Spiking network simulations

Tim U. Krause, Phil Y. Schrör, and Rolf P. Würtz

Institut für Neuroinformatik, Ruhr-Universität, Bochum, Germany
e-mail: utz.krause@web.de, phil.schroer@rub.de, rolf.wuertz@ini.rub.de

Action potentials, also called spikes, are a very widespread, though not universal, communication mechanism between neurons. Their biophysics are well understood and extensively modeled [1, 2].

It is less well known what the precise code of these spike trains is. Classically, it is assumed that the *frequency* of spikes codes for the activation of the neuron. The evidence for that is strong at the sensory and motor end of the nervous system. It takes, however, relatively long integration times (at least 3 spikes) to measure such a frequency for further processing. Therefore, a system using this code throughout would be rather slow. Also each spike costs energy, and it would be rather inefficient to require many spikes for some bits of information.

On the other hand, the timing of spikes carries much more information than the frequency, to a theoretical limit of a real number for each spike. That precision is, of course, also limited by the noise on the timing. There is a continuum of possible codes from pure frequency coding to relevant information carried by a single spike time.

To speed up processing, it has been suggested by Thorpe [3] that the order of arrival times of spikes at a neuron can distinguish between $w!$ cases, with w the number of incoming synapses. We have exploited that idea for learning of (arbitrary) invariances by rank-order coding [4, 5]. We could also show that timing noise as well as interfering spikes from bursting can be tolerated to a certain extent without breaking the performance of the network.

Furthermore, it has been observed in real neurons that the precise timing of spike arrival can be an important variable for plasticity or weight learning. This phenomenon is called spike-time dependent plasticity (STDP) [6, 7].

Beyond biological relevance the question arises what technical problems can be solved by computation based on spike-times. We have started to explore that question experimentally by computer modelling. In the current work we will completely abstract from spike shape and propagation dynamics and describe each spike by a single floating point number, which is its creation time.

For that view, a neural network consists of a directed graph with neurons as nodes and connections as edges. Edges have two scalar properties. The first is the classical *weight*, which specifies how much the potential of a postsynaptic neuron is changed by one incoming spike. The second is the time one spike needs to travel from the creating neuron to the postsynaptic one, which we will call *delay*.

Neurons accumulate incoming weighted spikes in a local *potential* and create a new spike once a threshold has been passed. The second relevant parameter for neurons is the *decay rate* of the potential, the third a possible *refractory period*, during which incoming spikes have no effect.

The evolution of the network is calculated by adding delays to creation times, updating neuron potentials, and recording new spikes. We have built a simulator [8] to model such a network efficiently by simple bookkeeping of the times new spikes are created in the network. The implementation is able to simulate large numbers of spikes, such that comparisons between rate coding and temporal coding can be made.

We present first results on small networks like a frequency bandpass filter, a coincidence detector, and a fully connected network. We also compared STDP to rate-based Hebbian learning in a feedforward network in a supervised training mode.

We have made some experiments on image segmentation [9], which must be fast to account for the speed of perception.

Future applications will include more learning experiments. A particularly interesting question is how delays can be learned (by, e.g., by myelinization), what the time constants and implications for information processing are.

References

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