Indian Institute of Science Education and Research, Mohali

Summer Internship Lab Report

Reconstructing STN-LFP signals using Neural Networks and Rossler Dynamics

Name - Krishna Aggarwal (MS21169)

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SUBMITTED TO:

Prof. V. Srinivasa Chakravarthy

Professor

Computational Neuroscience Laboratory

Bhupat and Jyoti Mehta School of Biosciences Building

IIT Madras

DECLARATION

I hereby declare that the following project work is an authentic record of the work I have done under the guidance of Prof. V. Srinivasa Chakravarthy in CNS Lab at IIT Madras.

Krishna Aggarwal
MS21169

ACKNOWLEDGEMENT

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Finally, I would like to thank IIT Madras for providing a conducive platform to explore and learn new sciences through this summer internship.

Introduction

The basal ganglia are a group of interconnected neurons located deep within the brain's cerebral hemispheres. They play crucial roles in movement, cognition, and the brain's exploration and decision making processes, modulated through reinforcement learning. The basal ganglia comprise several key structures, including the striatum, globus pallidus, subthalamic nucleus (STN), and substantia nigra. These components work together to execute the functions attributed to the basal ganglia.

Motor control influenced by the basal ganglia operates through two main pathways that impact the motor cortex, which is responsible for body movement and environmental interaction. The direct pathway, or the "Go" pathway, activates the thalamus, facilitating the transmission of signals to the motor cortex to initiate movement. Conversely, the indirect pathway, known as the "NoGo" pathway, inhibits the thalamus, thereby suppressing movement (see Fig. 1).

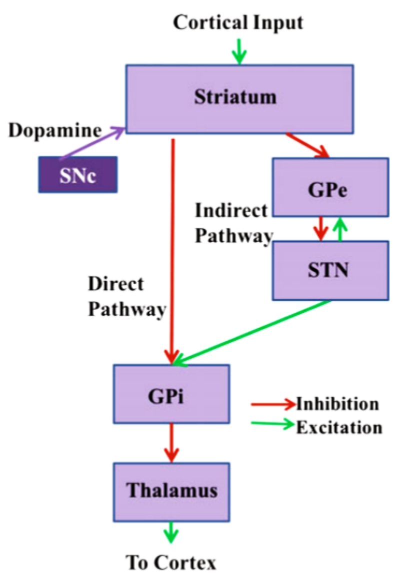


Figure 1: Schematic showing the direct and indirect pathways of basal ganglia

This project aimed to design a neural network model capable of learning and replicating the local field potential (LFP) signals generated from the STN in the indirect pathway. By accurately modelling these LFP signals, the project seeks to provide deeper insights into the neural dynamics associated with movement inhibition and decision-making processes, particularly in the context of Parkinson's Disease (PD). Understanding these dynamics could contribute to improved therapeutic strategies for managing motor symptoms in PD patients.

1 Rossler Network & Complex Coupling

The **Rössler attractor**, a system of three non-linear ordinary differential equations proposed by Otto Rössler in 1976, is notable for its chaotic dynamics. In this project, I employed Rössler network oscillators to generate the wave input signal for the neural network due to their richer dynamics, which are efficient for learning complex signals such as local field potential (LFP) signals. To achieve synchronization and stabilization of phase differences, feedback coupling and complex coupling were utilized, enhancing the learning efficiency of the model. Feedback coupling mimics the reinforcement learning effect seen in the interaction between dopamine in the Substantia Nigra pars compacta (SNc) and the Subthalamic Nucleus (STN), where it can synchronize and desynchronize the STN signals based on dopamine concentration.
Complex coupling involves using complex numbers to define interactions between different oscillators. In our Rössler network, the states x and y of an oscillator are combined to form a complex number representing the oscillator state: $Z_i = x_i + iy_i$, where i represents the no. of oscillators. The working of complex coupling could be understood by the figure below:-

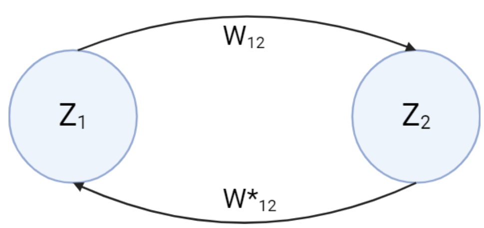


Figure 2: Complex Coupling between two oscillators Z_1 and Z_2

In the figure above, W_{12} and W^*_{12} are coupling weights used to represent the interaction between oscillators. The coupling weights between a pair of oscillators should be complex conjugates of each other. That is, if $W_{12} = a + ib$,then $W_{12}^{*} = a - ib$. The coupling weight W_{12} from Z_1 to Z_2 indicates that Z_1 is multiplied by W_{12} and the real and imaginary parts are then added to the respective states of Z_2.This process follows the equation where the coupling weights are arranged in a Hermitian matrix, which is then multiplied by the vector of Z values. The resulting matrix provides the real and imaginary parts that should be added to the x and y states of the oscillator, respectively as shown below:-

