Constructing EEG Spectrograms from fMRI Data using an Artificial Neural Network

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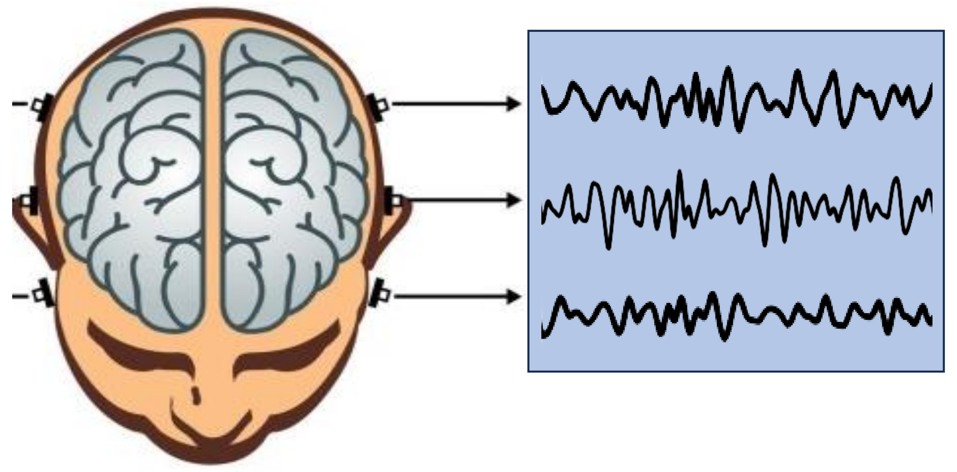
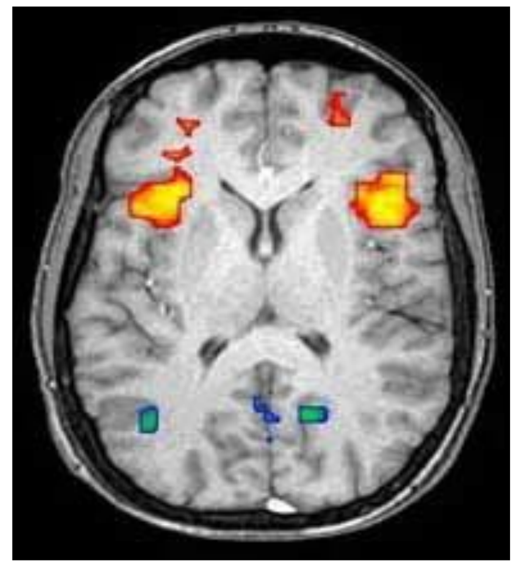
Background

Electroencephalogram (EEG)



*EEG measures electrical brain activity with **high temporal resolution** but **low spatial resolution**, enabling detection of rapid neural events while offering poor localization of their cortical origins. [1]*

Functional Magnetic Resonance Imaging (fMRI)



*fMRI measures blood oxygen level dependent (BOLD) signals with **high spatial resolution** but **low temporal resolution**, enabling precise localization of brain activity while lacking the ability to capture rapid neural dynamics.[2].*

Introduction

Correlating these EEG and fMRI signals enables us to associate patterns of EEG activity with the specific brain regions responsible for them. Prior approaches primarily used traditional statistical methods, but these techniques are ill-suited to such noisy data and cannot capture the complex, nonlinear relationship between EEG and fMRI signals. To overcome this, I developed a neural network architecture to predict an EEG spectrogram from fMRI data, thereby modeling this relationship.

