Functional Connectivity Classification in ECoG during Speech Perception and Production

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Abstract

Functional connectivity (FC) is a well established technique used to elucidate how different brain regions interact. However there are limited studies investigating these interactions in language processing. Here, we address this by leveraging human electrocorticography (ECoG) data during language perception and production. The high spatiotemporal resolution and signal-to-noise ratio of ECoG data, enable robust classification of connectivity patterns across different cognitive states spanning language perception through production using a multi-class Support Vector Machine (SVM) method. The results demonstrate dissociable cognitive states based on FC patterns, with some overlap between speech production and baseline states. Further, examining the model contributions (hyperplane boundaries) revealed unique spatial connections that characterize specific states. We find consistent patterns across participants, with distinct connectivity signatures for auditory perception, visual tasks, and speech production across peri-sylvian cortices. Taken together, this research highlights the potential of functional connectivity in advancing our understanding of language processing.

Keywords: Functional Connectivity; Classification; Support Vector Machine; Electrocorticography; Speech Perception and Production

Introduction

Functional Connectivity (FC), is a prevalent technique in neuroimaging used to elucidate brain networks and their dynamics by examining how brain regions communicate during cognitive tasks. A significant body of the literature focuses on intrinsic networks derived from resting-state data (Fox & Raichle, 2007) as well as cognitive tasks (Cole, Bassett, Power, Braver, & Petersen, 2014). However, a gap exists in understanding how these specific connections relate to language processing during perception and production. This is compounded by motor artifacts that non-invasive techniques are sensitive to.

Human electrocorticography (ECoG) data presents a unique opportunity to investigate the neural mechanisms involved in language perception and production with a combined high temporal and spatial resolution. A large body of work has investigated speech perception and production using ECoG, however there is a paucity of functional connectivity studies. Our goal in here is to bridge the existing gap in the literature by exploring the FC patterns across various stages of language perception (auditory, visual) and production aiming to elucidate the neural interactions that support these functions.

Data Collection and Preprocessing

We recorded Electrocorticography data from ten participants, while they performed a battery of language tasks (Auditory word repetition, picture naming and visual word reading). The battery was designed to elicit the same set of words across the different tasks. We extracted the analytic amplitude of high-gamma broadband using a band-pass filter within 70-150 Hz followed by a Hilbert transform. We focused on recordings during three event-related stages of the tasks: Comprehension, word production and baseline. For our analysis, in each stage we focused on 500ms intervals relative to the event time stamps. Putting all tasks together, we defined five cognitive states: Auditory perception, picture perception, word reading perception, speech production (shared by all tasks), and baseline (shared by all tasks). For each participant, we then computed Pearson's Correlation as the measure of functional connectivity between electrodes in each trial of these states. This resulted in symmetric square correlation matrices with the size of number of electrodes.

Results

First, we were interested in identifying the predominant connections in each cognitive state. To do so, we looked into the distribution of all the functional connections for each participant separately, and identified the most significant ones (Laplacian distribution; p-value$<$0.05). In Figure 1.A., we are plotting the significant connections (red for positive and blue for negatively correlated) in a single exemplar subject. Comparing the connections across the cognitive states, we show many overlapping connections. Although this analysis shows the strongest connections present, it fails to to identify connections that specifically dissociate different cognitive states (i.e. auditory perception, speech, etc.).

In order to address this, we employed a classification approach based on the functional connectivity matrices. These were classified using a linear Support Vector Machine (SVM) multi-class model. The feature space was created by flattening the upper triangle of each connectivity matrix. Each trial in each cognitive state is considered a single observation and matches a single class label. Using SVM, we trained five classifiers, each producing a decision boundary hyperplane separating the observations of one class from all others. More details on this analysis is shown in Figure 1.B.. We measured the classification accuracy for each participant using 5 fold cross-validation and plotted the confusion matrix of the exemplar subject in Figure 1.C. The results show high classification accuracy across cognitive states, with some confusion between speech production and baseline. Thus, the cognitive states can be linearly separable in the feature space (corresponding to electrode pairs).

The linear SVM classifier gives us the ability to delve deeper into the decision boundary hyperplanes, and since they have the same dimensionality as the functional connectivity matrices, we plot them on the brain as connections. We use a similar distribution approach to assess significant weights in the hyperplanes and their corresponding connections. These connections represent the dimensions in the feature space that mostly explain the differences between cognitive states, and their weights show the direction and importance. For example, a positive weight means for that specific class, the corresponding connection is more likely to have a large positive value, thus the two connecting regions have a more correlated neural activity in that state. In Figure 1.D. we show these connections for each cognitive state in the same exemplar participant. Comparing the results with Figure 1.A., we can see that the connections have become more unique and sparse, providing a better representation of the underlying state-specific connections.

