Exploring Neural Dynamics: A Long Short-Term Memory for Brain Effective Connectivity Analysis in EEG

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Introduction

- **Long Short-Term Memory (LSTM)** networks are capable of learning long-term dependencies in sequential or time series data.
- **Effective connectivity (EC)** in electroencephalography (EEG) refers to the *influence one neural system exerts over another.*
- However, model-driven whole-brain analyses of EC patterns remain challenging, an in-depth study specific to individual scenarios has not been extensively explored.
- ***We propose using LSTM to analyze EC*** on simulated EEG data as an alternative to dynamic causal modeling (DCM), which involves estimating and testing hypotheses about the directional influences between neural systems in the brain.

Jansen-Rit Model

- The Jansen-Rit model [6] is a system of differential equations (Figure 1) used to ***simulate the activity of neuronal populations in the brain***.
- It involves three different types of neuronal populations - ***pyramidal*** neurons, ***excitatory*** interneurons, and ***inhibitory*** interneurons.
- The model uses a system of ***differential equations*** to describe the time evolution of the average membrane potential for each population.
- By altering the parameters in these equations, we can simulate ***variations in brain activity*** in a given brain region.
- The activity in different brain regions can be simulated by coupling different Jansen-Rit models. By estimating these couplings from EEG recording, an EC estimate can be obtained.
- The main Jensen-Rit (JR) parameters are described in Table 1.

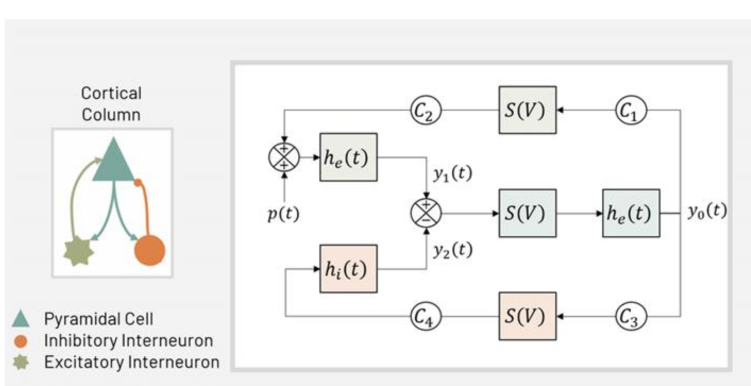

Figure 1 : The Jansen-Rit Model Illustrating Three Populations. Modified from [4].

Parameter	Description	Typical Values
A	Average excitatory synaptic gain	3.25 mV
B	Average inhibitory synaptic gain	22 mV
a	Time constant of excitatory postsynaptic potential	10 ms
b	Time constant of inhibitory postsynaptic potential	20 ms
C	Average number of synapses between the populations	135
a1	Average number of synapses established by principal neurons on excitatory interneurons	C
a2	Average number of synapses established by excitatory interneurons on principal neurons	0.8 × C
a3	Average number of synapses established by principal neurons on inhibitory interneurons	0.25 × C
a4	Average number of synapses established by inhibitory interneurons on principal neurons	0.25 × C

Table 1. Jansen-Rit parameters description and typical values.

LSTM

- LSTM networks (Figure 2) are a type of deep learning model designed to ***process sequences of data*** and make predictions.
- In scenarios where the ***mathematical model*** of a system is too ***complex*** or unknown, LSTMs can be used to approximate the system's behavior.
- In our case, an LSTM can be trained to estimate the parameters from Jansen-Rit models from EEG recordings and learn about the dynamics and the EC between different regions.

