they may not be best ones to be paired with our data.

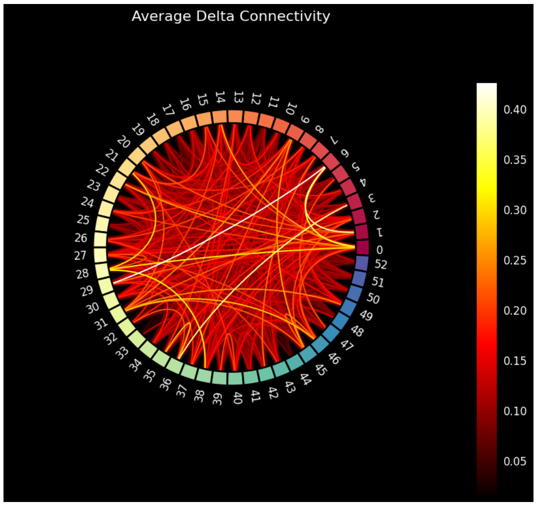
The current challenges with the model can only be explored by doing more exhaustive sweeps over the models currently tested and by testing more models. With regard to data, if it is an issue with the setup or testing data configuration, only time and testing can improve that. If it is about the classification of the data, we can hypothesize that this may be a challenging task to do. It is possible that it is hard for models to be able to determine what the monkey is looking at from ECoG data, encountering similar problems to a recent attempt to train a diffusion model on MRI data and construct images seen by patients [15]. There are little in the way of general trends and features that the classification models can pick up on.

4.2 Coherence

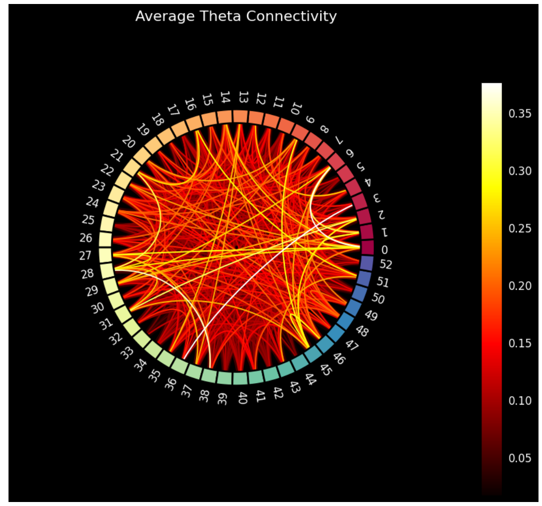
While we were unable to identify any differences in coherence between video clips, we were able to identify patterns between frequency bands. As seen in the average connectivity plots (Figure 3), while coherence varies between bands as a whole, a small number of independent components remain highly connected regardless of frequency. The original paper references seven components with ”busy interactions,” which they identified as representative of seven major cortical areas (the visual, parietal, prefrontal, medial prefrontal, motor, anterior temporal, and posterior temporal cortices)[1]. While we lack the experience needed to associate components with cortical areas, we can hypothesise the the busy components we have identified (for example, component 6) are similarly matched to busy cortical areas.

5 Contributions

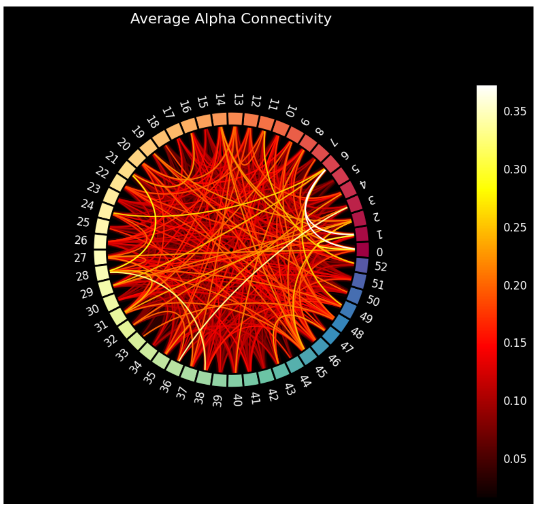
Every author did a thorough testing of the data, learning how the data was organized, finding connections to what described in the paper and in the metadata, as well as seeing what EEGLab was able to visualize and what aspects of the paper we could test out and visualize. Theo worked on Matlab



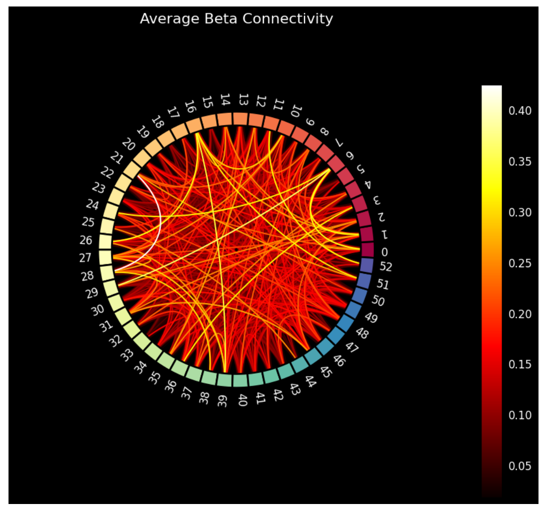
(a) Delta Coherence



(b) Theta Coherence



(c) Alpha Coherence



(d) Beta Coherence

Figure 3: Average Connectivity Estimate for Each Wave Band

scripting and exporting to Colab, Ian on PCA/ICA and causality within Python/MNE, and Katie took point on creating, finding, and testing models for video segment classification as well as the write-up.

References

[1] F. N. Chao ZC, Nagasaka Y, "Cortical network architecture for context processing in primate brain," *eLife*, 2015.

[2] T. M. Inc., "Matlab version: 9.13.0 (r2022b)," 2022.

[3] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[4] T. M. Inc., "Eeglab toolbox toolbox version: (r2022b)," 2022.

[5] T. M. Inc., "Signal processing toolbox version: (r2022b)," 2022.

[6] T. M. Inc., “Statistics toolbox version: (r2022b),” 2022.

[7] T. M. Inc., “Source information flow toolbox version: (r2022b),” 2022.

[8] T. M. Inc., “Optimization toolbox version: (r2022b),” 2022.

[9] T. M. Inc., “Image processing toolbox version: (r2022b),” 2022.

[10] J. Himberg and A. Hyvärinen, “icasso122,” 2013.

[11] J. S. Hugo Gävert, Jarmo Hurri and A. Hyvärinen, “Fastica,” 2013.

[12] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen, and M. S. Hämäläinen, “MEG and EEG data analysis with MNE-Python,” *Frontiers in Neuroscience*, vol. 7, no. 267, pp. 1–13, 2013.

[13] T. M. Inc., “Chronux toolbox version: (r2022b),” 2022.

[14] J. E. K. S. M. P. M. Hemant Bokil, Peter Andrews, “Chronux: A platform for analyzing neural signals,” *J Neurosci Methods*, 2010.

[15] S. N. Yu Takagi1, “High-resolution image reconstruction with latent diffusion models from human brain activity,” 2023.