Regional Band Oscillations Orchestrate Human Conscious Content – Analysis of the Cogitate Datasets

Christina Yi Jin[1]

1. Research Center for Frontier Fundamental Studies, Zhejiang Lab, 311100 Hangzhou, China

Abstract

In the current study, we trained neural decoders with spatial/frequency (S/F) features using the Cogitate dataset batch #1. The feature selection processes using the neural decoder gave 57 informative features in decoding the conscious content individually. The final neural decoders achieved performance significantly above the chance level and the best individual decoder having a balanced accuracy of 0.94, indicative of the efficiency of decoding. We examined the spatial loading of each selected S/F feature and found regional differences between the bands. In particular, the current results showed that the alpha and low/middle beta bands had dominant activity at the parietal region, and the delta and theta bands involved neural activity at the frontal sites. The former largely supports the Integrated Information Theory (IIT) at the alpha/beta bands while the latter might indicate the Global Neuronal Workspace Theory (GNWT). We propose that the reliability of the current finding can be proved by a similar result found with Cogitate dataset #2.

Results

The current analysis used the Cogitate dataset – batch #1, which contains simultaneous Magnetoencephalography (MEG) when participants were performing a visual discrimination task (Melloni et al., 2023). Raw MEG was cleaned and epoched with MNE-Python following the FLUX pipeline (Ferrante et al., 2022) and a further time-frequency analysis was applied to transform each two-dimensional MEG epoch to a three-dimensional time-frequency cube (frequency range 2-39Hz, Fig. 1b). We then performed the Principal Component Analysis (PCA) to decompose the channel dimension and concatenated the top three PCs for each frequency, referred to as the spatial/frequency (S/F) dimension (Fig. 1b). The S/F time series will be fed to the convolutional neural network as inputs. Currently, we only included the magnetometer channels.

The structure of the convolutional neural network is shown in Fig. 1a. The decoding goal is to predict the label of epochs (T: target, R: relevant non-target, N: irrelevant non-target). Initially, we involved all the S/F components (n_S/F=114) for training. In each run, we trained individual models and disabled each involved S/F component (also referred to as feature) sequentially and re-assessed the model performance with the disabled feature. The performance with disabled feature was compared to the original performance and a negative change indicated the feature's importance. The "important" features were selected for the next run of modeling. The iteration continued until the feature number converged, meaning no more features are excessive. A five-fold cross-validation was used to assess the model performance. As shown in Fig. 1c, the feature number was efficiently dropping over runs with preserved performance during cross-validations. Statistics show that the modeling performance on the 7th run (n_feature=11) was significantly lower than that of the 5th run (n_feature=57, pair-wise comparison p=0.001, FDR-corrected). Meanwhile, the performance of the 5th run did not differ from the previous runs (ps>0.05), we thus took the 57 S/F features used in the 5th run as features for the final model.

The performance of each individual decoder is shown in Fig. 1d. The overall performance remarkably exceeds the channel level (0.333). The best individual decoder achieves an overall accuracy of 0.93 and a balanced accuracy of 0.94. The decoding efficiency of the current neural networks proves that the selected 57 S/F features provide sufficient information to understand the different neural processes for discriminating the three types of stimuli.

