Adaptive STDP Learning with Lateral Inhibition for Neuromorphic Systems

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Abstract

Implementing biologically plausible learning rules on neuromorphic chips is essential to explore the learning mechanisms in the brain. Spike-timing dependent plasticity (STDP) is one such rule but its multi-bit circuit implementation requires too much area. In our previous study, we proposed a hardware-friendly learning rule named adaptive STDP and experimentally showed that its performance was similar to STDP learning in a very basic biologically plausible spike pattern detection task using a single neuron. In this study, we extend the adaptive STDP learning rule with lateral inhibition, a common motif observed in the brain, and apply to a spike pattern detection model with multiple neurons that compete to detect multiple patterns. Our results show that the performance is similar to that with STDP learning.

Keywords: Adaptive STDP, Pattern detection, Synaptic efficacy, Neuromorphic chips, Lateral inhibition

1. Introduction

Significant amounts of resources are being spent worldwide to understand the information processing and learning mechanisms in the brain. Design of neuromorphic chips with biologically plausible neuron and synapse circuits is an integral part of this effort [1]. In the brain, neuronal cells interact at the microcircuit level via various (yet unknown) network motifs. Exploration of these motifs via a bottom-up construction at the level of neuronal cells and synapses is crucial to improve our understanding of microcircuits in the brain. Neuromorphic chips contribute to this exploration via this “analysis by synthesis” methodology. Their neuron and synapse circuits are used to create scalable versions of known network motifs and can help develop insights into their network dynamics via real-time emulation.

In this study, we focus on the neuromorphic implementation of one such widely observed network motif, lateral inhibition with spike-timing dependent plasticity (STDP), and present post-silicon-validated circuit models for the same. Lateral inhibition is easily implemented in neuromorphic chips but ideal STDP learning models generally require synapse circuits with very high efficacy resolution (>10 bits). Resolution of synapses in the brain is not clearly known. However, recent findings with high resolution imaging techniques show that individual synapses have multi-bit resolution [2]. A high resolution is achieved in pure analog circuits that store efficacy on a capacitor [3]. However, due to capacitor leakage, the learned efficacy is lost over time. Bi-stable synapse circuits [4] compensate for this leakage and have two long-term stable states but have low resolution of about 1.5 bits. In mixed-signal circuits,

efficacy is implemented using digital-to-analog converters (DACs) and digital memories. The area and power consumption of DAC doubles for every 1-bit increase in its resolution. Hence, even though lower-resolution synapses deteriorate the performance of STDP learning, the synapse resolution is restricted to about 4 to 6 bits in most chips [1], [5].

As a potential solution to this problem, an adaptive STDP learning rule that uses just 4-bit synaptic efficacy was proposed in a previous study [6]. It was successfully applied to a very basic biologically plausible spike pattern detection model comprising a single neuron and its performance in numerical simulations as well as on a mixed-signal neuromorphic chip was demonstrated to be similar to ideal STDP learning [6], [7]. In this study, the application of adaptive STDP is validated on a more realistic biologically plausible network comprising multiple neurons that laterally inhibit each other. Models of this motif were described in a previous study that used the ideal STDP learning rule and synapses with 64-bit floating-point resolution efficacy [8]. We use the same motif but apply adaptive STDP learning rule with 4-bit synapses and compare the performance with ideal STDP learning.

The rest of the manuscript is organized as follows. The network model with details of the input spike trains, neuron, synapse, and the learning rule is presented in section 2. Results are presented in section 3 and the final section concludes with a discussion of the results and possible future works.

2. Network Model

The target network comprises nine neurons that inhibit each other in an all to all fashion. Each of them receives stochastic input spikes via 2048 4-bit excitatory synapses empowered with adaptive STDP learning. Three different spike patterns are embedded repeatedly in these stochastic spike trains and the goal of the network is to recognize the embedded spike patterns. The input spike trains are similar to the ones used in the reference study [8]. They assume only the statistical properties generally assumed in neuroscience. The embedded spike patterns are characterized purely by spike times mimicking the temporal neural code observed in various regions of the brain. The procedure to generate the spike train is described next.

