

Electrophysical Source Imaging based on the Spatiotemporal Neural Network

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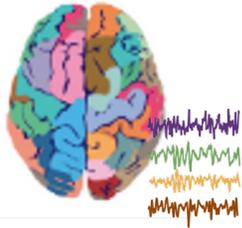
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Abstract

Electrophysiological source imaging (ESI) aims to localize brain activity from EEG/MEG data but lacks ground truth training data for machine learning approaches. We propose training a neural network model on simulated EEG and corresponding cortical activations from biophysical neural mass models (NMMs) to solve the ill-posed ESI inverse problem. Our model combines a spatial encoder and spatiotemporal translator to map EEG to source activations. Trained entirely on simulated NMM data, it generalizes to localize activations accurately compared to anatomical priors. This demonstrates the feasibility of data-driven machine learning for high temporal resolution EEG/MEG brain mapping by leveraging simulated training data.

Introduction

Tracking brain activity is crucial for understanding brain function and diagnosing disorders. Electroencephalography and magnetoencephalography (EEG, MEG) offer high temporal resolution for brain activity tracking but suffer from limited spatial resolution due to the few measurement electrodes. Electrophysiological source imaging (ESI) aims to overcome this spatial limitation by solving an optimization problem to infer underlying brain activity from EEG/MEG data, termed the EEG/MEG inverse problem. Traditional ESI methods involve constrained physical brain models or ad-hoc parameter estimation, while recent studies explore independent component analysis[1] and artificial neural networks[2].

However, machine learning approaches require substantial training data, which is scarce for the desired ground truth of actual brain activity. Recent studies thus use neural mass models (NMMs) to simulate brain activity and generate EEG/MEG data. In this study, we trained an artificial neural network combining a spatial encoder and a spatiotemporal translator on an NMM-generated dataset, approached the EEG inverse problem, and confirmed that this model exhibits superior localization performance compared to prior knowledge of brain structure.

The network architecture used combined a spatial encoder structure with a spatiotemporal translator structure. The spatial encoder was implemented as a multilayer perceptron with residual skip-connections. The spatiotemporal translator part consisted of a recurrent unit and a segment-based spatiotemporal prediction structure, inspired by LightTS[4]. Figure 1 provides a schematic diagram of the network.

The network was implemented using PyTorch, the standard MSE loss and the Adam optimizer was used for training.

Results

Evaluation on the test dataset generated through the neural mass model showed that the Pearson correlation coefficient between the predicted and ground truth relative regional activities was 0.85 ± 0.05 . In terms of the temporal aspect, the PCC between the signals in source regions was 0.98 ± 0.03 . This indicates that the trained network is sensitive to and accurately responds to both temporal and spatial characteristics. Figure 2A, 2B, 2C summarizes the results for one of the test dataset samples.

Figure 2D shows the result of source localization performed using the trained network for the auditory-evoked potential occurring during an auditory oddball task[5], clearly estimating the auditory cortex.

Methods

We first parcellated the brain into 994 regions of similar volume using the fsaverage template. Based on this information, we used the Jansen-Rit model [3], one of the interconnected NMMs, to randomly activate each of the 994 regions relative to the others, generating signals for each regions. From the generated signals, we extracted the time range where a spike occurred in the stimulated region.

To represent a single source, we randomly selected around 20 neighboring regions from the source region to form a group of regions. For each data point, we randomly sampled spike signals from regions within two source regions and corresponding regional groups, linearly combined them to generate a virtual signal. A forward calculation was applied to the virtual signal to generate a simulated EEG signal. The leadfield matrix used was estimated for a standard 64-channel 10-20 system EEG montage to the fsaverage template, using MNE-Python.