Methods

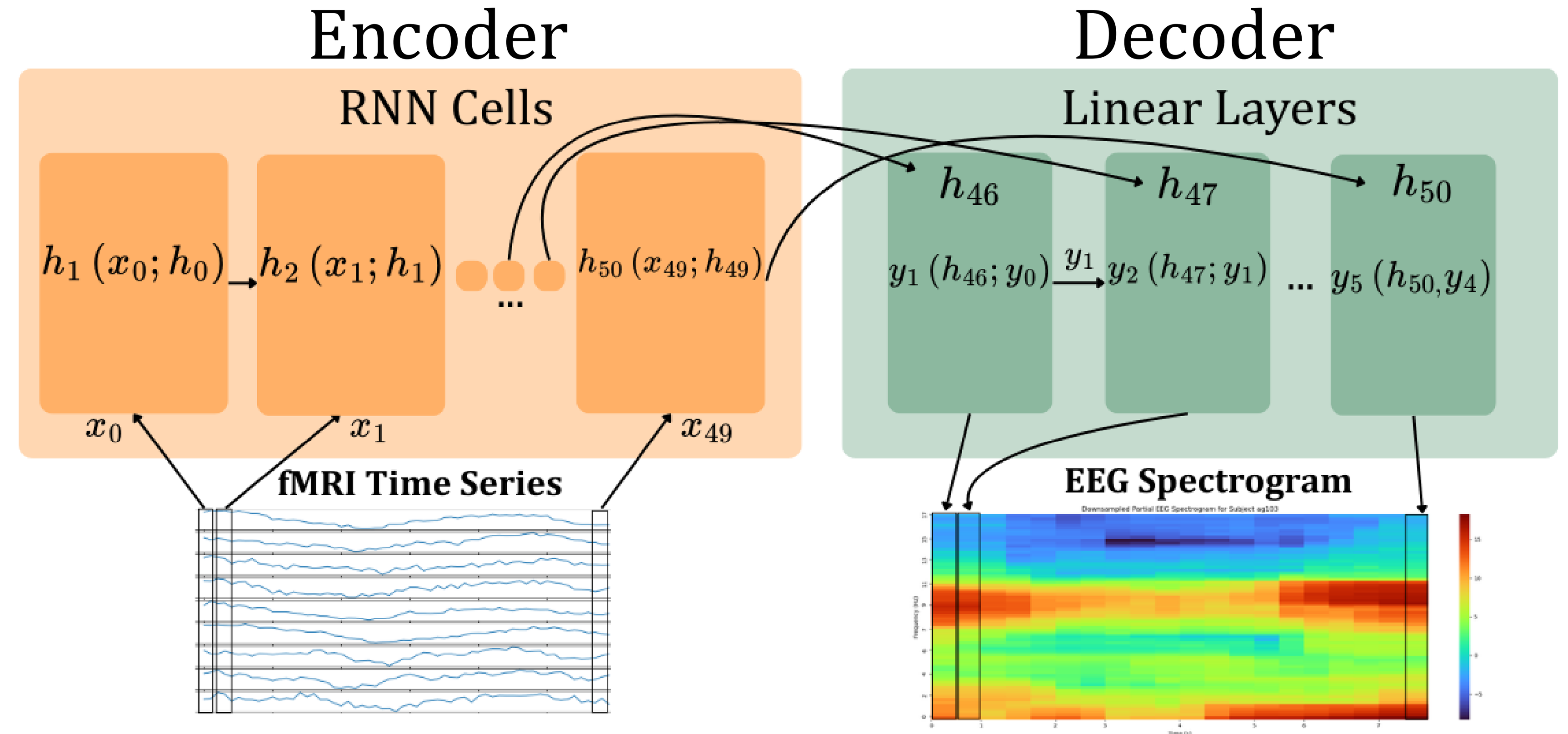


***Figure 1. fMRI-to-EEG Translation Model.** This architecture is composed of an encoder and decoder. The encoder is a recurrent neural network (RNN) that process a 50-TR fMRI window sequentially, creating informative representations (hidden states) of the input. The decoder is a linear layer that use these hidden states to autoregressively generate a 5-TR EEG spectrogram centered within the fMRI window. This architecture draws inspiration from sequence-to-sequence models in natural language translation, adapting them to translate between distinct neuroimaging modalities.*

