

Research Article

Is There a Direct Relation Between EEG Band Spectrum and DMN Activity in fMRI? A Multivariate Exploratory Study

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This study uses an EEG-fMRI dataset to examine the relation between fMRI BOLD signals from Default Mode Network (DMN) regions and the conventional EEG band spectral data. Our results indicate that the DMN activity corresponds to the EEG band powers of multiple frequency bands especially from midline electrode sites. The results also indicate that the DMN may be acting similarly in rest and light sleep stages but start to slightly deviate in N2 and largely deviate in N3 stage. This will help us better understanding the relation between EEG parameters (which capture more network-level activity) and fMRI data (which captures more anatomically restricted activity).

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1. Background

EEG and fMRI are extensively employed in neuroscience research, each with their own advantages and limitations. While fMRI offers high spatial resolution but low temporal resolution, EEG provides high temporal resolution but suffers from low spatial resolution. The data from simultaneous acquisition of EEG-fMRI provides an opportunity to capture the distinct advantages of each modality in a single setting. In this paper, we aim to utilize such an EEG-fMRI dataset to explore the relationships between the signals of these two modalities. We are particularly interested in examining the relation between fMRI BOLD signals from Default Mode Network (DMN) regions, a resting state network, and the conventional EEG band spectral data. Through this approach we hoped to clarify whether DMN activity could be reflected

by a single band power change in a specific region (like frontal midline theta power increase) or by a multi-band global change in EEG power. Notably, this research question has largely been unanswered.

2. Methods

We used an EEG-fMRI open dataset of a previous study^{[1][2]} made available as an OpenNeuro/NEMAR Dataset. The initial preprocessing of the EEG data was done (including automated fMRI artefact removal) in EEGLAB toolbox and the fMRI data was done in CONN toolbox^[3], both in MATLAB. Then ‘.mat’ files were generated using custom scripts where, the 2.1s EEG epochs and the time-locked fMRI data (ROIs extracted based on default template of CONN toolbox) were extracted and assigned the sleep stage corresponding to the scoring file from the dataset. These files were then imported into Python to do further analysis. The fMRI data of DMN included 4 ROIs (MPFC, PCC, Bilateral parietal lobules), whose mean was taken as the DMN value per time point. From the time-locked EEG data segments (2.1s each), power spectral density was calculated using the Welch method (1s window) to obtain one power value per band per channel mapped to the fMRI data. Thus, we obtained a total of 7 frequency bands (delta, theta, alpha beta1, beta2, gamma1, and gamma2) from each of 28 electrodes, giving rise to 196 features per DMN activity time point. This data was then separated according to sleep stages. Outliers were removed using the Isolation Forest algorithm and then subjected to a regression model based on Random Forest algorithm (196 EEG feature trained to predict average DMN value from fMRI). We did a leave-one-out cross validation to compute prediction error (mean square error or MSE) and feature importance values per subject. The importance values for each feature were stored and plotted on topoplots to visualise which of the electrodes and which frequency bands contributed more to the prediction. The average of all the subjects were taken before plotting.

3. Results

We were able to effectively train the models to predict DMN values using 196 features from EEG data for the wake and sleep stages, evidenced by low average MSE values across subjects (within the range of 0.04 - 0.06) (Table 1). Considering well trained models, we next investigated the feature importance distribution of these models. This would let us know which frequency band and electrode location of EEG data were important in accurately predicting DMN values from simultaneously acquired fMRI data (see Figure 1). Our main finding is that the power in multiple frequency bands helped predict DMN activity in fMRI data, and though most electrode sites were important, the midline sites consistently showed

highest values. Furthermore, there were only minimal differences between wake, N1 and N2 stages regarding the abovementioned pattern. N3 stage showed drastic difference, with more peripheral electrode pockets showing high importance. More specifically, midline alpha and gamma power were more predictive of DMN activity in wake stage. Centroparietal delta power and beta2 power were more predictive of DMN activity in N2 stage. Left temporo parietal gama1 power was more predictive of DMN activity in N3 stage.

Wake	Stage N1	Stage N2	Stage N3
0.052	0.055	0.064	0.049

Table 1. The table represents the MSE (Mean Squared Error) for each stage averaged across subjects.