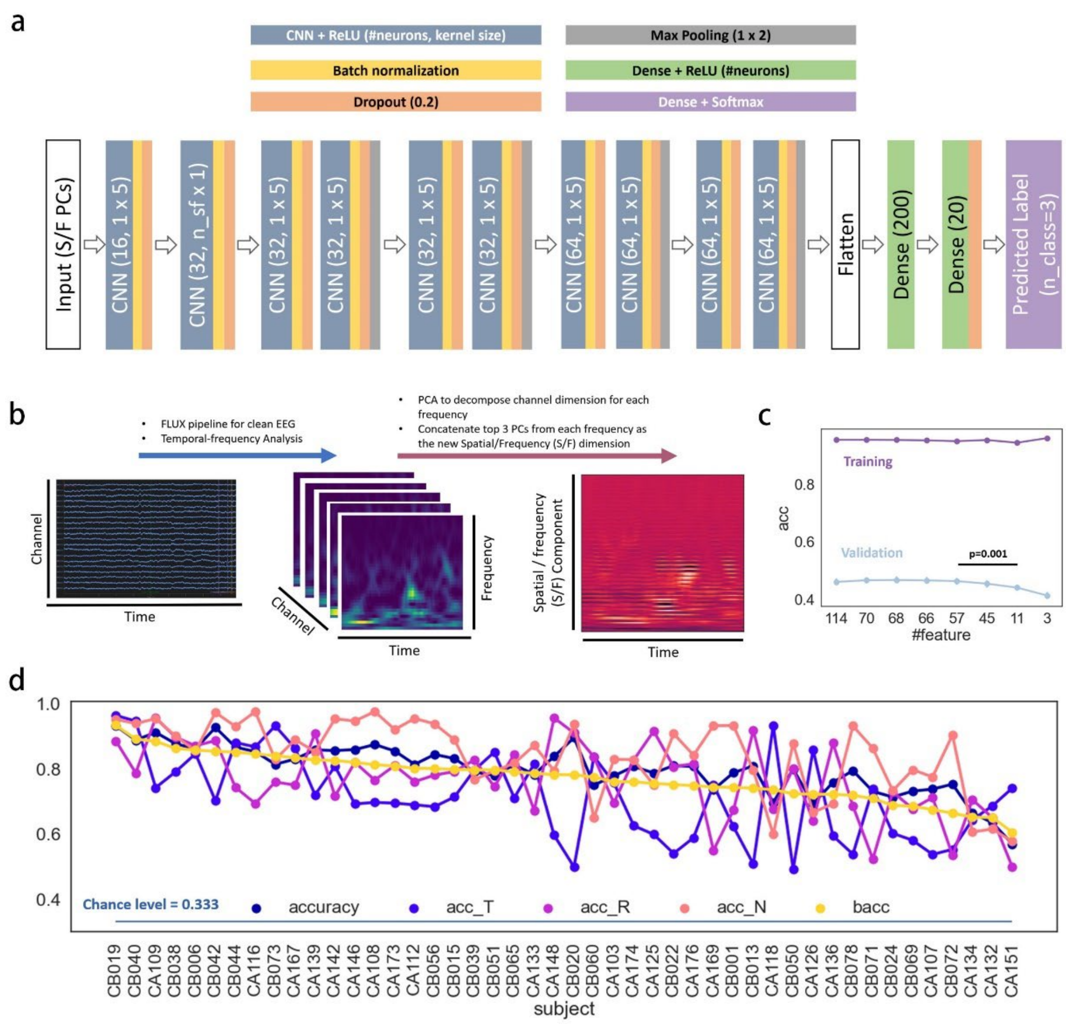

Fig 1. Neural decoder with MEG data.

a. Structure of the neural decoder using the Convolutional Neural Network (CNN). Training goal is to identify the stimuli type (T: target, R: relevant non-target, N: irrelevant non-target). **b.** Data preparation from raw MEG to the Spatial/Frequency (S/F) components as the input to the decoder. **c.** Feature selection processes. Performance started to drop since the 6th run. We thus used the features in the 5th run to train the final model. **d.** Performance of the final individual decoders, sorted by the balanced accuracy (bacc). accurcy=overall accuracy, acc_T=target accuracy, acc_R=relevant non-target accuracy, acc-N=irrelevant non-target accuracy.

We plotted the PC loading for each S/F component in Fig. 2. It shows that the dominant regions depend on band or frequency. For slower frequency bands, such as delta and theta bands, the dominant neural activity comes from the bilateral frontal areas extended to the temporal areas (PC1 for frequency 2-7Hz). The alpha band activity, however, is dominated by bilateral parietal regions (PC1 for frequency 9-12Hz). More centrally clustered neural activity at the parietal region is found with the low and middle beta bands (PC1 for frequency 14-18Hz). In the high beta band, the dominant region moves to the central sites (PC1 for frequency 22-24Hz). While most of the gamma band frequencies were discarded in the feature selection processes, the lower edge of the gamma band shows a dominant neural activity at the occipital region (PC1 for frequency 31, 32Hz).

Discussion

In the current study, we trained individual neural decoders with PCA-decomposed neural activity. We found all the delta, theta, alpha, and beta bands contribute to the efficient neural decoders. For the gamma band, however, only a few frequencies at the lower edge can decode the neural activity of the discrimination task. Furthermore, the results show that the regional distribution of neural activity is band-specific. In that case, strong evidence supports the Integrated Information Theory (IIT) that the alpha band together with the low/middle beta bands show a dominant neural activity at the parietal sites. Instead, the Global Neuronal Workspace Theory (GNWT) might be supported by the lower frequency bands such as delta and theta bands since their dominant neural activity contains frontal sites.

