Available online at www.sciencedirect.com

ScienceDirect

Neurocomputing 70 (2007) 2009–2016

NEUROCOMPUTING

www.elsevier.com/locate/neucom

Temporal pattern identification using spike-timing dependent plasticity

Frédéric Henry[a,*], Emmanuel Daucé[a,b], Hédi Soula[c]

[a]*Movement & Perception (UMR6152), Faculty of Sport Science, University of the Mediterranean, 163, avenue de Luminy, CP910, 13288 Marseille CEDEX 9, France*

[b]*École Centrale de Marseille, Technopôle de Château-Gombert, 38, rue Joliot Curie, 13451 Marseille Cedex 20, France*

[c]*Physiopathologie des Lipides et des Membranes, Institut National des Sciences Appliquées, Bâtiment Pasteur, 69621 Villeurbanne Cedex, France*

Available online 9 November 2006

Abstract

This paper addresses the question of the functional role of the dual application of positive and negative Hebbian time dependent plasticity rules, in the particular framework of reinforcement learning tasks. Our simulations take place in a recurrent network of spiking neurons with inhomogeneous synaptic weights.

A spike-timing dependent plasticity (STDP) rule is combined with its ‘‘opposite’’, the ‘‘anti-STDP’’. A local regulation mechanism moreover maintains the postsynaptic neuron in the vicinity of a reference frequency, which forces the global dynamics to be maintained in a softly disordered regime.

This approach is tested on a simple discrimination task which requires short-term memory: temporal pattern classification. We show that such temporal patterns can be categorised, and present tracks for future improvements.

Keywords: Synaptic plasticity; Spike-timing dependent plasticity; Random recurrent neural network; Dynamics reduction; Reinforcement learning

1. Introduction

Since the first observations of synaptic plasticity [3], the measurement techniques have considerably grown up. Important interest has recently come over the fine dependence on the timing of spike arrival in the synaptic potentiation or depression phenomena. Those time dependent mechanisms have been popularised as ‘‘spike-timing dependent plasticity’’ (STDP), and various models and implementations have been proposed. It can be noticed, however, that both ‘‘positive’’ and ‘‘negative’’ spike-timing dependences have been observed, depending both on the animal and on the location. At the present time, too few measurements have been made for an exhaustive description of the spike-timing dependent rules to be given.

More generally, the biological mechanisms of knowledge acquisition and memory formation remain at a very early stage of understanding. We propose in the present paper to explore the mechanism of a dual application of STDP and anti-STDP for the realisation of a classification task in an artificial neural network. The idea is to use the spontaneous capacity of random recurrent neural networks to form complex patterns of activity, and to use STDP and anti-STDP mechanisms as positive and negative reward to ‘‘shape’’ those patterns of activity in order to fulfill at best the external constraints.

Our paper is organised in the following way. The second section gives the model of neuron, the STDP rule, and the structure of the network we simulate. The third section presents some basic features on the effect of STDP and anti-STDP on the local and global neuronal dynamics. In the fourth section, we present the simulation results of the main learning task we use: a temporal sequences classification task. The fifth section gives our conclusions and tracks in terms of biological plausibility and future improvements.

2. Neuron and network models

We are mainly interested in the group behaviour of artificial neurons. For that, we simulate rather simple and classical models of integrate-and-fire neurons.

*Corresponding author.
E-mail address: fred@reveries.info (F. Henry).

0925-2312/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2006.10.082

2.1. Neuron model

The model of neuron we use is the leaky integrate-and-fire [13]. This well-known model does not fulfill every biological constraint, but reasonably models the temporal behaviour of spiking neurons. It is easy to implement, and thus allows the simulation of large networks on long periods of time.

We actually use a discrete implementation of this model where a time step roughly corresponds to 1 ms. The membrane potential of neuron i at step t is given by

$$u_i(t) = \gamma u_i(t-1) + \sum_{j=1}^{N} w_{ij}\delta(t - T_j), \tag{1}$$

where γ is the neuron's leak, w_{ij} the synaptic weight from neuron j to neuron i, T_j the date of the last EPSP arrival from neuron j, and δ is the discrete Dirac.

If $u_i(t) > \theta_i(t)$, the neuron fires, and its potential is reset to its resting potential 0. In our model the threshold is noisy: $\theta_i(t)$ is given by a Gaussian process of mean $\bar{\theta} = 1.0$ and standard deviation $\sigma_\theta = 0.2$.