$$\begin{vmatrix} 0 & \mathrm{W}_{12}^{*} \\ \mathrm{W}_{12} & 0 \end{vmatrix} * \begin{vmatrix} \mathrm{Z}_1 \\ \mathrm{Z}_2 \end{vmatrix} = \begin{vmatrix} \mathrm{c}_1 + id_1 \\ \mathrm{c}_2 + id_2 \end{vmatrix}$$

Matrix multiplication in complex coupling

After discussing Feedback and Complex coupling in the Rossler network, Here are the modified equations of the Rossler system with feedback and complex coupling.

$$\frac{dx}{dt} = -\omega y - z + k(d - \bar{x}) + k^{'} c_i \tag{1}$$

$$\frac{dy}{dt} = \omega x + ay + k^{'} d_i \tag{2}$$

$$\frac{dz}{dt} = b + z(x - c) + I_{ext} \tag{3}$$

where x, y and z are the states of the oscillator. ω represents the frequency of the Rossler system, its value is a uniform distribution within a range of 0.8 to 1.3 for each oscillator. I_{ext} represents the cortical input(see Fig.1). d represents the set-value in feedback & k is a constant analog to the dopamine concentration. c_i and d_i are the real and complex counterparts, $k^{'}$ is the coupling constant.

Parameter	values
a	0.05
b	0.2
c	5.7
d	8
I_{ext}	0.08
k	0.01
$k^{'}$	0.008

Parameter values in Rossler Network

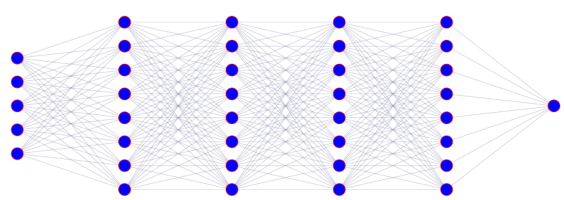
2 Neural Network Architecture

In this study, we utilized the dataset named Matrix-DBS, sourced from the University of Oxford's MRC Brain Network Dynamics Unit, containing base (PD) and DBS signals from 26 patients. The dataset served as the foundation for our investigation.

In this project, I implemented two types of Neural Networks: Feed-forward Neural Networks (FNNs) and Feedback Neural Networks (FBNs). Each network architecture was meticulously designed and deployed to analyze the dataset effectively. The following sections provide an in-depth description of the specific architectures used for each type of network and present the corresponding output results, focusing on the target Local Field Potential (LFP) signal of **patient number 20** generated by these models.

2.1 Feed-forward Neural network

This neural network is a 6-layered neural network with 4 hidden layers written in **pytorch** module. The model architecture is as follows:-



(input size,100) $\rightarrow$ (100,50) $\rightarrow$ (50,25) $\rightarrow$ (25,10) $\rightarrow$ (10,5) $\rightarrow$ (5,output size)

Where input size is equivalent to the number of oscillators, output size represents the batch size equal to 1 in the model. The LFP signal used in this study was subjected to a low band-pass filter with a cutoff frequency of 50 Hz. The filtered LFP signal, spanning a total duration of 60 seconds, was segmented for model training and testing. A 10-second segment of the filtered LFP signal was extracted for training, specifically from 0 to 10 seconds. This segment served as the training dataset, and to evaluate the model's performance, the subsequent 10-second segment of the LFP signal, immediately following the training data, was used as the test dataset. This approach ensures that the test signal is distinct from the training signal while maintaining continuity in the temporal structure of the data.

