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A new biologically plausible supervised learning method for spiking neurons

Aboozar Taherkhani, Ammar Belatreche, Yuhua Li and Liam Maguire

Intelligent Systems Research Centre, University of Ulster, U.K.

Abstract. STDP is believed to play an important role in learning and memory. Additionally, experimental evidence shows that a few strong neural inputs can drive a neuron response and subsequently affect the learning of other inputs. Furthermore, recent studies have shown that local dendritic depolarization can impact STDP induction. This paper integrates these three biological concepts to devise a new biologically plausible supervised learning method for spiking neurons. Experimental results show that the proposed method can effectively map a random spatiotemporal input pattern to a random target output spike train with a much faster learning speed than ReSuMe.

1 Introduction

Spiking neural networks (SNNs) are able to capture the rich dynamics of biological neurons, hence complex information processing in the brain can potentially be modelled by SNNs [1]. Significant efforts have been made to design learning algorithms for SNNs. Existing learning methods such as SpikeProp [2] and the multi-spike learning algorithm [3] are based on the estimation of the gradient of an error function and can suffer from the problems of local minima and silent neurons. ReSuMe is another existing supervised learning algorithm which uses a combination of Spike-timing-dependent plasticity (STDP) and anti-STDP learning windows to adjust synaptic weights [4]. In addition, biologists have studied various forms of local spike-based learning and synaptic plasticity in biological neurons [5]. The intrinsic complexity and discontinuity of spiking neurons require the development of more effective and efficient learning approaches inspired from neuroscience and biological concepts in order to improve the processing ability of SNNs and increase their applicability in solving real-world problems.

In this paper, we propose a new biologically plausible supervised learning approach for spiking neurons, called BPSL (Biologically Plausible Supervised Learning), which uses the following three biological concepts: STDP, teacher inputs and dependency of STDP on local dendritic depolarization. The following section briefly introduces the biological concepts used in this work and describes the proposed BPSL method. Section 3 presents the simulation results. Finally, section 4 concludes the paper.

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2 Materials and Methods

This section discusses the biological background and principle of the proposed learning method.

Supervised learning with teacher inputs: Supervised learning at the neuron level has been shown experimentally by Fregnac and Shulz [6]. A few strong neural inputs can affect the neuron response and therefore drive the learning of other inputs. Therefore, these strong inputs can act as a teacher for the postsynaptic neuron to perform a specific task [6]. We have used this biological concept to divide a neuron's synaptic inputs during learning into sensory synaptic inputs (SI_1, SI_2, … SI_n) and teacher synaptic inputs (TI_1, TI_2, … TI_m).

STDP: It is believed to play an important role in learning and memory formation [7]. Phenomenological models of synaptic plasticity based on spike timing were discussed in [8] where synaptic plasticity can depend on spike timings, synaptic weight and membrane potential. The modification of a weight during STDP takes place at the pre and post synaptic spike times. Two local variables x_j and y_i are used to implement STDP where x_j and y_i are low-pass filtered version of the pre- and postsynaptic spike trains (which are denoted by SI_j and O_i, respectively, in Figure 1).

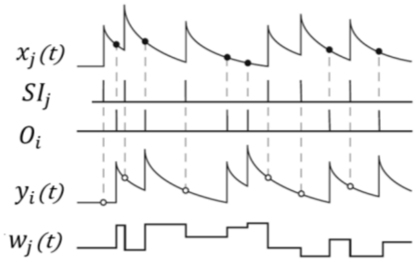

Fig. 1: The principle of a pair-based STDP. The figure is adopted from [8].

At the instance of a presynaptic (postsynaptic) spike the synapses are depressed (potentiated) in proportion to the momentary trace of the postsynaptic (presynaptic) spike, y_i (x_j), which is represented in Figure 1 by unfilled (filled) circles. So, the STDP can be summarized by the following equation.

$$dw_j(t) = \begin{cases} +x_j(t), & t = t^f \\ -y_i(t), & t = t_j^f \\ 0 & Otherwise \end{cases} \tag{1}$$

Where t^f is the firing time of the f^{th}spike in O_i. t_j^f is the firing time of the f^{th}spike in SI_j. $w_j(t)$ is the neuron j^{th} synaptic weight at time t (Figure 1).

Impact of local dendritic depolarisation on STDP: The impact of the sub threshold Post Synaptic Potential (PSP) on synaptic plasticity was discussed in [5]. Several recent studies have investigated how dendritic synapse location affects STDP [9]. Local dendritic depolarization can be used to manage synaptic plasticity [5]. In

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this research it is assumed that the teacher and sensory inputs are from different branches of the dendritic tree and therefore have different plasticities. The strength of teacher synapses are constant and the STDP applied to sensory synapses is affected by the local PSP produced by the sensory inputs.

