Complex Networks of Spiking Neurons: Collective Behavior Characterization

Alexander M. Duda & Stephen E. Levinson
University of Illinois at Urbana-Champaign
Department of Electrical and Computer Engineering
Beckman Institute for Advanced Science and Technology
{amduda, selevins}@illinois.edu

Single neurons are understood to be noisy, stochastic, and in many ways unreliable. However, large complex networks of neurons are able to give rise to stable brain states that serve as the foundation for our mental states. The exact details of how this collective behavior arises and leads to the formation of a reliable system remains an open question.

We are currently investigating different ways to characterize the collective behavior observed in a large population of spiking neurons [5]. We are examining those population-level features that show a high level of stability and robustness even in spite of the instability at the neuronal-level. Specifically, we are considering a number of different spiking features and topological features that could be said to "characterize" the population of spiking neurons.

Our computational study begins with the construction of a multi-scale ab initio network of Hodgkin-Huxley (HH) neurons [4]. Using the canonical HH neuron model [7] whose axon carries three primary currents: I_K (voltage-gated persistent K^+), I_{Na} (voltage-gated transient Na^+), and I_L (Ohmic leak), we allow the directional strength of connection (synaptic weight) to evolve according to a Hebbian plasticity rule [6, 9] based on the synchronous spiking of adjacent neurons. The network is initialized with an adjacency matrix capturing a reasonable spatial distribution (the strength of connection between neurons has an inverse dependence: those that are spatially near one another are likely to have a strong non-zero connection while those that are spatially far from one another are likely to have a very weak non-zero connection).

Neurons in the network are then fed signals from the outside world. (We are in the process of running the model on an NCSA supercomputer and connecting it to Bert, an iCub humanoid robot designed by the RobotCub Consortium). Over time, the signals sent to the population will cause the synaptic weights to evolve throughout the network. We are interested in characterizing this evolution and enabling a mapping between the signals sent to the sensors in Bert and the dynamic trajectory a population traverses. We are currently investigating a number of ways to characterize this trajectory and determining which metrics are most robust for a given sensory input.

Specifically, we are examining different spiking features: phase synchrony [3, 2], spike timing, spatial spike clustering, temporal spike clustering, and spiking density. Furthermore, we are examining different topological features: diameter, degree distribution [10, 1], weighted path distribution, time until paths of a given weight emerge, expected diffusion radius, diffusion time, and emergence of directed subgraphs with certain canonical structure (K_n, C_n, etc.). We are developing methods to measure these features in real-time and use them as a means of building an associative memory [8, 11].

We will explain some of the aforementioned features and the methods used to measure them. Moreover, we will review their performance as a means of mapping real-world objects to neuronal population representations.

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