2.1. *Input Spike Train Model*

Input spike trains for each afferent (total 2048 afferents) were generated via an inhomogeneous Poisson process with the instantaneous firing rate varying between 0 to 90 Hz. The smallest interval for the frequency to change from 0 to 90 Hz was 50 ms. Each afferent spiked at least once in 50 ms establishing 54 Hz as the average frequency of each spike train. Upon generation of 225 s long stochastic spike train, three randomly selected 50 ms long segments (spike patterns to be embedded) were copied from it. This ensures that the spike patterns have similar characteristics to the stochastic Poisson spikes. Next, the spike train was divided into 50 ms long sections and based on the chosen pattern appearance frequency (11.1% for each pattern) a certain number of these sections were replaced by the spike patterns to be embedded. In other words, the three spike patterns occupy one-third of the total simulation time. Additionally, a Gaussian jitter with zero mean and 1ms standard deviation is added to the spike patterns during the copy-paste procedure. This copy-and-replace procedure is applied only to half of the randomly chosen afferents. The remaining afferents encode only stochastic spikes. In this copy-and-paste process, consecutive 50 ms sections were avoided. The population average spiking rate inside and outside the 50 ms long spike patterns is the same and the patterns are characterized only by the precise spike timing of the afferents. Subsequently, 10 Hz spontaneous spikes were added to all the spike trains increasing the population average firing rate of the afferents to approximately 64 Hz.

2.2. *Neuron, Synapse, and Learning Models*

Structure of the network is shown in Fig.1. The neurons are modeled using the reduced compartment technique. It comprises two compartments, a passive dendritic compartment (shaded grey in Fig.1) and an active somatic compartment (shaded green) that can generate neuronal spikes. A unidirectional resistor (R_c) connects them and only allows the current to flow into or out of the somatic compartment based on their potential difference. Detailed arguments for choosing these models, their ideal model equations, and their circuit details are described in our previous studies [6], [7]. Here we focus on the implementation of lateral inhibition.

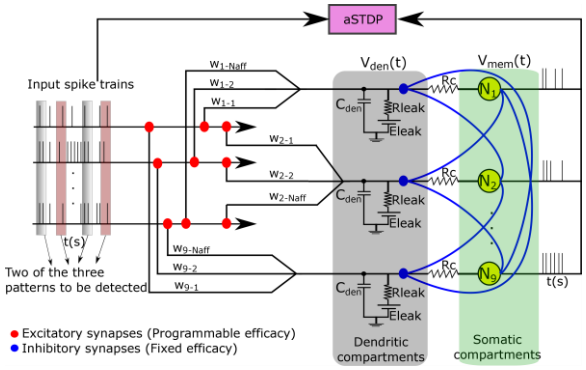

Fig. 1: Network for lateral inhibition with adaptive STDP learning. N_{aff} is the number of afferents.

To implement the lateral inhibition, the somatic compartment of every neuron is connected to the dendritic compartments of other neurons via inhibitory synapses. With successive coincidences of spike patterns, the adaptive STDP learning rule directs the neurons to spike in the presence of these patterns [6]. For every neuronal spike, each neuron hyperpolarizes the dendritic membrane potential of all other neurons via inhibitory connections (blue lines in Fig.1). The dynamics of the dendritic compartment are given by:

$$C_{den}\frac{dV_{den}}{dt} = I_{syn\_exc} + I_{syn\_inh} - \frac{V_{den}-E_{leak}}{R_{leak}}, \quad (1)$$

where V_{den} is the dendritic membrane potential, C_{den} is the dendritic capacitance fixed at 48 pF, R_{leak} and E_{leak} are the parameters of the leak resistor set at 50 MΩ and 305 mV, respectively. I_{syn_exc} is the excitatory synaptic current generated by input synapses and I_{syn_inh} is the inhibitory synaptic current that implement lateral inhibition. They are described by

$$I_{syn}(t) = I_{sw}.(-exp^{-t/\tau_r} + exp^{-t/\tau_d})\Big/a_{scale}, \quad (2)$$

where τ_r and τ_d together control the rising and falling time constant of the synaptic current, their values are set at 1ms and 3ms (10ms) for I_{syn_exc} (I_{syn_inh}), respectively. The scaling factor a_{scale} sets the amplitude of the synaptic current equal to the value of the synaptic efficacy denoted by I_{sw}. The efficacy of inhibitory synapses is constant. The initial synaptic efficacies of excitatory synapses are set randomly and are modified by the adaptive STDP learning rule. It is given by

