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Reservoir Computing Using Activity-Dependent Axonal Delay

In spiking artificial neural networks (SANNs) the conduction delays between neurons, which along with the synapses determine how information is transmitted through the network, are usually constant. Conduction delays in live neurons, however, are activity dependent [1]. Here, we compare constant delays to conduction delays recorded from live neurons in a hybrid computing system tasked with predicting a complex signal. We measured axonal delays changing as much as 12 ms in response to elevated stimulation rates in living dissociated neocortical rat neurons grown on a micro-electrode array (MEA). A single electrode within the array was stimulated with a sequence of electric pulses, and responses were recorded on 59 electrodes on the MEA. Synaptic communication between neurons was blocked pharmalogically (see [2]). Recorded action potentials were thus representative of how the electrical stimulation was being processed by the axons within the culture. This processing was viewed as a 'dynamical reservoir' in a reservoir computing framework [3], by considering the stimulation pattern as an 'input' signal, the axonal responses as a randomly generated functions of this input history, and then using linear regression to map the axonal response to some desired ('computed') output.

The interstimulus intervals in the stimulation sequence were varied to simulate a signal-encoding, variable somatic firing rate. We chose to encode a recording of the speed deviation of a generator in a modeled power system, under perturbation from a 1 Hz pseudo random binary signal. This power system signal was chosen as it is an example of a difficult to predict system that is of interest to the computational intelligence community. These generator speed deviation values were first time dilated by a factor of 400, and then mapped to interstimulus intervals (between 33 and 1000ms). The 5 most responsive sorted units were used in the hybrid system. These units can be thought of as representing the spike patterns of 5 points along the axonal arbor of a single neuron whose soma fires with the stimulation pattern, or as the axons of several different neurons whose somata all fire with the same stimulation pattern. To model how a post synaptic neuron might recombine these features to form a prediction of the original input signal, we generated 5 'rate' values and 10 'coincidence' values from the first recorded responses to each pulsatile stimulus. These were then filtered to generate a total of 45 'feature' vectors. The computational utility of the set was evaluated by using it for multiple time step ahead prediction. Linear regression was used to map feature values to predictions of what the original input signal would be, between 0 and 1000 seconds ahead.

Prediction performance varied most significantly as a function of the phase of the original signal, with normalized mean squared error varying between 10.46% and 23.34%. We then compared this prediction performance with the performance of a completely artificial predictor that lacked the delay dynamics of the hybrid system. This constant-delay predictor performed better than the hybrid predictor at predicting the signal only a few seconds ahead, but was surpassed by the hybrid predictor at 300 seconds ahead prediction (corresponding to 0.75 seconds ahead prediction for the original speed deviation signal). This suggests that the commonly used 'constant delay' model for axons overestimates their utility in signal reconstruction, but underestimates their contribution to creating flexible, nonlinear transforms. It should be noted that the transformations performed by the different recorded units in this study are likely a function of both the excitability of the axons, as well as the geometric relationship between the axons and the recording and stimulating electrodes. Future studies will investigate how axonal processing can be be optimized [2] for different tasks. An improved understanding of axonal processing will enable the construction of parsimonious mathematical models to inform the creation of cutting edge SANNs [4] that can be used in more brain-like control systems.

References

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This work was supported in part NSF EFRI grant # 1238097, and NIH 1R01NS079757-01, and the ASEE SMART fellowship to RT Zeller-Townson.
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