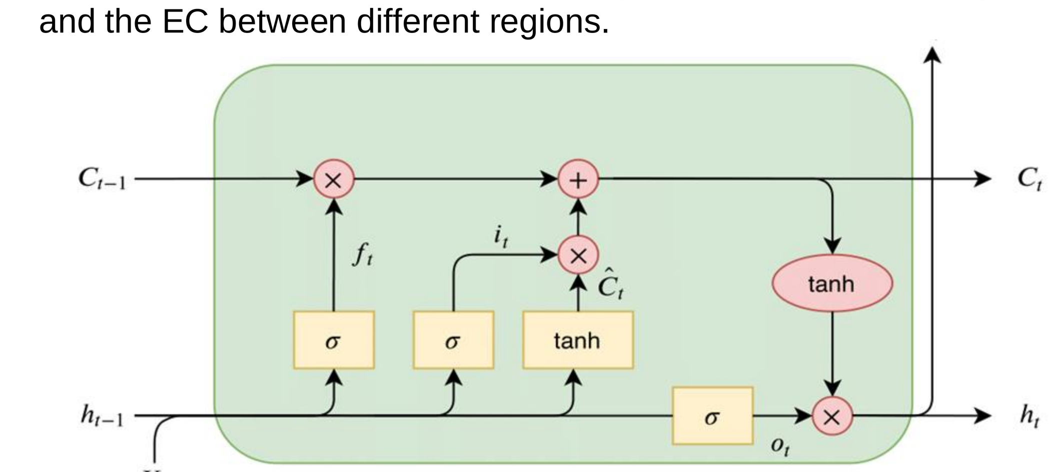

Figure 2: Long Short-Term Memory (LSTM) Model Architecture. X_t: input time step, h_t: output, C_t: cell state, f_t: forget gate, i_t: input gate, O_t: output gate. Operations inside the light red circle are pointwise. Image from [5].

Dataset Simulation

Synthetic dataset construction involved the following steps:

- We used the literature-informed model parameters, which were systematically varied to generate different neural dynamics.
- The pulse stimuli were designed to activate at every second, with the generated events driving the source simulator. We took care to discard transients at the beginning of the simulation to avoid initial condition effects, ensuring that only the stabilized responses were analyzed, thereby enhancing the validity of our results.
- This setup utilizes a subject from MNE's sample dataset for montage, creating a highly realistic EEG sensor configuration and forward model, thereby enhancing the applicability of our research.
- The simulation employed event-related dynamics to reflect responses to stimuli akin to event-related potentials (ERPs) in EEG recordings. The source activity was modeled to originate from the caudal middle frontal gyrus, using a predefined label from a cortical parcellation.
- Figure 3 shows ERP derived from our simulated sources, capturing the brain's response to specific stimuli.
- In Figure 4, we observe the Simulated Distribution of Parameters in the JR Model, which offers a view into the variability and distribution we might expect in recorded EEG data.

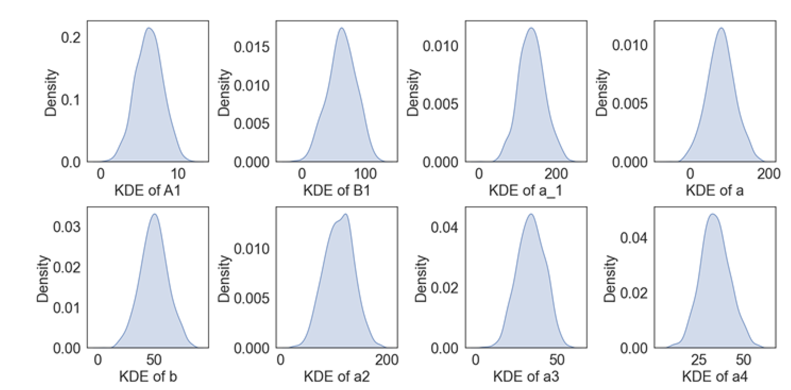

Figure 4: Simulated Distribution of Parameters in the Jansen-Rit Model.

- Figure 5 presents the topographic distribution of neural activity over time.
- Simulated experiments have been conducted **under conditions** with ***no noise interference*** (i.e., no external or internal source of noise was added to the JR simulations)