The next step will be an effort to replicate the results on the Cogitate dataset – batch #2. We will run the same data preparation steps and again train neural decoders for efficient S/F features. Replicated results should indicate a similar finding that dominant band activity at different locations. Specifically, we expected to observe the alpha and low/middle beta bands at the parietal region, and the delta and theta bands at the frontal region being able to discriminate the conscious content, as evidence of the IIT and GNWT respectively.

Note that the current analysis does not involve a typical functional connectivity analysis which often uses correlation of neural activities or oscillatory phase coherence as ways of showing the regional connectivity. The current analysis, instead, uses S/F components to show a synthesized neural activity over the observed spatial locations as an indication of orchestrated oscillations within a region. This way allows us to examine multiple bands and frequencies and thus contributes to the current major finding of band-specific regional activation. Further study can check if the inter-band connection exists to clarify how the different neural oscillations ensemble for encoding the information during conscious activity.

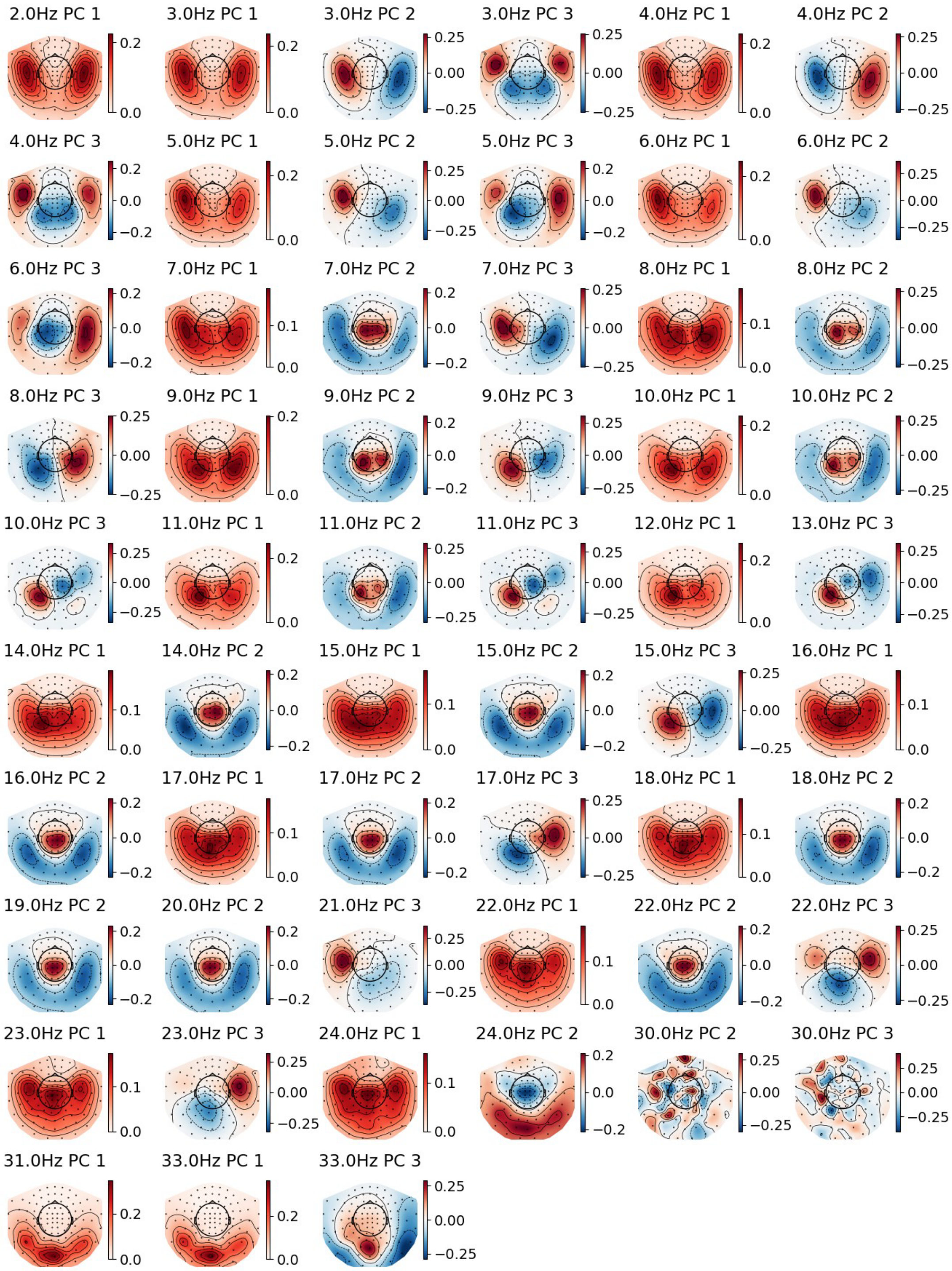

Fig 2. Loading of the selected S/F component.