The proposed BPSL method: BPSL is applied to a single neuron to enable it to map a spatiotemporal input pattern to a desired target output spike train. The neuron is connected to a number of sensory inputs (SI) and a number of teacher inputs (TI); the latter are applied during the training phase only. The structure of the neuron during training is illustrated in Figure 2 (A). A copy of the desired spike train is presented to the neuron at each teacher input. However, it is also possible to use a single teacher input with a much stronger weight instead of multiple teacher inputs with smaller weights as used in this work. Poissonian spike trains are used at sensory and teacher inputs. Examples of a teacher spike train and a sensory spatiotemporal input pattern are shown in Figure 2 (B) and Figure 2 (C), respectively.

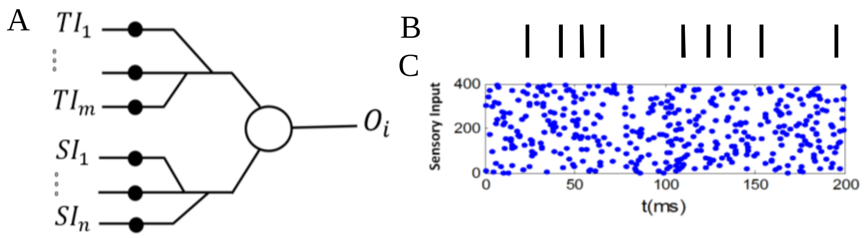

Fig. 2: (A) Neuron structure during training with multiple teacher inputs (TI) and sensory inputs (SI). (B) The desired spike train presented at each TI. (C) A sensory spatiotemporal input pattern applied through SIs (400 sensory inputs are shown here).

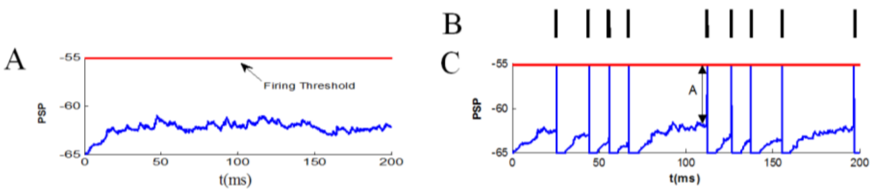

Fig. 3: (A) Neuron PSP in response to the sensory inputs before learning. (B) The desired spike train. (C) Actual spike train and PSP during learning.

In the first stage of the learning, the synaptic weights of the sensory inputs are chosen low enough to prevent the neuron from firing without teacher inputs. Figure 3 (A) illustrates the PSP of the neuron before training in response to the sensory input spatiotemporal pattern and in the absence of the teacher inputs. Therefore, in the first stage of the learning the sensory inputs have no role in exciting the neuron.

The output spike train and PSP of the neuron in the first stage of learning (when both sensory and teacher inputs are applied) are shown in Figure 3 (B) and Figure 3 (C), respectively. At this stage the actual output is the same as the desired spike train

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presented at the teacher inputs. The high synaptic weights of the teacher inputs cause a jump in the PSP at the instance of a desired spike time and force the neuron to fire. In Figure 3 (C) the amplitude of the jump in the PSP is denoted by 'A'.

During learning, appropriate sensory weights should be adjusted to increase the contribution to the PSP, $v_s(t)$, from the sensory inputs so that the desired output spike train is sustained when the teacher input is removed. The learning is terminated when the neuron produces the desired output spike train in the absence of the teacher inputs. The teacher inputs cause the neuron to fire at the desired times and are used in the proposed BPSL to find appropriate weights. BPSL also uses STDP for adjusting the weights of sensory input connections that have a spike shortly before the desired times. Additionally, the amount of weight update depends on the PSP produced by the sensory inputs. If the PSP at a desired spike time is low and is far from the threshold level, the algorithm applies higher updates to the appropriate weights to bring the current PSP, $v_s(t)$, closer to the firing threshold. In contrast, BPSL applies small weights updates when the PSP at a desired spike time is slightly lower than the firing threshold. The weight change is summarised by the following equation:

$$dw_j(t) = \begin{cases} +A(t)x_j(t), & t = t^f \, and \; t^f \in D \\ -\beta, & t = t^f \; and \;\; t^f \notin D \\ 0, & Otherwise \end{cases} \tag{2}$$

Where $D = \{t^1,\ t^2, \ldots, t^N\}$ represents the set of desired output spike times, β is a learning constant that reduces the weights when an undesired output spike occurs (i.e. an output spike occurs at time t^f and $t^f \notin D$), $x_j(t)$ represents the value of the trace caused by the input spike train j at time t. The term $A(t) = V_{th} - v_s(t)$ is the difference between the firing threshold, V_{th}, and the sensory PSP at time t, $v_s(t)$. Only sensory input connection weights are updated using equation (2), the connection weights of teacher inputs remain constant.