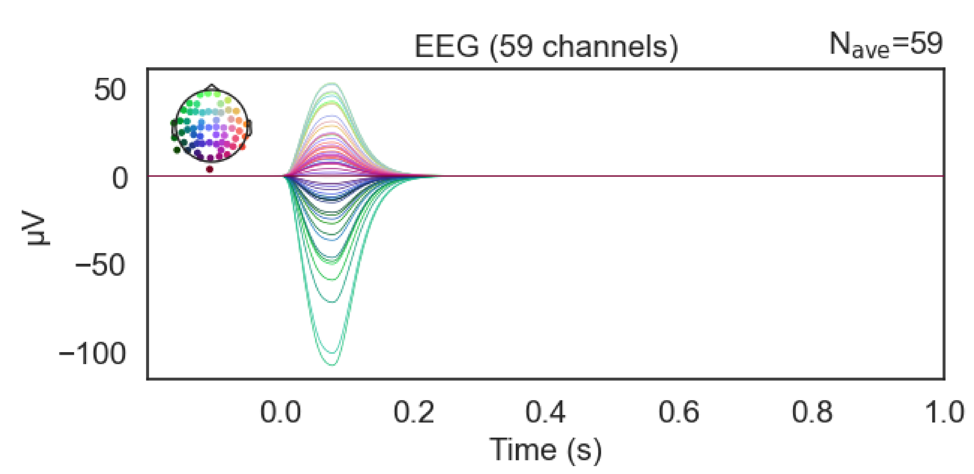

Figure 3: Event-Related Potentials (ERP) from Simulated Sources in the Jansen-Rit Model and EEG Data Simulated Using MNE-Python.

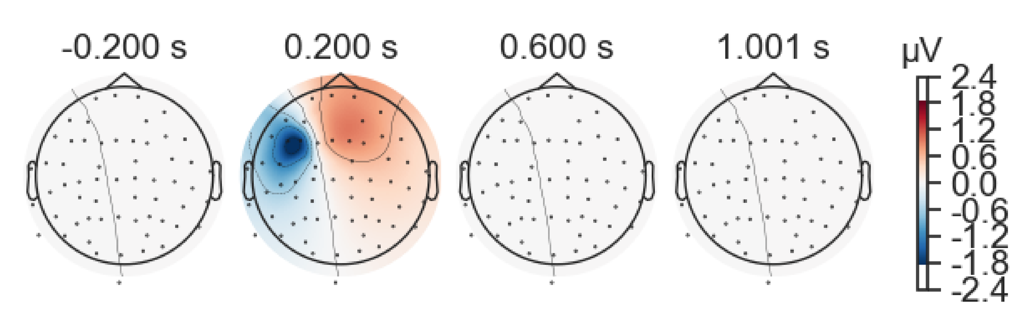

Figure 5: Topographic distribution of neural activity over time, visualized through a sequence of scalp maps. The color intensity represents the magnitude of the recorded signals, capturing dynamic changes across different time points. The peak activity observed at 0.200 s correspond to a **pulse stimulus** at ***caudal middle frontal region in the left hemisphere***.

Sensitivity Analysis of Parameters

- Before trying to learn parameters from Jansen-Rit, we performed a sensitivity analysis to determine if these parameters were learnable (i.e., if they have an impact on the simulated EEG; Figure 6).
- This analysis facilitates the understanding of how individual parameters influence the model output, which is pivotal for interpreting the underlying neural processes and optimizing model fit to empirical data.
- Particularly noticeable in Figure 6 is the distinct activity pattern associated with parameter A1, suggesting it undergoes a bifurcation as it transition from smaller values to larger values. A similar observation can be made for parameter a.