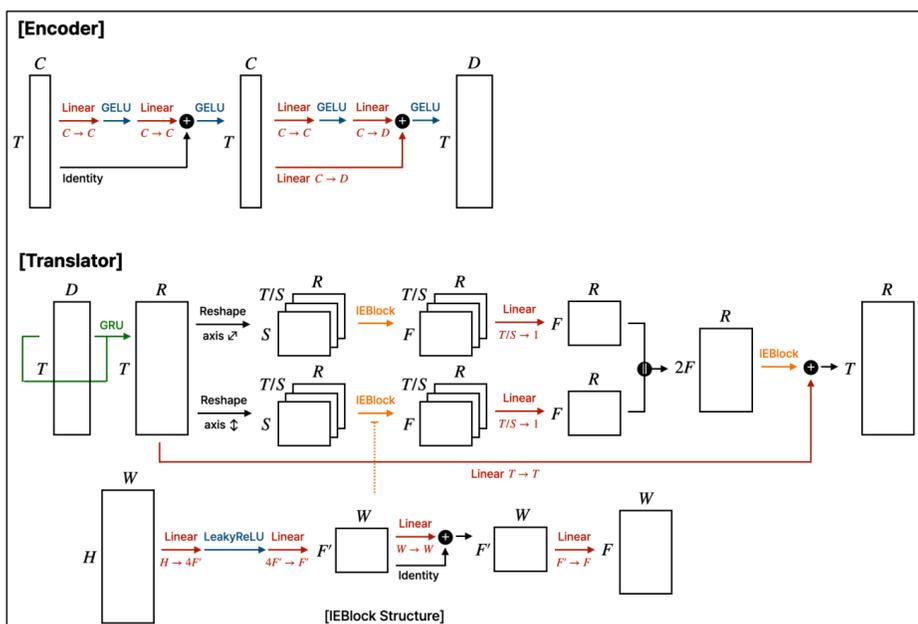


Figure 1. Schematic Diagram of the Proposed Network

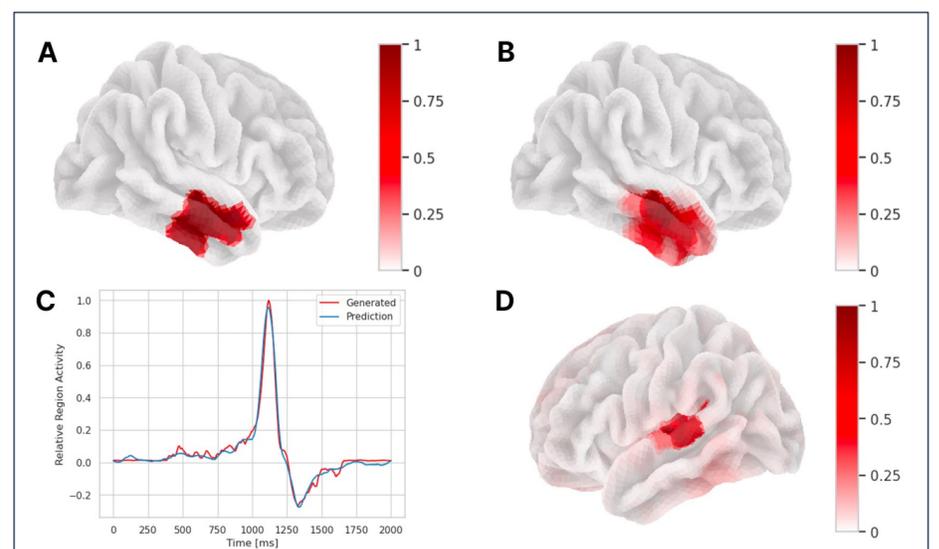


Figure 2.

(A, B) Ground Truth (A) and Estimated (B) Source of a Generated Sample Test Data
(C) Ground Truth and Estimated Potential of a Source Region of a Generated Sample Test Data
(D) Estimated Source of the Auditory-Evoked Potential Elicited in the Auditory Oddball Task

In summary, although further validation on real EEG data is still needed, the proposed neural network architecture exhibits sufficient potential for utilization in ESI by sensitively responding to both the temporal and spatial characteristics of brain activity without anatomic priors.

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