A simple spiking neuron model based on stochastic STDP
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5. Simulations

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

\[ p^r(x) = A_r e^{-\frac{x}{\beta}} \quad \text{and} \quad p^s(x) = A_s e^{-\frac{x}{\alpha}} \]

Such functions enable to close to biological experiments:

Parameters for the figure are: \( A_r = 1 \), \( \beta = 0.4 \), \( A_s = 0.1 \), \( 100 \text{ms} \) as in [6]. These parameters have to be adjusted to fit the first ones \( \beta, \alpha, A_r, A_s \). Time of influence of a spike 1ms so \( \beta = 1 \). Firing rates of neurons are bounded by \( \alpha, \beta \) \( \beta \). STDP parameters are in the following range: \( \tau^r_{\text{max}} \in [2, 40] \). \( A_{\text{max}} \in [0, 1] \). Finally, \( v \in [0, 1] \).

Analytic versus Numeric: First, we wanted to visually show our limit model is licit. In simulations, an easy value to get is the sum of jump weights of neurons:

\[ w_{ij} = \int_{0}^{1} p^r_{\text{jump}} d\tau + \int_{0}^{1} p^s_{\text{jump}} d\tau \]

We get similar results in the case of 2 neurons. In higher dimension it is hard to get equivalent analytic and numerical precision.

Weight divergence: A big problem in plasticity models is the divergence of weights. We could have put hard bounds or soft bounds but we wanted to see in which limits weights diverged without them. We tested some criteria of non divergence of weights in our model. In particular in the article [7], such criteria is to have the integral of the learning window negative. Nevertheless, it is not the case for our model. In a real simple case, our limit model enabled us to find parameters for which this criteria leads to a weight divergence.

One weight free and 2 neurons: We get a birth and death process with \( w_{12} \) fixed, \( w_{21} = w_{12} + \Delta w_{12} \rangle; \quad r_{12} \rangle; \quad r_{21} \rangle; \quad r_{21} \rangle; \end{eqnarray}\]

In that particular case, \( \Delta w_{12} \) \( w_{12} \in [0, 1] \) \( \beta = 1 \). \( \alpha = 0.5 \) and \( v = 0.1 \), we have no divergence in short time with low initial weights and selection of one weight from big initial ones, \( W_{12}^{\text{max}} = 50 \).

The selected weight is different from one trajectory to another.

6. Conclusion

We showed divergence of weights even when integral of the learning window is negative. Additive terms, depending on weights, seem necessary to avoid divergence in the context of biophysical parameters. However, our first mathematical results are encouraging for deeper study and our model showed more interesting behavior than those already presented: bidirectional as unidirectional connections can be strong.

7. Perspectives

Maths:
- Weight dynamics
- Mean field approximations

Modeling:
- Simulations to test other plasticity rules
- Neuronal states from discrete to continuous

References
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