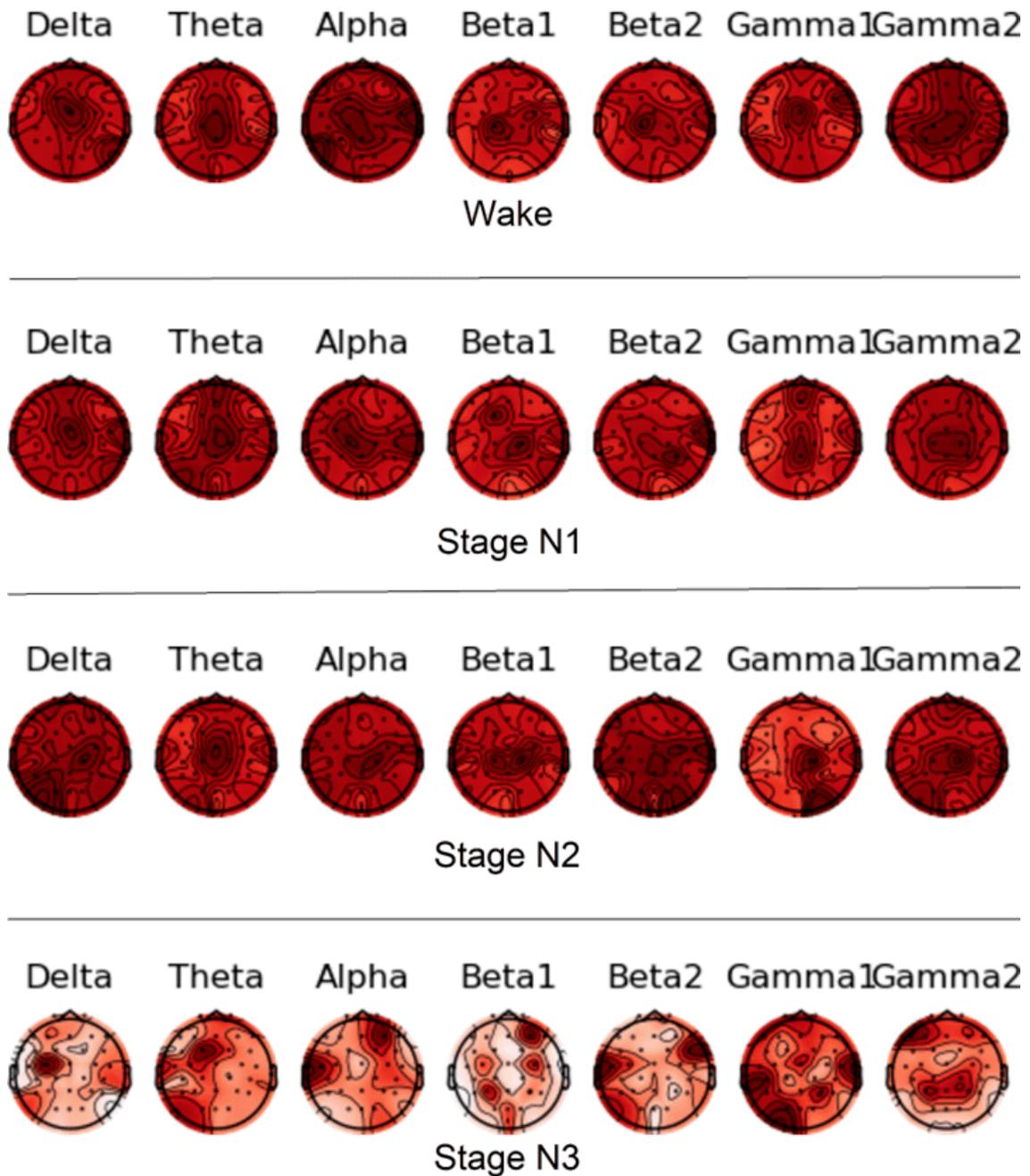


Figure 1. The figure represents the importance values of each feature in each stage averaged over all the subjects. The intensity of the colour indicates the level of importance of that feature in the prediction. The rows represent different stages of consciousness (wake, N1, N2 and N3) and the columns represent different frequency bands (Delta, Theta, Alpha, Beta1, Beta2, Gamma1 and Gamma2).

4. Discussion

Our results indicate that the DMN activity as determined from fMRI data, corresponds to the EEG band powers of multiple frequency bands (contribute almost equally) especially from midline electrode sites. The results also indicate that the DMN may be acting similarly in rest and light sleep stages but start to slightly deviate in N2 and largely deviate in N3 stage. The fact that a smaller number of subjects reached N2 and N3 stages compared to wake or N1 stages could have contributed to this difference, but the models were still well trained with low MSE values across subjects. A limitation of the feature importance value is that it doesn't inform whether an increase or decrease in power value predicted the DMN activity. Hence for further research, we plan to use SHAP Explainer (a game theory inspired approach to provide explainable feature importance values), though it is computationally very expensive. We could also examine in future whether source-level power values from such low-density EEG data could provide more anatomically localisable patterns. Overall, our approach, though simple, shows good promise in better understanding the relation between EEG parameters (which capture more network-level activity) and fMRI data (which captures more anatomically restricted activity), thereby helping design EEG studies and interpret their results in a better way.

Statements and Declarations

Acknowledgments

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Conflicts of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Ethical Statement

The primary work was approved and monitored by the Institute Ethical Committee of National Institute of Mental Health and Neuro Sciences (NIMHANS), Bengaluru, India.

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Declarations

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Potential competing interests: No potential competing interests to declare.