A simple spiking neuron model based on stochastic STDP

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1. Framework

STD. Thought to be responsible for memory, synaptic plasticity is the change of strength of neuron’s links. Popular plasticity models are based on Spike Timing Dependent Plasticity (STD):

Hebb’s law (1949): “When an axon of cell A, "firing regularly with some degree of accuracy, takes part, however briefly, in firing another cell B, [ . . . ] the efficacy of the connection between them is increased.”

Problem: Current models use deterministic plasticity rules whereas the biological mechanisms involved are mainly stochastic ones. Moreover, there exists few mathematical studies that take into account the precise spikes timings. Finally, there is a need to understand how the time scale gap at the synapses and how weights dynamics interplay with the network one.

Novelty: Stochastic STD rule with discrete synaptic weights which allows a mathematical analysis of their dynamics.

2. Model constraints

• Rich enough to reproduce biological phenomena
• Simple enough to be analyzed mathematically and simulated
• Observe global properties of the network due to neurons firing

5. Simulations

Biologically coherent parameters:

Even if simple, our model depends on many parameters. First, let’s detail the probability to jump:

\[ p^+(s) = \frac{1}{4} \text{ and } p^-(s) = \frac{1}{2} \text{ for } s > 0 \]

Such functions enable to close to biological experiments:

In that particular case, \( \lim_{s \to -\infty} \tau_{w,\epsilon}(s) = \tau_{w,\epsilon} \) and we can prove the process converges to its unique invariant measure if \( \tau_{w,\epsilon} > 0 \). We computed, thanks to (1), the difference \( r_w(w) - r_w(\epsilon) \). It depends on \( \omega = (w_1,w_2) \). We found parameters: \( \tau_{w,\epsilon} = 0.8, \alpha = 0.7, w_{2,\epsilon} < 70 \), for which \( w_2 \) diverges when the integral of the learning window is negative:

\[ \int_{t=0}^{T} \frac{w_2(t) - w_2(\epsilon)}{\tau} = \int_{t=0}^{T} \frac{w_2(t) - w_2(\epsilon)}{\tau} \]

10 neurons:

When depression is really higher than potentiation, weights seem to converge to a stationary distribution and have such trajectories:

However, initial weights play an important role. With parameters \( \alpha = 0.8, \beta = 0.9, \beta = 1, \epsilon = 0.03, w_2(\epsilon) = 0.5 \) and \( \epsilon = 0.1 \), we have no divergence in short time with low initial weights and selection of one weight from big initial ones, \( W_1 = 50 \).

The selected weight is different from one trajectory to another.

References