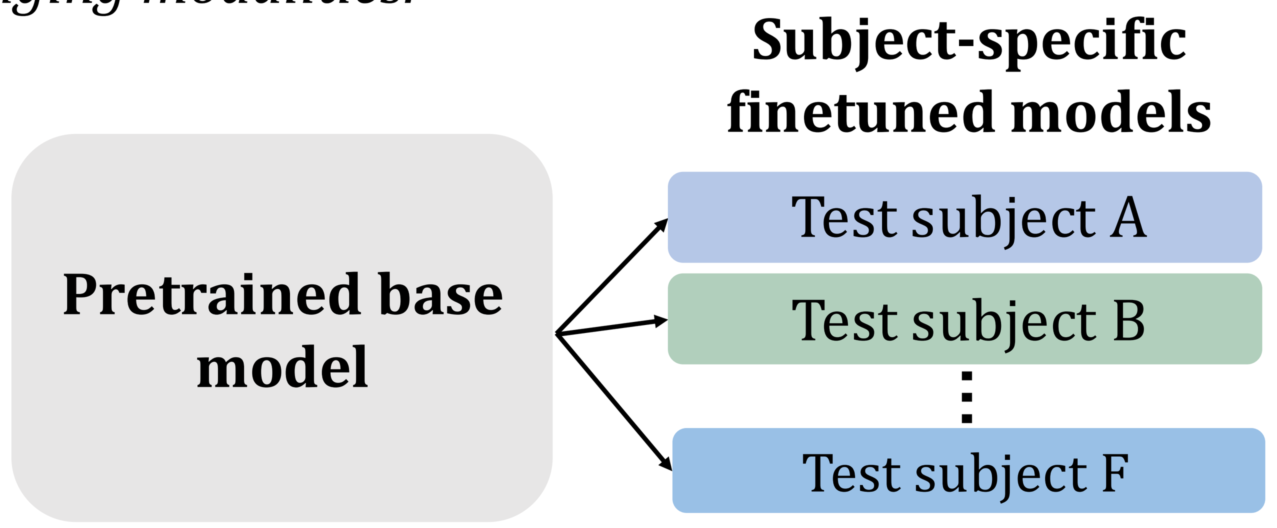


***Figure 2. Subject-Specific Finetuning.** To address limited data, we employed a 5-fold cross-validation with an 80/20 training-test split per fold. The pretrained base model was then fine-tuned separately on each test subject's data to capture subject-specific features. For complete spectrogram reconstruction, we trained multiple subject-specific models, with each model predicting a distinct temporal segment of the output.*

