Model-based reconstruction of neuronal networks

Duane Q. Nykamp

January 19, 2004

Summary for Computational Neuroscience Conference

The ability to determine patterns of connections among neurons would facilitate discovering how the brain performs computations. However, it has proven difficult to estimate the connectivity from measurements of neural activity because only a small subset of neurons can be measured simultaneously. In particular, a direct connection between two measured neurons is difficult to distinguish from a connection onto both neurons from a third, unmeasured neuron. We refer to the latter configuration as the common input configuration. We address the case where one simultaneously measures two neurons in a network and attempts to distinguish the direct connection configuration from the common input configuration.

This distinction is especially difficult because one typically does not directly measure the internal state of neurons, but records only the neuron's discrete output events, called spikes. From simultaneous recordings of two neurons' spike times, one can analyze the joint statistics of the two spike trains in hopes of detecting a direct connection. Two widely used tools are the joint peristimulus time histogram (JPSTH) and its integral, the shuffle-corrected correlogram [3, 1, 2]. Unfortunately, inferences from the JPSTH or correlogram about the connections between the two measured neurons are ambiguous because these measures cannot distinguish a direct connection from common input.

The joint statistics of the two spike trains alone may be insufficient to distinguish a direct connection from common input. If one could measure the neurons inducing the common input effects, then the joint statistics of all the measured spike trains is sufficient, and one can use analysis tools such as partial coherence [4] to distinguish a direct connection from common input. However, when one cannot measure all possible sources of common input, one cannot rule out common input through partial coherence.

Our approach is to analyze the joint statistics, not just of the measured spike trains, but also of an experimentally controlled stimulus. The idea motivating this approach is that the joint stimulus-spike statistics may be sufficient to distinguish the direct connection configuration from the common input configuration even if the neurons inducing the common input are unmeasured. In particular, if the common input arises from neurons that respond to the stimulus differently than the two measured neurons do, then the distinction should be possible. This statement can be made precise in the context of a model.

Our analysis is fundamentally model-driven. The structure imposed by an explicit model gives the necessary framework to make the subtle distinction between a direct connection and common input. Here we base the analysis on a model network of interacting linear-nonlinear systems responding to a white noise stimulus. Given a network of n neurons, the probability of a spike of neuron p depends on a stimulus $\mathbf{X}$ and the spikes of other neurons:

$$\Pr\big(R_q^i = 1 \big| \mathbf{X} = \mathbf{x}, \mathbf{R} = \mathbf{r}\big) = g_q\left(\mathbf{h}_q^i \cdot \mathbf{x} + \sum_{p=1}^{n} \sum_{j \geq 1} \bar{W}_{pq}^j r_p^{i-j}\right), \tag{1}$$

where $R_q^i = 1$ if neuron q spikes at discrete time point i and is zero otherwise. The coupling parameters $\bar{W}_{pq}^j$ indicate how a spike in neuron p increases (or decreases if negative) the spiking probability of neuron q after j discrete time steps. The kernel $\mathbf{h}_p$ represents the stimulus features to which the neuron responds, and $g_p(\cdot)$ is a nonlinear function.

We focus on the case where only two neurons, say neuron 1 and 2, are measured. In this case, the only data available are the spike times of these neurons (R_1^i and R_2^i) and the stimulus $\mathbf{X}$. With this simple model, we can compute a system of equations where stimulus-spike statistics (i.e., statistics of R_1^i, R_2^i, and $\mathbf{X}$) are given as analytic expressions of the model parameters. If we assume that unmeasured neurons (neurons 3 through n) have kernels that are dissimilar to the kernels of neuron 1 and neuron 2, we can invert the resulting system of equations and solve for the direct connection strength between neuron 1 and 2. In this way we successfully remove effects due to common input.

We demonstrate that resulting method can successfully distinguish a direct connection from common input with simulations of networks linear-nonlinear neurons (i.e., model (1)) in response to white noise. The distinction is possible as long as the kernel of any neuron that gives common input is not nearly parallel (when viewed as a vector) to the kernel of neuron 1 or neuron 2. We discuss how the case of similar measured neurons may be addressed.

References

[1] A. M. H. J. Aertsen, G. L. Gerstein, M. K. Habib, and G. Palm. Dynamics of neuronal firing correlation: Modulation of "effective connectivity". *J. Neurophysiol.*, 61:900–917, 1989.

[2] G. Palm, A. M. H. J. Aertsen, and G. L. Gerstein. On the significance of correlations among neuronal spike trains. *Biol. Cybern.*, 59:1–11, 1988.

[3] D. H. Perkel, G. L. Gerstein, and G. P. Moore. Neuronal spike trains and stochastic point processes. II. Simultaneous spike trains. *Biophys. J.*, 7:419–440, 1967.

[4] J. R. Rosenberg, A. M. Amjad, P. Breeze, D. R. Brillinger, and D. M. Halliday. The Fourier approach to the identification of functional coupling between neuronal spike trains. *Prog. Biophys. Mol. Biol.*, 53:1–31, 1989.