Methods

Preprocessing of MEG

The preprocessing of the MEG data followed the FLUX pipeline using MNE-python (Ferrante et al., 2022). Steps included bad channel detection, max filtering, artifact annotation for muscle activity, and Independent Component Analysis (ICA) for ocular and cardiac artifacts. The continuous MEGs were downsampled to 200 Hz and then segmented to epochs of [-0.2, 2] s time-locked to the stimulus onset. A time-frequency analysis was performed on the epochs to get the single-trial power of frequency linearly increasing from 2 to 39 Hz with the step of 1 Hz. The cycles of the kernel linearly increased from 3 to 7 and the time bandwidth was fixed at 2 s.

The preprocessing pipeline generated two errors when processing data CA123 and CB999, which could not be fixed. The current report thus excludes the two datasets and involves the other 46 datasets of Cogitate batch #1.

The Spatial/Frequency Features

We performed the incremental PCA using the *sklearn* toolbox in Python to decompose the spatial (channel) information over all participants in a frequency-wise way. We then took the top 3 PCs for each frequency and concatenated them to form the spatial/frequency (S/F) dimension as the input to the CNN decoder.

Neural Decoder

The input into the decoder was a three-dimensional matrix sized of (n_epochs, n_S/F, n_time points). Each dataset was scaled to 0-1. We chose a five-fold cross-validation to assess the model performance.

The neural decoder contained an initial 2D-convolutional layer with 16 neurons, kernel size of (1, 5), and stride size of (1, 2) to learn along the time dimension. The second CNN layer with 32 neurons used a kernel sized of (n_S/F, 1) to synthesize the information over all S/F features. Following that, four CNN blocks were stacked each containing two identical layers kernel size of (1, 5) to further learn along the time dimension. Each block was followed by a max-pooling layer (kernel 2x2). The neurons of the CNN blocks were 32, 32, 64, and 64 respectively. All the CNN layers used ReLU as the activation function. The output from the final CNN block was flattened and fed to two dense layers with 200 and 20 neurons respectively, and ReLU as the activation function. The final layer is a dense layer with softmax as the activation function and three neurons for the final predictions (T/R/N).

The current structure also involved batch normalization layers, drop-out layers with the rate of 0.2, and an L2-regularization at 0.01 to control fitting. We used the categorical cross-entropy as the loss function and Adam optimizer with a learning rate of 0.0005 to optimize the model. The optimization was achieved in 100 epochs with batches sized 50.

Feature Selection

Initially, the input involves all the 114 S/F features. After obtaining the individual decoders, we muted each S/F feature by setting the column value to 0.5 (average of the input) and compared the model's performance with the muted feature to the original performance. A muted feature with dropping performance indicated its importance in the model. We then kept the "important features" in the next run of modeling. Such a process iterated until the feature number converged. The best feature number was decided by the performance during cross-validation (Fig. 1c).

The final decoder was trained with the optimal S/F features.

Statistics

Statistics such as pair-wise comparison were performed using the *Pingouin* package in Python.

Open Code Statement

Code for analysis is openly available on https://github.com/christina109/Cogitate_data_challenge.

References

Ferrante, O., Liu, L., Minarik, T., Gorska, U., Ghafari, T., Luo, H., & Jensen, O. (2022). FLUX: A pipeline for MEG analysis. *NeuroImage*, 253, 119047.

Melloni, L., Mudrik, L., Pitts, M., Bendtz, K., Ferrante, O., Gorska, U., ... & Tononi, G. (2023). An adversarial collaboration protocol for testing contrasting predictions of global neuronal workspace and integrated information theory. *PLoS One*, 18(2), e0268577.

Vallat, R. (2018). Pingouin: statistics in Python. *Journal of Open Source Software*, 3(31), 1026.