COGITATE Connectivity Data Challenge @BIOMAG 2024

Team name: *Conscientious Unbelievers*

Introduction

Magnetoencephalography (MEG) contributes to unraveling regional and large-scale brain activity, shedding light on neural oscillations, event-related brain responses, functional connectivity between brain regions, and network communication within the brain (Baillet, 2017). The fine temporal resolution of MEG allows for the analysis of rapidly changing neural activity, offering advantages over fMRI-based connectivity measures that operate on longer time scales (Larson & Lee, 2014).

Both Global Neuronal Workspace (GNWT) and Integrated Information (IIT) theories of consciousness predict specific synchronization functional connectivity patterns, though between different regions. On the one hand, GNWT predicts that a conscious experience requires phase-synchronization in the gamma/beta band between the prefrontal cortex (PFC) and category-selective visual areas in the temporal lobe (i.e., the Fusiform Face Area (FFA) for faces and the Lateral Occipital Complex (LOC) for objects). On the other hand, IIT predicts phase-synchronization between the mentioned category-selective areas and low-level visual areas (e.g., V1/V2) (Melloni et al., 2023).

<u>Selection of Functional Connectivity Measures</u>

Each of the different measures of connectivity has its merits and disadvantages with respect to what can be interpreted from those measures and the ease with which they can be computed. An overview of the different connectivity measures and their main characteristics is summarized in Table 1 (copied from Supek & Aine, 2019).

	Directed interactions	Freq/time domain	Multi-/bivariate	Linear	Sensitive to field spread
Amplitude envelope correlation	–	f	b	+	+
Coherence	–	f	b	+	+
Cross-correlation function	+	t	b	+	+
Cross-frequency interactions	–	f	b	–	+
Directed transfer function	+	t	m	+	+
Dynamic causal modelling	+	t/f	m	–	+
Granger causality	+	t/f	b	+	+
Imaginary part of coherency	+	f	m	–	–
Mutual information	–	t/f	b	–	+
Partial directed coherence	+	f	m	+	+
Phase lag index	+	f	b	–	–
Phase locking value	–	f	b	–	+
Phase slope index	+	f	b	–	–
Synchronization likelihood	+	t	b	–	–
Transfer entropy	+	t/f	b	–	–

Table 1. Overview of different connectivity measures and their main characteristics (copied from Supek & Aine, 2019).

When analyzing task-based MEG data, it is beneficial to use a combination of these measures. This approach allows for a comprehensive examination of both the linear and non-linear interactions, as well as the directional flows of information that occur in response to specific cognitive tasks.

We selected the following connectivity measures: Coherence (Coh), Phase Lag Index (PLI), Phase Locking Value (PLV), Imaginary Part of Coherency (ImCoh), and Granger Causality (GC).

These were chosen because they directly address phase synchronization in the gamma/beta band, which is crucial for testing the GNWT and IIT predictions. They are either robust against field spread (PLI, ImCoh) or are standard measures for phase synchronization (Coh, PLV). GC provides additional insights into directed interactions.

Objectives

1. Find patterns of functional connectivity in MEG regarding gamma/beta band coherence that support or challenge the predictions of GNWT and IIT.
2. Test whether gamma/beta band coherence is the ideal measure for establishing connectivity in task-based MEG data or if other connectivity measures are better-suited for this.

Methodology

Preprocessing

Raw data was denoised using Signal Space Separation (SSS) and Maxwell filtering methods from MNE-Python (Gramfort et al., 2013). Artifact removal will be done for the final report. The data was epoched according to the events annotated into the BIDS-format files. Channels from regions of interest (ROIs) (i.e. PFC, LOC, FFA, V1/V2) were chosen based on sensor coordinates.

Functional Connectivity Metrics

Coh, PLI, PLV, and ImCoh were computed using the MNE-Python connectivity library (Gramfort et al., 2013). GC will be completed for the final report using the same library. Complete analyses, including corrections to the code for the selection of epochs and channels, will be completed for the final report.

Statistical Analysis

The following statistical analyses will be conducted for the final report:

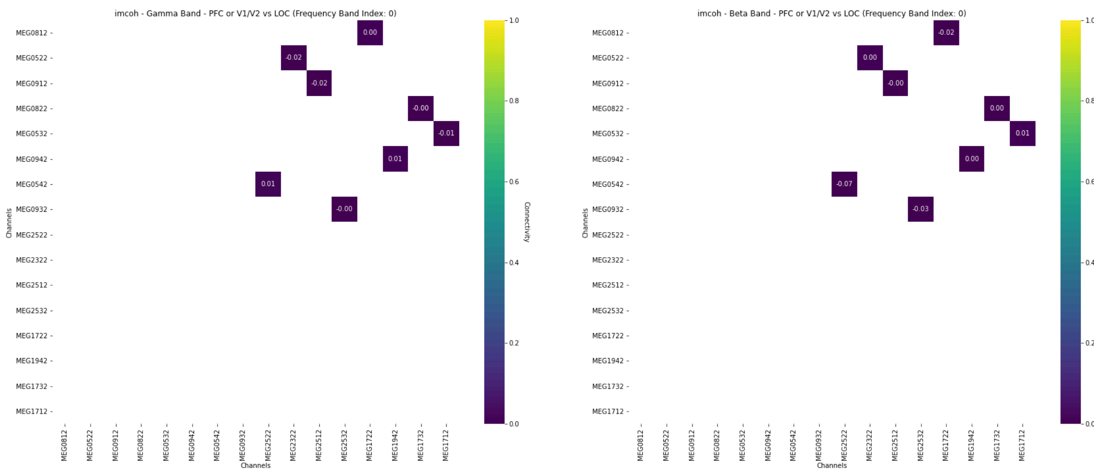
1. Surrogate Data Testing: (a) Phase Randomization: Create surrogate datasets by shuffling phases of MEG signals to estimate the probability of observed synchronization by chance. (b) Permutation Testing: Shuffle data labels and recalculate connectivity measures to create a null distribution for reference. (c) Bootstrapping: Create resampled datasets by random sampling with replacement to estimate variability and confidence intervals.
2. Connectivity Pattern Comparison: (a) Condition Comparison: Paired t-tests and ANOVA to compare connectivity patterns across different experimental conditions. (b) Multivariate Analysis: MANOVA to assess the combined effects of multiple participant's baseline conditions on connectivity measures.
3. Overfitting and Reliability: (a) Data Splitting: Dividing dataset into training and test sets to validate performance. (b) Cross-Validation: K-fold cross-validation to estimate performance and variability. (c) Regularization Techniques: L1 (Lasso) and L2 (Ridge) regularization to prevent overfitting.

Results

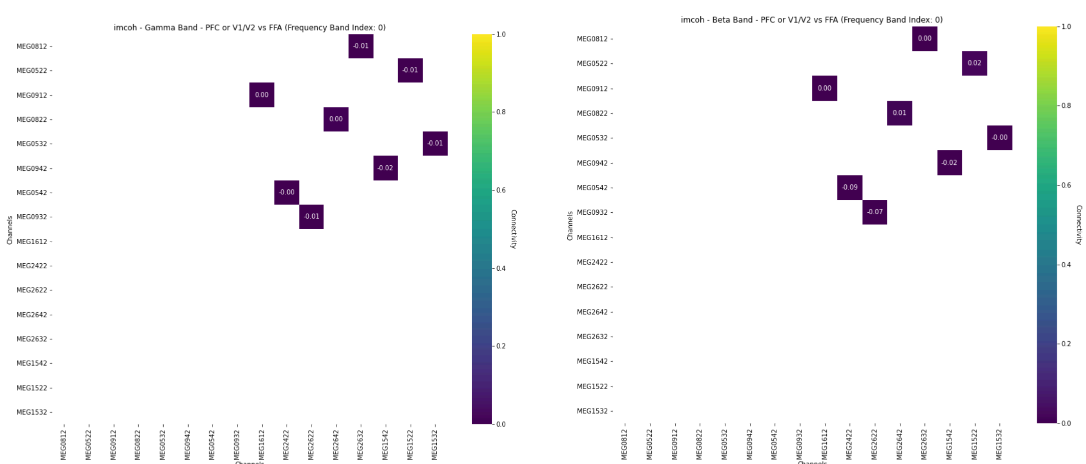
The connectivity analysis has a bug that includes NaN values to the connectivity matrixes, thus rendering a lot of the image white and its interpretation practically ineffecive. This bug will be fixed for the final report, where the final results will be shown. It is possible that we also change the plot to other type of graph. GC connectivity analysis is not included and will be done for the final report.

Following is an example of the current results. Coh, PLV, and PLI in beta and gamma band for PFC vs FFA, and PFC vs LOC gradiometers, as well as Coh, PLV, and PLI in beta and gamma band for V1/V2 vs FFA, and V1/V2 vs LOC gradiometers were not included due to the limited space. All results can be seen in the code. Only gradiometers results were included here. For the final report, we will show all results.