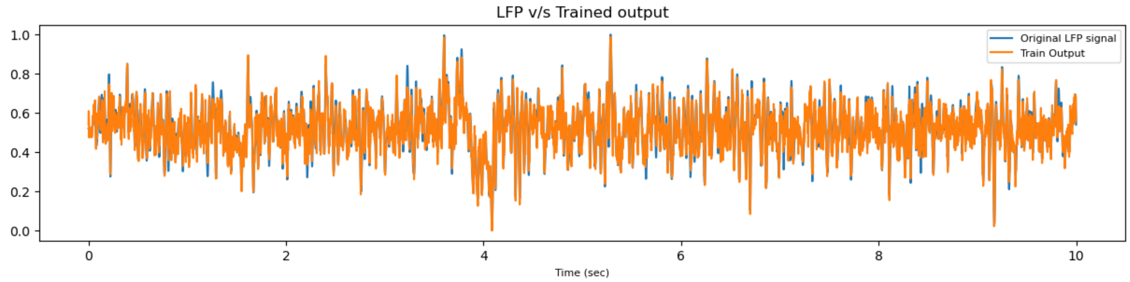


Figure 3: Plot of LFP train signal and Model Output after training

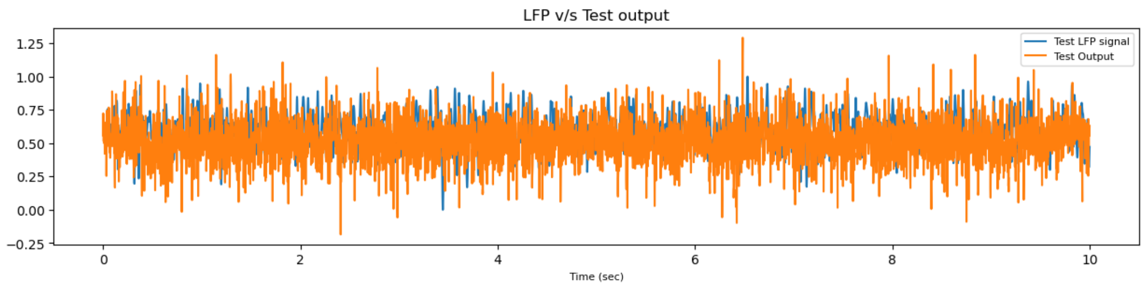
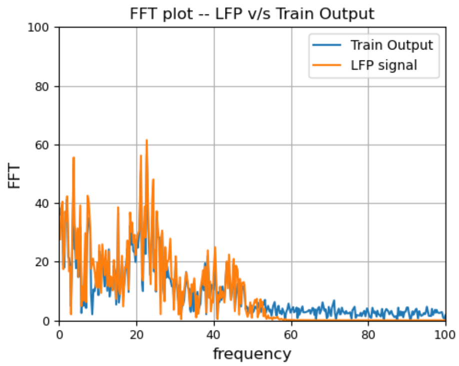


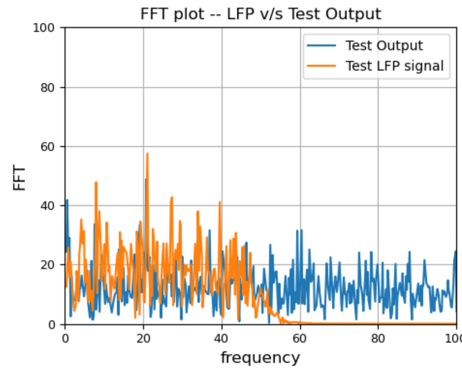
Figure 4: Plot of LFP Test signal and pre-trained model output

Figure 5: 10-second overlapped signal plots of the Local Field Potential (LFP) signal and the model output after training.

We used the Fast Fourier Transform (FFT) to compare the frequency of the model output and Local Field Potential (LFP) signals. The FFT is an efficient algorithm for computing the Discrete Fourier Transform (DFT) and its inverse. The DFT converts a sequence of values from the time domain into the frequency domain, revealing the signal's frequency components.
It was previously observed that LFP signals during Parkinson's Disease (PD) conditions exhibit a particular pattern. Unlike normal unsynchronised LFP signals, PD patients' LFP signals show synchronized behaviour in the 11-30 Hz frequency range. This phenomenon is called β synchronization and the frequency range is referred to as the β range.



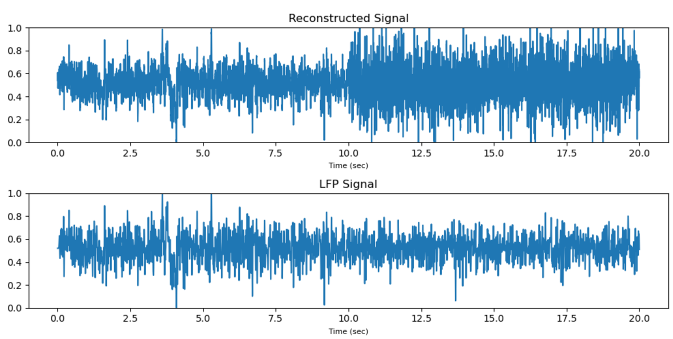
(a) FFT plot between train LFP signal and Model Output



