Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 119 (2017) 166–173

Procedia Computer Science

www.elsevier.com/locate/procedia

6th International Young Scientists Conference in HPC and Simulation, YSC 2017,
1-3 November 2017, Kotka, Finland

On the effect of stabilizing mean firing rate of a neuron due to STDP

Alexander Sboev[a,b], Roman Rybka[a], Alexey Serenko[a]

[a]*National Research Centre "Kurchatov Institute", Moscow, Russia*
[b]*MEPhI National Research Nuclear University, Moscow, Russia*

Abstract

We show by numerical simulations that a neuron with additive Spike-Timing-Dependent Plasticity with restricted symmetric nearest-neighbor spike pairing scheme, receiving Poisson input, establishes mean firing rate that does not depend on input rates, in a sufficiently high range of input rates. The established rate also does not depend on the number of inputs and the existence of inhibitory inputs, and depends only on the neuron and STDP parameters. A possible way to utilize this effect in learning is shown.

Peer-review under responsibility of the scientific committee of the 6th International Young Scientist conference in HPC and Simulation

Keywords: Spike-Timing-Dependent Plasticity; spiking neural networks; computational neuroscience

1. Introduction

Spike-Timing-Dependent Plasticity [1], a biologically inspired Hebbian long-term synaptic plasticity model, gains interest not only from biological, but also from practical point of view. Involving just presynaptic and postsynaptic spike timing, STDP is attractive to be implemented on memristive devices [2], because, unlike conventional back-propagation which is performed offline [3], STDP can be implemented directly on the chip. This gives relevance to the question of utilizing STDP for practical learning purposes.

STDP was already used in a clusterization task [4], but no algorithm for classification has yet been developed. The principal possibility of supervised STDP learning to restore desired synaptic weights on base of input and output trains prepared in advance was proved in [5] for the all-to-all spike pairing scheme. Our previous work [6] numerically reproduced the results of Legenstein for three nearest-neighbour pairing schemes and showed that the weights convergence is possible with the presynaptic-centered and the restricted symmetric schemes, but not with the symmetric one (see Section 2.1 for the explanation of the schemes).

E-mail address: serenko@phystech.edu

1877-0509
Peer-review under responsibility of the scientific committee of the 6th International Young Scientist conference in HPC and Simulation
10.1016/j.procs.2017.11.173

At the same time, another mentioned [7] feature of additive STDP is its ability to modify the synaptic weights so that to sustain a certain persistent mean firing rate of a neuron. This was previously proven analytically [8] for the presynaptic-centered spike pairing scheme. The goal of this paper was to assess numerically the rate stabilizing effect for the other spike pairing schemes. In Section 3.1 we show that for the restricted symmetric scheme the sustained mean output rate does not depend on the input rates (except for high input rates, in which case all synaptic weights are potentiated), number of inputs, and existence of inhibitory inputs. It does, however, depend on the STDP (Section 3.2) and neuron (Section 3.3) parameters.

Thereby, the rate stabilizing effect holds for the same spike pairing schemes, for which the weights convergence under the protocol of Legenstein is possible.

The advantage of the rate stabilizing effect is the possibility to utilize it for learning with input encoded by mean frequencies of spike trains. We briefly show the possibility of such an approach in Section 4, training two neurons to distinguish two classes of random binary vectors.

2. Methods

2.1. Synaptic plasticity model

In Spike-Timing-Dependent Plasticity a synaptic weight $0 \leq w \leq w_{\max}$ changes by Δw according to the relative timing of presynaptic spikes t_{pre} and postsynaptic spikes t_{post}:

$$\Delta w = \begin{cases} -\alpha\lambda \cdot \left(\dfrac{w}{w_{\max}}\right)^{\mu_-} \cdot \exp\left(-\dfrac{t_{\text{pre}} - t_{\text{post}}}{\tau_-}\right), \text{if } t_{\text{pre}} - t_{\text{post}} > 0; \\ \lambda \cdot \left(1 - \dfrac{w}{w_{\max}}\right)^{\mu_+} \cdot \exp\left(-\dfrac{t_{\text{post}} - t_{\text{pre}}}{\tau_+}\right), \text{if } t_{\text{pre}} - t_{\text{post}} < 0. \end{cases} \tag{1}$$

Here $\lambda = 0.01$ is the learning rate that can be chosen as small as the computational resources permit, , $\alpha = 1.035$ and $\tau_+ = \tau_- = \tau = 20$ ms were chosen as in [9]. We consider additive STDP with $\mu_+ = \mu_- = 0$, because non-additive forms with $0 < \mu \leq 1$ are not expected to exhibit the rate stabilization effect due to lack of competition between synapses [10].

In case of additive STDP the additional constraint is needed to prevent the weight from falling below zero or exceeding the maximum value $w_{\max} = 1$:

$$\text{if } w + \Delta w > w_{\max}, \text{ then } \Delta w = w_{\max} - w; \text{ if } w + \Delta w < 0, \text{ then } \Delta w = w.$$

An important part of STDP rule is the spike pairing scheme. In the all-to-all scheme each postsynaptic spike is taken into account in the rule 1 with all preceding presynaptic spikes and each presynaptic spike is paired with all preceding presynaptic ones. There also exist several nearest-neighbour schemes that are worth studying because used in highly cited literature [1]. We consider the restricted symmetric scheme (C in Fig. 1).

2.2. Neuron model

Our previous findings [11] showed that the choice of the neuron model does not qualitatively affect the STDP features under consideration. So we used the Leaky Integrate-and-Fire neuron, with the membrane potential dynamics

$$\frac{dV}{dt} = \frac{-\left(V(t) - V_{\text{resting}}\right)}{\tau_{\text{m}}} + \frac{I_{\text{syn}}(t)}{C_{\text{m}}},$$