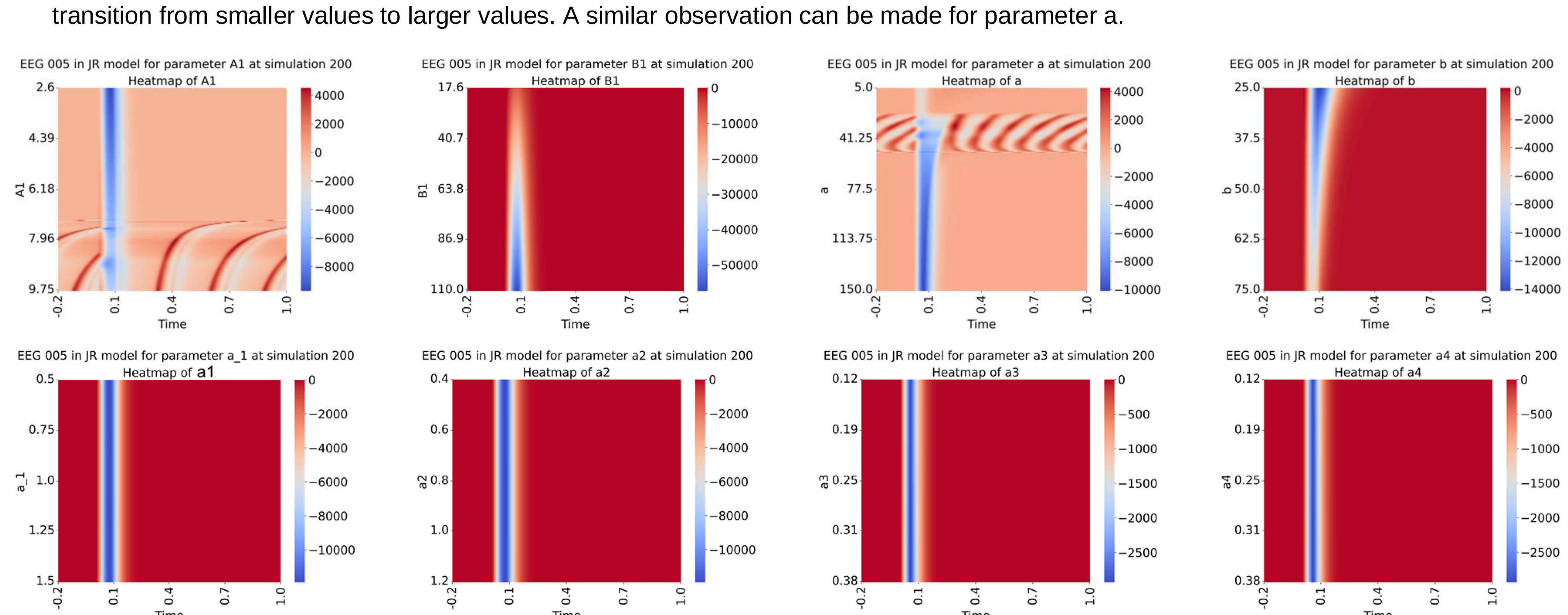

Figure 6: A comprehensive sensitivity analysis of various parameters (A1, B1, a, b, a_1, a2, a3, a4) in the Jansen-Rit model as applied to channel EEG 005. Each subplot is a heatmap illustrating the changes in parameter values over time and their effect on neural activity. The color gradients represent the magnitude and direction of the parameter's influence at different time points.

Results

- The results of the LSTM-based approach to modeling EC in EEG data demonstrate promising potential. As illustrated in Figure 7, the regression plots show ***a strong linear relationship*** between the predicted values of the LSTM model and the actual parameters of the Jansen Rit model used in our simulations.