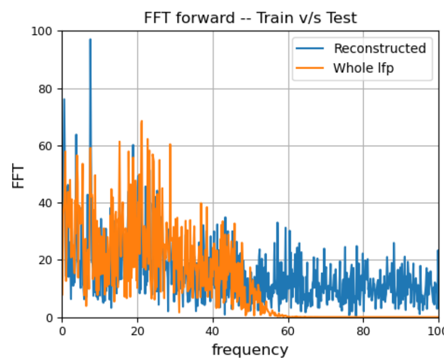
(b) FFT plot between test LFP signal and trained model output

Figure 6: Fast Fourier Transform(FFT) plots for train and test outcome of the model. There is a peak(maxima) in the β range, depicting β synchronization as observed in PD patients

The next figure would show the comparison between model output on Rossler network data and the LFP signal chunk of 20 seconds i.e. containing both train and test LFP signal.



(a) Plot of LFP signal v/s pre-trained model output



(b) FFT plot between LFP signal and model output of 20-second chunk

Figure 7: The comparison between 20-second LFP signal containing train and test signal and model output after training

These are the results, obtained by using a feed-forward neural network. The model was trained for 20,000 epochs with a learning rate of 0.01 and the sigmoid activation function was used in the hidden layers.

2.2 Feedback Neural Network

Feedback neural networks, also known as recurrent neural networks (RNNs), are a type of artificial neural network where connections between neurons form directed cycles. Unlike feed-forward networks, their architecture allows the network to maintain a form of memory, and they could capture temporal dependencies i.e. processing in a sequence of inputs. This makes them more suitable for processing sequential or time-series data.

In this model, we have used the LSTM feedback network, which uses the mechanism of gates(input, output, and forget gates), which helps in capturing complex features and helps in better flow of information. This network is better for processing long-term dependencies or longer sequence data than traditional RNNs.

The model is made in **pytorch** and contains an LSTM layer(see documentation) and one linear layer which gives a one signal array output.

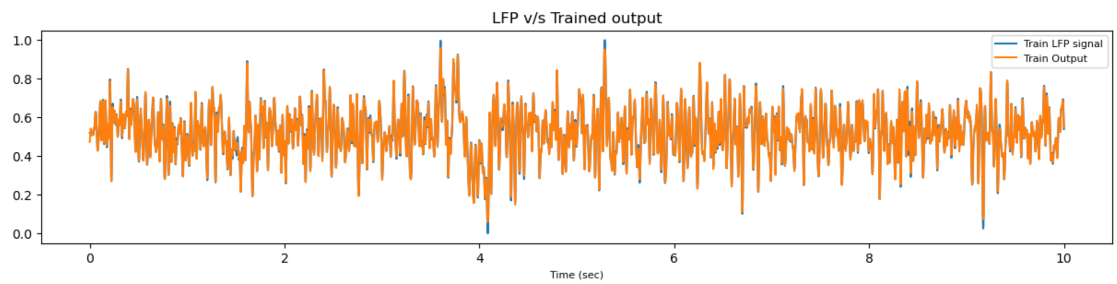


Figure 8: Plot of LFP train signal and LSTM Model Output after training

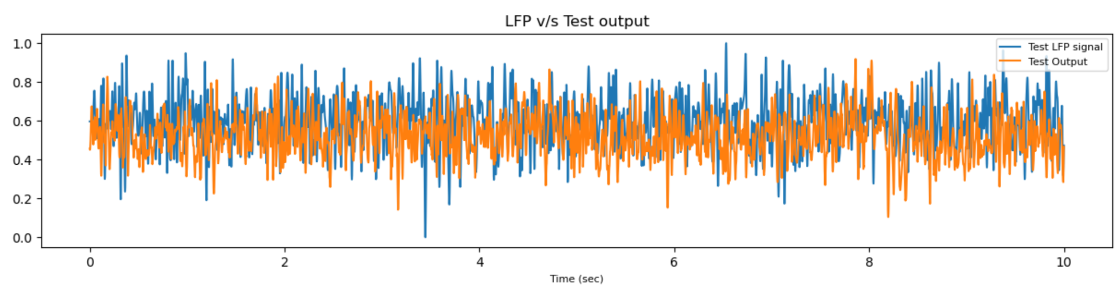
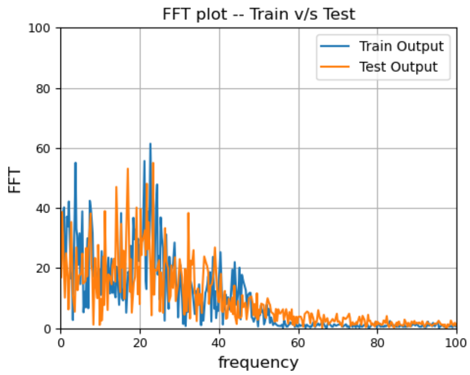


