Project Proposal

Ben Walker

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Single-unit recording is a method of neurological observation that produces measurements of the action potential of a single neuron over time. These measurements allow us to observe the state of a given neuron at any point in time. After observing the states of several neurons in a brain region, we would like to establish how these neurons causally influence each other, so that predictions about the structure of information flow through the region can be established. Such predictions allow us to understand the function of a brain region and how it processes information moving through it.

When pairs of connected neurons are recorded, the firing process (which rapidly decreases the potential of one neuron and increases the potential of the other) can be directly observed. However, only a small fraction of the neurons in a brain region can actually be recorded at any time, so analysis must instead find indirect causal relationships, where changes in the state of one neuron correlate with later changes in the state of another. This is a complicated problem, due to the large number of degrees of freedom in the network relative to the amount of information observed.

To find causal links between pairs of neurons, we will use a multivariate transfer entropy calculation. Transfer entropy from a random source process X to a random target process Y measures the improvement in prediction of future values of Y using past values of both X and Y over future prediction using only past values of Y [2]. The change in a neuron's state is dependent on the inputs it receives from other neurons, not its past state, so transfer entropy is well suited to measuring information flow in networks of neurons.

Because of the invasiveness of single-unit recording, this project would develop methods using large amounts of simulated data according to coupled stochastic differential equations. These SDEs will represent a system of discrete units for which the coupling interactions create information flow. From this data, we will apply transfer entropy estimators to predict the information flow.

Previous research has shown success in using transfer entropy to reconstruct known structure in simulated data [1]. However, these studies have generally used measurements from more than the small fraction of relevent neurons that can be commonly measured with single-unit recording. Thus, we seek to extend these methods to situations with sparser data.

The first stage of the project is to investigate the usage of transfer entropy on a simple system, N particles exhibiting Brownian motion in 1 dimension with time-delayed coupling, as given by the SDE

$$dX_i(t) = \sum_{j=0}^{N} k_{ij} \left(X_j(t - u_{ij}) - X_i(t) \right) dt + \sigma dW$$

where $X_i(t)$ is the position of particle i, k_{ij} is the coupling constant between particles i and j, and u_{ij} is the time delay of the connection. The goal will be to determine how information flows through the system from observations of $X_i(t)$, focusing on a sparse k_{ij} and observation of significantly fewer than N particles. We will attempt to extract information about k_{ij} and u_{ij} from these measurements.

Given two random variables X and Y, the transfer entropy $TE(X \to Y)$ To prepare for application to real data, we will next test the methods on a system of integrate-and-fire neurons. These neurons follow the SDE

$$dX_i = -g(X_i - \mu)dt + \sqrt{2\sigma}dW$$

Once the potential X_i reaches 1, the neuron fires, resetting its potential to 0 and adding or subtracting a certain amount to the potential of any connected neurons after some delay.

Once we have tested transfer entropy methods on simulated data, we can move on to analyzing experimental data.

References

[1] Shinya Ito, Michael E. Hanson, et al. Extending transfer entropy improves identification of effective connectivity in a spiking cortical network model.

[2] Michael Wibral, Raul Vicente, and Michael Lindner. Transfer entropy in neuroscience.