<u>GNWT predictions</u>



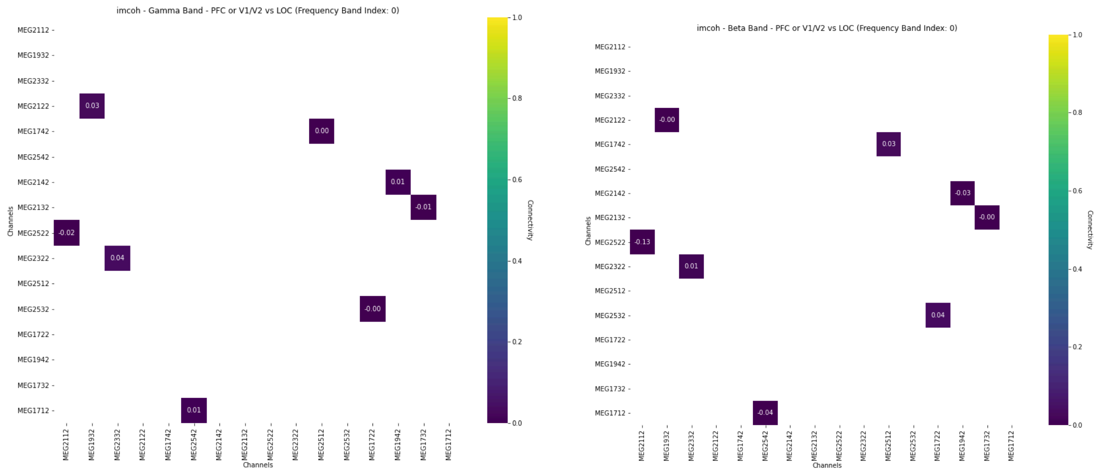
PFC vs LOC



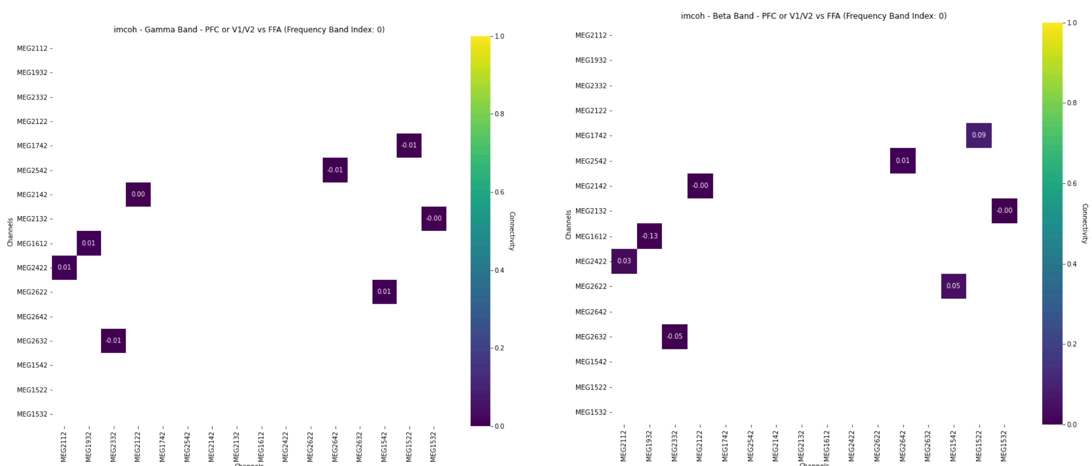
PFC vs FFA

Fig 1. Imaginary Coherence (ImCoh) in beta and gamma band for PFC vs FFA, and PFC vs LOC gradiometers

IIT predictions



V1/V2 vs LOC



V1/V2 vs FFA

Fig 2. Imaginary Coherence (ImCoh) in beta and gamma band for V1/V2 vs FFA, and V1/V2 vs LOC gradiometers

Discussion

Higher coherence in the gamma/beta band between PFC and FFA/LOC would support GNWT, while similar patterns between FFA/LOC and V1/V2 would support IIT. Results will be completed for the final report.

There are several factors that should be considered for interpretation of results. Firstly, multiple sensors pick up the signals from a single source due to the nature of the electromagnetic signals, known as field spread, as well as volume conduction (Sarvas, 1987). Both these phenomena may lead to erroneous estimates of functional connectivity. Secondly, the mixture of signals originating from spatially separated brain areas can result in under- or overestimation of functional connectivity (Schoffelen & Gross, 2009). Demixing the contribution from spatially separate sources and enabling a more straightforward interpretation of the functional data in relation to its underlying structure are, therefore, the main reasons to perform an analysis in source-space.

Many functional connectivity estimators are available, yet most measures are sensitive to the effects of volume conduction and field spread. Coh and PLV are some of the main statistics for assessing functional connectivity but have the drawback that they do not provide information on the direction of information flow and are liable to the effects of volume conduction and field spread. ImCoh (Nolte et al., 2004) and PLI (Stam et al., 2007) are inherently insensitive to these biases, so they are useful measures. PLI has the additional advantage that it does not directly depend on the amplitude of the signals. Moreover, GC has emerged as a statistically principled way to provide directional information (Supek & Aine, 2019).

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