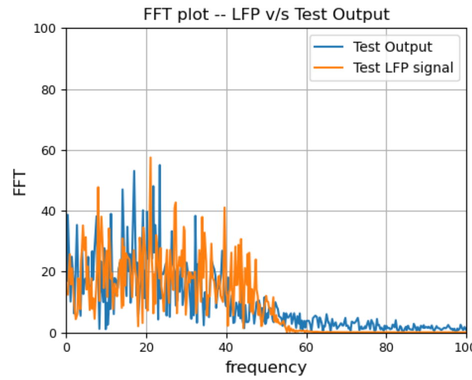
Figure 9: Plot of LFP Test signal and pre-trained LSTM model output

Figure 10: 10-second overlapped signal plots of the Local Field Potential (LFP) signal and the LSTM model output after training.

We also plotted the FFT spectrum of the LFP signal and LSTM model output after training, as shown in Fig. 11.



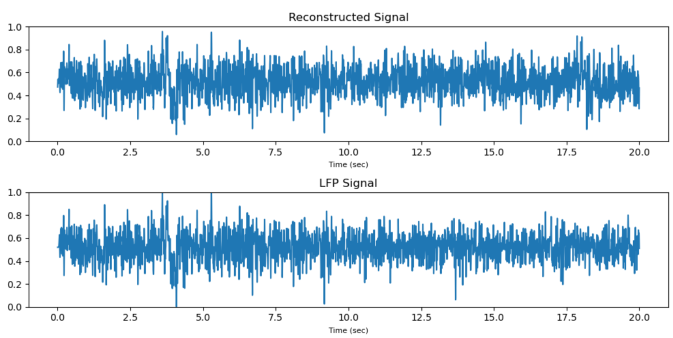
(a) FFT plot between train LFP signal and LSTM Model Output



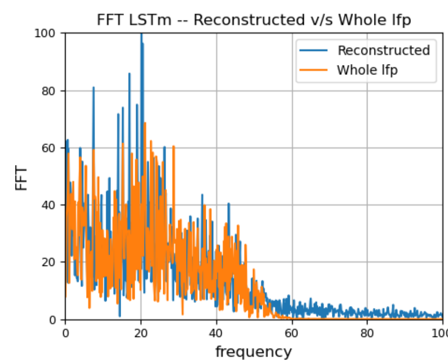
(b) FFT plot between test LFP signal and trained LSTM model output

Figure 11: Fast Fourier Transform(FFT) plots for train and test outcome of the LSTM model.

The plots above show the LFP signals' FFT spectrum and LSTM model output. Both spectra show peaks in the 11-30 Hz range (β range), thus replicating the LFP signal of a PD patient effectively.



(a) Plot of LFP signal v/s pre-trained LSTM model output



(b) FFT plot between LFP signal and LSTM model output of 20-second chunk

Figure 12: The comparison between 20-second LFP signal containing train and test signal and LSTM model output after training

These are the results obtained by using the LSTM neural network model. The model was trained for 1000 epochs with a learning rate of 0.01. The parameters used and their values for the LSTM layer are given below.

Parameter	values
Input size	5 (no. of oscillators)
Hidden size	100
number of layers	2
Output size	1

Parameters in LSTM layer

Summary

This report describes the development of a Deep Oscillatory Neural Network (DONN) model to reconstruct Subthalamic Nucleus Local Field Potential (STN-LFP) signals. The model employs an oscillator network based on Rössler dynamics, incorporating feedback and complex coupling to stabilize phase differences and achieve synchronization between the oscillators. Both feed-forward and feedback Long Short-Term Memory (LSTM) neural networks were utilized for signal reconstruction. The model's output, after training, consists of Fast Fourier Transform (FFT) plots that demonstrate β synchronization, a characteristic observed in Parkinson's Disease patients.
From the results, we conclude that the LSTM neural network outperformed the feed-forward neural network. The reconstructed signal for the 20-second chunk was better in the LSTM model compared to the feed-forward model, and the FFT plot between the LFP signal and the test output overlapped better in the LSTM model. The LSTM only required 1000 epochs to effectively learn the signal, achieving an approximate training loss value of 0.00008. In contrast, the feed-forward network took 20,000 epochs to reach an approximate training loss value of 0.00141.