2.2. Learning rule

Our synaptic update rule is a particular implementation of the STDP [2], where the long-term potentiation is additive while long-term depression is multiplicative [14]. The weight change Δw depends on the temporal difference $\Delta t = t_{\text{pre}} - t_{\text{post}}$ between the pre-synaptic EPSP arrival and the post-synaptic spike. The weight change is given by $\Delta w = F(\Delta t)$ with

$$F(\Delta t) = \begin{cases} A_+ \alpha\, e^{\Delta t/\tau} & \text{if } \Delta t < 0, \\ -A_- \alpha w\, e^{-\Delta t/\tau} & \text{if } \Delta t > 0, \end{cases} \tag{2}$$

where A_- and A_+, and α are the learning coefficient, and τ is the relaxation rate. We set $\tau = 10$ and $A_+ = 1$; thus two parameters are still needed in order to characterize the rule: α and A_-. The "anti-STDP" simply corresponds to a STDP with a negative α.

2.3. Network structure

The network we simulate belongs to the category of random recurrent neural networks. All the synaptic weights are set according to a Gaussian draw (see Fig. 1 for the precise parameters). Those parameters are set in order to allow the internal self-sustained activity to compete with the external stimulation. It can be noticed that a precise analysis of the spontaneous activity of comparable random networks of integrate-and-fire neurons is given in [11].

In this particular setup, we use a three-layer network. The first layer is composed of input neurons, which receive the signal from the environment. Those neurons send connections toward every neuron of the internal layer. The internal layer is composed 100 of fully connected neurons. At last, some output neurons receive synapses from the

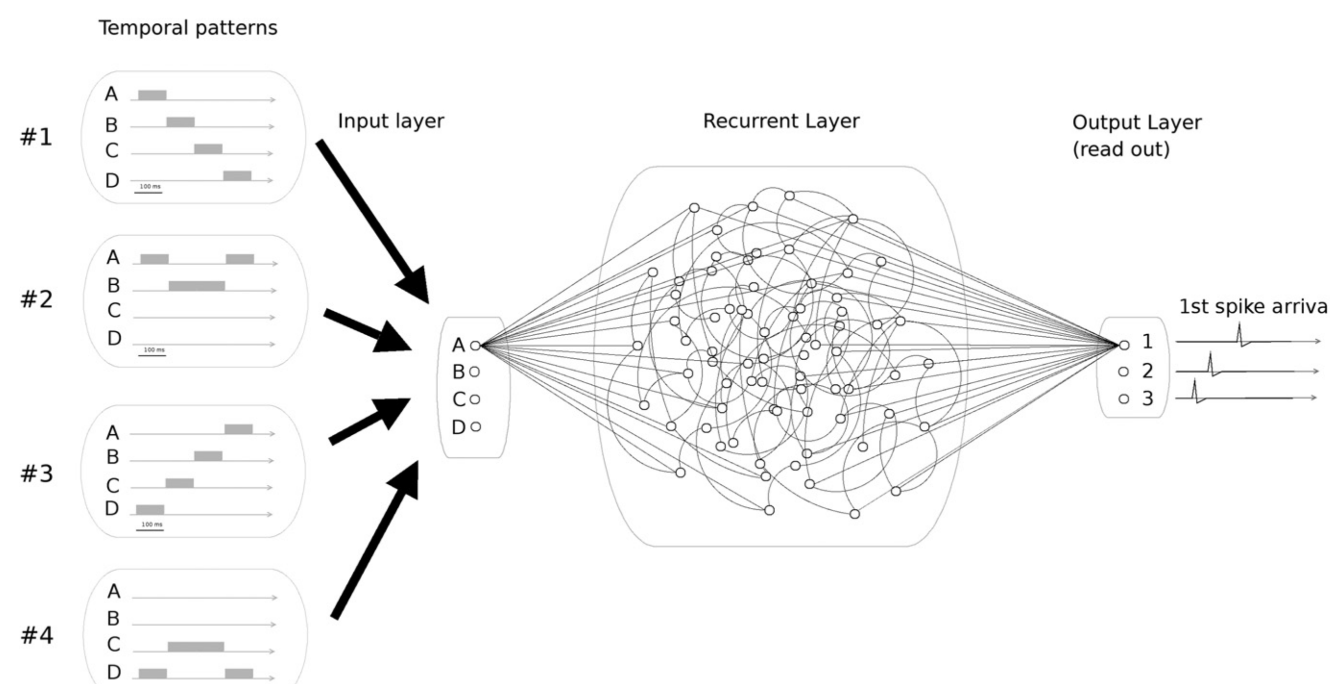

Fig. 1. Experimental setup. P temporal patterns (here $P = 4$) are to be presented to the network in order to be classified in K categories (here $K = 3$). The network is composed of three populations. The input layer is composed of 4 neurons (labelled A, B, C and D). The input connections follow a random Gaussian draw of mean zero and standard deviation 0.04. The hidden layer contains 100 fully connected neurons. The recurrent connections follow a random Gaussian draw of mean 0 and standard deviation 0.02. The output layer is composed of K neurons, with lateral inhibition (the lateral links are not represented). The output connections follow a random Gaussian draw of mean 0.09 and standard deviation 0.01. The lateral links values are homogeneous (−1).