On the Adapative Capabilities of Pulse-Coded Cable Neurons

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Abstract

We present various possibilities to implement adaptive behaviour of cable neurons and show their qualitative effect. We argue that incorporating these possibilities in local learning rules (or schemes) can account for adaptation that combines spatial and temporal properties. Experiments with a phasic XOR explain why a local learning rule based on detection of coincidence of a high local potential in the cable and the arrival of an input pulse, renders a network capable of performing the XOR function.

Neural networks that involve cable neurons, 1 bit delayed interconnections and group forming local learning rules could form the basis of neural systems with performant spatio-temporal information processing capabilities(1). Nevertheless, the Achilles' heel of this approach seems to be the local learning rule. Work on local learning rules is just starting, but it is already shown that local learning rules, apart from group formation(2), can account for conditioning(3) and certain biological phenomena(4, 5). And although no direct supervisor or gradient descent learning is possible, e.g. for quasi-supervised backprop at least error descent can be guaranteed(6).

In earlier work we demonstrated that, in a fixed network architecture, a simple local learning rule, which basically increments a weight upon detection of coincidence of a high post-synaptic potential and the arrival of an action potential at the very same synapse, could account for learning a tonic version of the classical XOR-problem with a low frequency input standing for a 0 and a high one for a 1 (3). In this paper we question why it does so and whether changing a weight is the sole or even the best way to implement adaptive behaviour. In fact, cable neurons provide for various a surplus of possibilities for adaptive behaviour as compared to add-multiply neurons. The latter can only be adaptive by changing their weights. Apart from this, the behaviour of cable neurons moreover is influenced by:

- The shape of the input pulse.
- The distance of an input from the soma, or more precisely from the axon hillock.
- In principle by all membrane variations. Here we will only consider change of R_i, the axial internal resistance, or R_m, the membrane resistance, as well as changing a neuron's geometry.
- By splitting an input in a number of equally or not equally delayed fractions that end in different synapses at different places.

Each kind of parameter has its own characteristic influence on a neuron's behaviour and might interfere for different purposes (e.g. synchronisation, control, etc.) and on different time scales (e.g. long for R_i, synapse placement or neuron layout; short for R_m, weight).

References

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