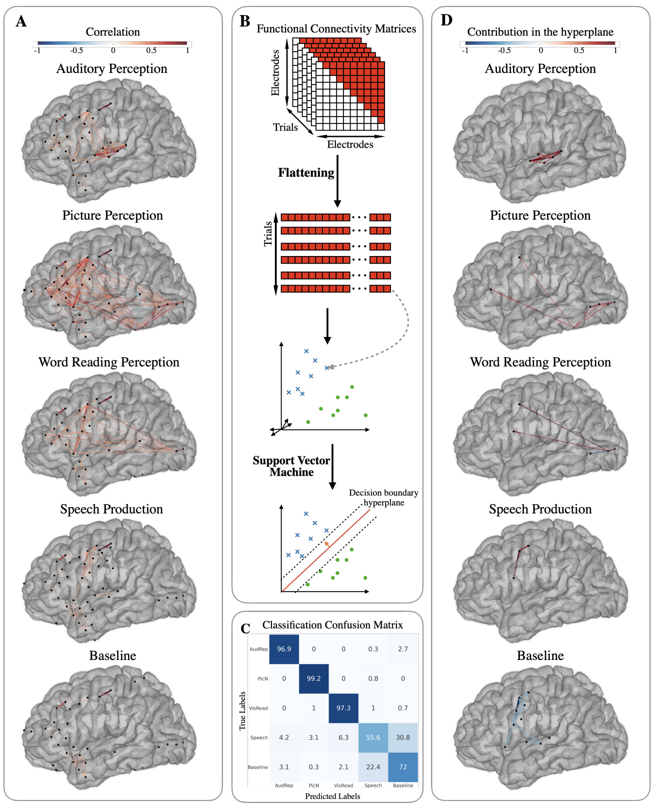

Figure 1: Functional Connections in different cognitive states in an exemplar subject. A) Significantly strong connections in each cognitive state (laplacian distribution; p-value$<$0.05). B) Classification framework. The SVM classifies each state compared to the rest, and results in a decision boundary hyperplane for each class. C) Classification confusion matrix using 5 fold cross-validation shown for the same subject. The class labels are as follows: AudRep: Auditory perception, PicN: picture perception, VisRead: word reading perception, speech and baseline. D) Connections with the most significant weight (laplacian distribution; p-value$<$0.05) in the separating hyperplane for each cognitive state.

We applied the above framework to all the participants. In Figure 2.A. we report SVM classification performance across all participants. The results show that the cognitive states are still linearly separable in each patient's specific feature space. Shifting back our focus on the separating hyperplanes of each state, we show the connections with the most significant weights across all the participants in Figure 2.B.. For auditory perception, we observe a majority of connection within superior temporal gyrus. However, significant connections from superior temporal to dorsal pre-central and inferior frontal gyri are observed. These latter connections are consistent with the findings in the literature regarding the involvement of these frontal regions in language perception and cued production (Flinker et al., 2015; Khalilian-Gourtani et al., 2022; Ozker, Doyle, Devinsky, & Flinker, 2022).

For both visual tasks we observe significant connections between occipital cortex and inferior frontal and pre-central gyri (Whaley, Kadipasaoglu, Cox, & Tandon, 2016). Notably, the visual word reading task exhibits some significant connections within the speech motor cortex that can be attributed to the faster nature of this task, i.e. participants start to read the words as soon as they appear as the cue, while in picture naming, retrieving a word from a drawing requires semantic access and a longer processing time.

During speech production, we observe significant connections across the speech motor cortex. Interestingly, we observe a series of connections between speech motor cortex and superior temporal gyrus with a negative sign. This observation can be attributed to the dynamics of STG processing the feedback of the patients's own voice; i.e. as the patient speaks STG is activated due to auditory feedback of self-produced speech.

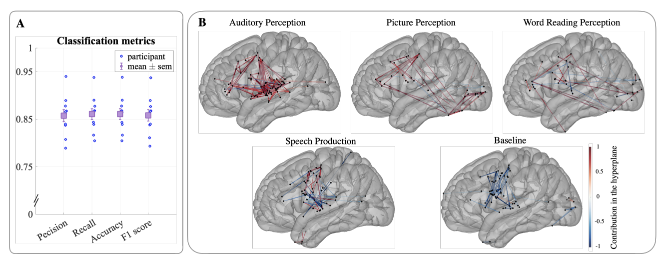

Figure 2: Functional Connectivity classification results over all participants. A) Classification performance metrics. Points indicate single participants, and the error bars show the mean and standard error over all participants. B) Overlaying all the connections with the most significant weights in the separating hyperplane, among all participants.

Conclusion

In conclusion, our study has offered valuable insights into the unique functional connectivity patterns during language processing. We identified significant connections within different cognitive states, revealing the importance of network interactions above and beyond local neural activity. Given that the significant connection weights in the baseline state were almost all negative (i.e. less or negatively correlated compared with other tasks), it likely indicates anti-correlation at rest. Taken together, these findings advance our understanding of functional connectivity across perception and production and underscore the potential of this approach in elucidating neural mechanisms underlying language processing.

Acknowledgment

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