The contribution of the local dendritic depolarization, i.e. the PSP produced at the sensory dendrite branch, to the sensory weights adjustment increases the speed of the learning by introducing larger weight updates when the level of the PSP is much lower than the neuron firing threshold at the time of a desired output spike. That is, if the PSP, $v_s(t)$, is much lower than the neuron firing threshold V_{th}, the weight update should be larger than when the PSP is near the threshold level. This larger modulation of the synaptic weights is achieved by the BPSL rule (2) through the use of the term $A(t)$. Aditionally, the weight changes for each synapse j, $dw_j(t)$, are accumulated during each epoch k. At the end of an epoch k, if the number of spikes in the actual output spike train, n_o, is equal to the number of spikes in the desired spike train, n_d, then the accumulated weight change, $\sum_{f=1}^{n_o} dw_j(t^f)$, is added to the current weight of synapse j. Otherwise, if $n_o > n_d$, the current weight of synapse j is decreased using the non Hebbian term , $\alpha(n_d - n_o)$, as described in equation (3).

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$$\mathrm{w_j^{k+1}} = \begin{cases} \mathrm{w_j^k} + \sum_{f=1}^{n_o} dw_j(t^f), & \mathrm{n_o = n_d} \\ \mathrm{w_j^k} + \alpha(\mathrm{n_d - n_o}), & \mathrm{n_o > n_d} \end{cases} \tag{3}$$

Where $\mathrm{w_j^k}$ represents the efficiency of synapse j at epoch k and α is a constant learning rate. When $\mathrm{n_o > n_d}$, the reduction in the weights decreases the activation of the neuron and may potentially reduce the number of actual output spikes, $\mathrm{n_o}$.

3 Simulation results

The LIF neuron parameters are set to the same values used in [4] (membrane time constant $\tau_m = 10$ms, refractory period $t_{ref} = 5$ms, membrane rest potential $E_r = -65$mv, firing threshold $V_{th} = -55$mv, membrane resistance $R_m = 10M\Omega$). The parameter β is set to 4×10^{-8} and the parameter α is set to 2×10^{-6}.

A correlation based metric, C, which is used in [10] is employed to evaluate the performance of the proposed BPSL approach. C measures the similarity between two spike trains (the actual and desired output spike trains in this work) such that C is equal to 0 for two uncorrelated spike trains and it is equal to 1 for two identical spike trains. In the following experiments, each simulation is repeated for 50 trials. The obtained C for each trial is smoothed to get a monotonically increasing curve. Each value of C is replaced by its previous value if there is a drop in the value compared to its previous one to smooth the C curve. Then the mean of the 50 smoothed values of C, denoted by Cm, is obtained and plotted for both methods as shown in Figure 4.

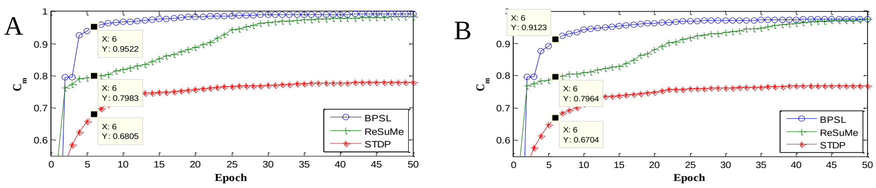

Fig. 4: $\mathrm{C_m}$ for BPSL, ReSuMe and STDP when (A) $\mathrm{T_t}$=200ms and (B) $\mathrm{T_t}$=300ms.

In the first experiment the performance of the BPSL, STDP and ReSuMe are compared when the input and output spike trains total duration is T_t=200ms. The C_m value for BPSL at the earlier epochs is higher than the others (Figure 4(A)). For instance, at epoch 6, C_m values for BPSL, ReSuMe and STDP are equal to 0.95, 0.80 and 0.68, respectively. The performances of the three algorithms are then compared for a longer duration, $\mathrm{T_t}$=300ms, of the input and output spike trains (Figure 4(B)). The BPSL algorithm has again achieved higher correlations $\mathrm{C_m}$ between the actual and desired output spike trains than ReSuMe and STDP at an earlier stage of the training. For example BPSL reached $\mathrm{C_m} = 0.91$ at the 6th epoch whereas ReSuMe and STDP achieved lower $\mathrm{C_m}$ values of 0.80 and 0.67, respectively. It is not until the 24th epoch when ReSuMe reaches $\mathrm{C_m}$=0.91. As for STDP, its $\mathrm{C_m}$ remained below 0.8

during the whole training process. Matlab simulations were carried out on a quad core PC with 3GHz and 16GB of RAM and the simulation of each epoch of the BPSL and ReSuMe learning algorithms takes 170ms and 146ms, respectively. Therefore, while the proposed BPSL approach requires 170×6=1020ms to reach C_m=0.91, ReSuMe (despite having a lower computational cost per epoch) takes a total of 146×24=3504ms to reach the same value of C_m.

4 Conclusion

This paper presented a new biologically plausible supervised learning (BPSL) method for spiking neurons. The proposed learning method is applied to a single neuron and integrates three biologically plausible concepts, namely teacher synaptic inputs, STDP and the dependency of the STDP on local dendritic depolarization. The teacher inputs drive the neuron to fire at the desired times at the beginning of the learning. The level of the local dendritic potential associated with the sensory input is used to determine the amount of weight update. Simulation results showed that the proposed BPSL approach can effectively map a spatiotemporal input pattern to a desired target output spike train at a faster learning speed than the established ReSuMe learning method.

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