Results

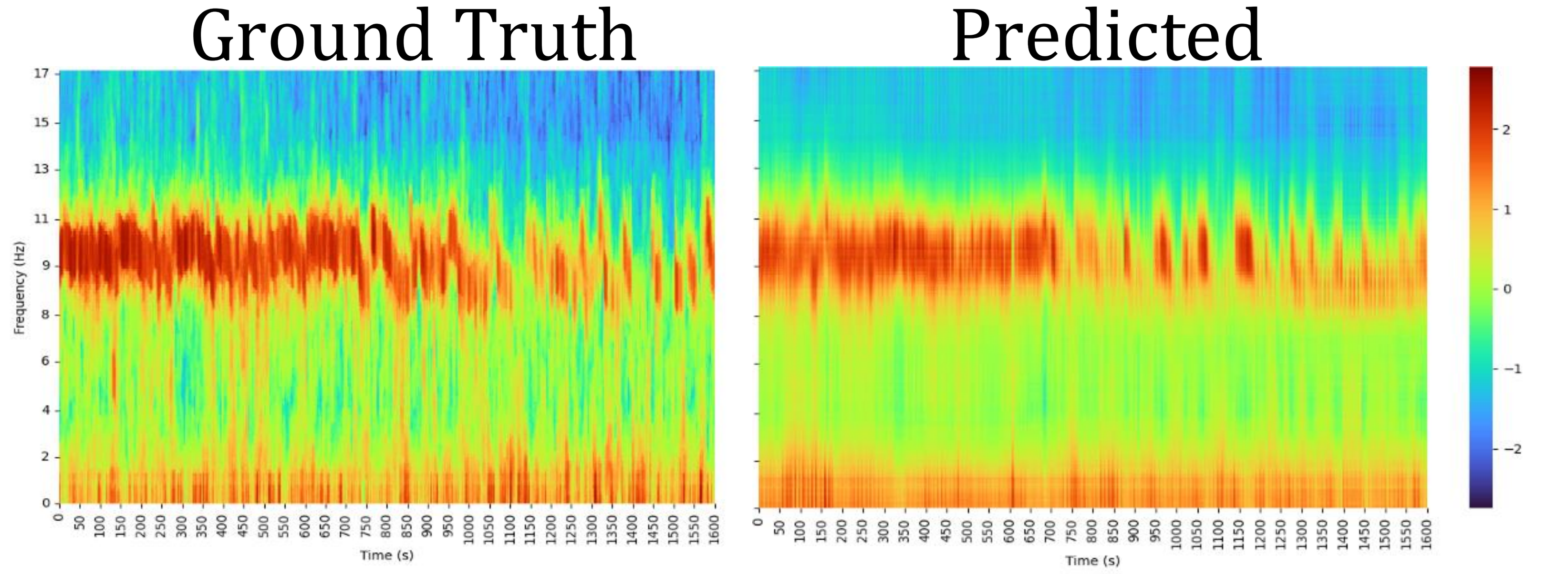


***Figure 3. EEG Spectrogram Prediction.** Our model predicts the EEG spectrogram with a high pearson correlation value of 0.8741*

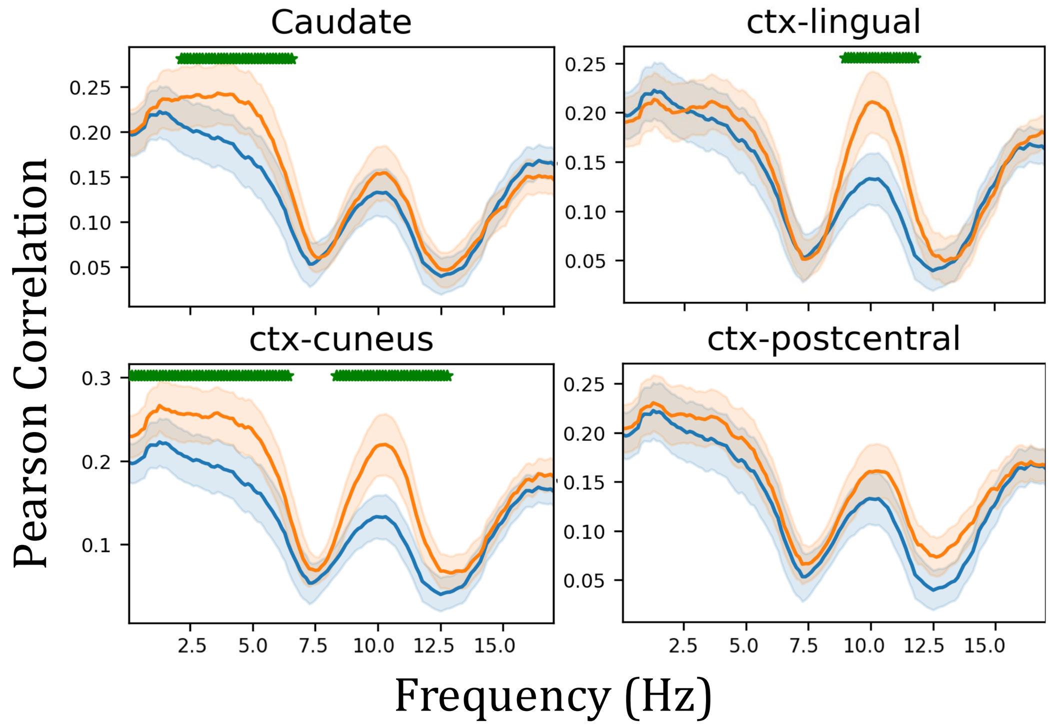


***Figure 4. Single brain region training.** This experiment highlights regions that significantly improve prediction of specific EEG features*

Conclusion

This framework predicts EEG spectrograms from simultaneously recorded fMRI. We are currently extending this framework to sleep data; this will allow us trace EEG features to the specific brain regions that control, generate, or are modulated by them. In future work, we plan to investigate other sequence-to-sequence architectures, such as transformers, and extend this framework to task-based EEG-fMRI experiments.

References
[1] "Electroencephalogram | First Choice Neurology" [Online]
[2] "fMRI Brain Scan - Functional Magnetic Resonance Imaging | EBME" [Online]