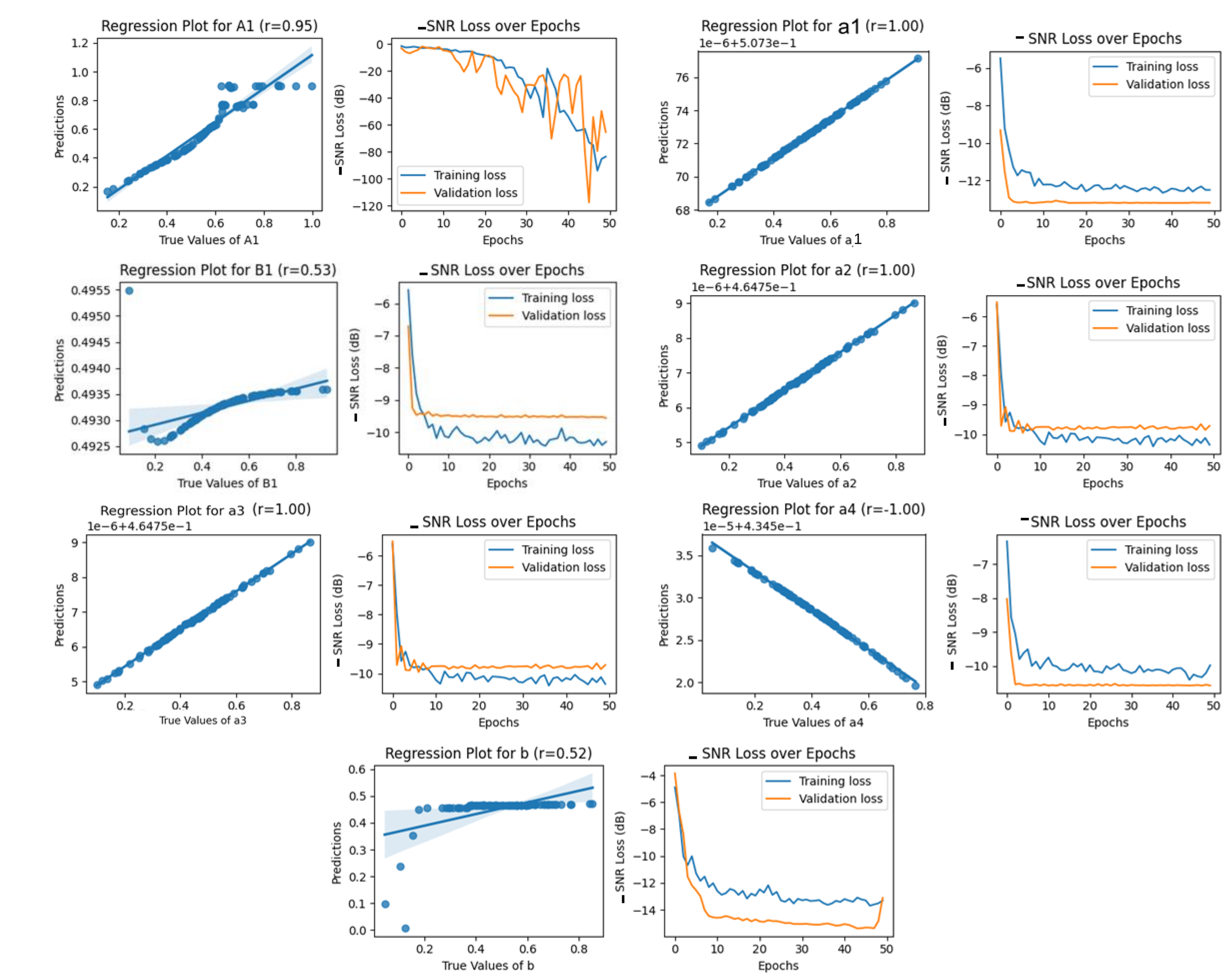

Figure 7: Regression Plots for LSTM-Based Predictions of Jansen Rit model parameters on Simulated Data.

Discussion

- We encountered challenges in deriving results for the parameter 'a' and are in the process of identifying the cause.
- The sensitivity analysis applied to the parameters of the Jansen-Rit model has highlighted their substantial impact on the EEG signal modeling, underscoring the importance of each parameter in the computational framework.
- The lower correlation for parameter B1 indicates a more complex relationship that the LSTM struggles to model. It could suggest that it is affected by more stochastic processes within the brain, or that it interacts with other variables in a way that the current model does not fully account for.
- The Signal-to-Noise Ratio (SNR) loss over epochs for each parameter provides further insight into the learning process. For parameters with a high correlation, such as a2 and a4, the SNR loss decreases and stabilizes over time, implying that the model is learning to predict these parameters with high fidelity.
- For parameters with lower correlation coefficients, such as B1, the SNR loss graphs show a reduction in loss that plateaus, indicating that while the model is learning, there is a limit to the predictability of these parameters based on the current model configuration and data.

Conclusions and Future Work

- Our study methodically focused on learning ***one parameter at a time***, which effectively ***reduced the complexity*** inherent in our problem. We found that the ***LSTM approach demonstrates a significant capacity for inferring*** and learning specific parameters of the brain's dynamical model, reducing complexity with respect to other methods like dynamic causal modelling.
- **Future work for our study**: The motivating results of these models suggest their applicability in more complex scenarios, particularly those ***involving the introduction of noise***. Also, we aim ***to extend the current model by simulating the Jansen-Rit model across multiple coupled brain regions***. This will allow us to create a more complex and detailed representation of brain activity. By estimating the couplings between these regions from EEG recordings, we anticipate being able to obtain a more nuanced estimate of EC, thereby enhancing our understanding of the intricate network dynamics within the brain.

References

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