$$\Delta w_j = \begin{cases} +1 \text{ bit, if } t_j \le t_i, t_i - t_j < t_{\text{pre}}, \text{and w} < w_{\max} \\ -1 \text{ bit, if } t_j > t_i, t_j - t_i < t_{\text{post}}, \text{ and w} > w_{\min} \end{cases}, \quad (3)$$

where t_j (t_i) represents the timing of the presynaptic (postsynaptic) spike and t_{pre} (t_{post}) is the maximum delay of the postsynaptic (presynaptic) spike after the presynaptic (postsynaptic) spike that leads to potentiation, LTP (depression, LTD). The 4-bit efficacy saturates at its maximum and minimum values of $w_{\max}$ and $w_{\min}$ representing synaptic current of values 15 pA and 0 pA, respectively. The learning parameter t_{pre} is 13 ms and t_{post} is adapted from 13 ms to increasingly higher values during the learning process saturating at 40 ms.

3. Results

Here we present the simulation results quantifying the performance of the network in Fig. 1. Simulations were run for 100 different inputs generated by the procedure described in section 2 and a run was considered to be successful if all three spike patterns were detected with a hit rate greater than 98 % and false alarms under 1 Hz in the last 75 s of the run (one-third of the total run time), similar to the criterion in [8].

The observed success rate was 70%, that is in 70 out of 100 runs, all three spike patterns were detected by at least 1 neuron. In 24 runs, only two spike patterns were detected and in 6 runs only 1 spike pattern was detected. These results are similar to the reference study that used STDP learning on the same task where it is reported that in more than two-thirds of the cases, all three spike patterns were detected by at least one neuron [8]. The superimposed membrane potentials of the neurons during a successful run are shown in Fig.2(A) and the same in the last second of the run is shown in Fig.2(B). Three different color-shaded regions represent the 50-ms long spike patterns within which the neurons learn to spike.

4. Discussion

The results above demonstrate that adaptive STDP learning with 4-bit synapses when applied to a lateral inhibitory network has a performance similar to STDP learning with high-resolution synapses. The circuits (of neuron, synapse, and learning rule) whose ideal models were used for simulation have been validated in silicon in previous studies [6], [7] and can be used for large-scale implementation and exploration of lateral inhibitory networks on neuromorphic chips.

The network motif, input spike train model, and biomimetic somatic compartment were chosen because of their biological plausibility. The reference study [8] used the single-compartment leaky integrate-and-fire

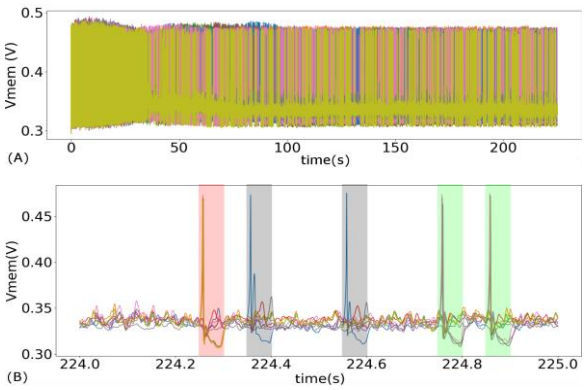

Fig. 2: Superimposed membrane potentials of nine neurons (A) for the entire duration of a run; (B) in the last second of the run. The neurons learn to spike within the patterns.

(LIF) neuron model. The unidirectional two-compartment neuron model used in this study is not biomimetic but is more biologically plausible than the widely used single-compartment neuron model as it incorporates the passive properties of the dendrites (ignoring their spatial morphology). The two compartments also provide flexibility to apply inhibition to either one of them or use biomimetic shunting inhibitory synapses for inhibition. The variations in performance and network dynamics due to these modifications will be explored in future studies.

All network parameters were tuned manually but the network is not sensitive to precise parameter values and similar results were obtained using a wide range of parameters. Their values can be chosen either based on biophysical values or to minimize silicon area (e.g., small C_{den} and high R_{leak}).

The network was limited to a single layer and the neurons learned a small segment in the 50-ms long patterns. As seen in Fig.2(B), the neurons learn to spike near the beginning of the patterns and thus only detect the initial segment of the pattern. Multiple layered network may detect patterns of longer duration. Also, during learning, only the parameter controlling depression, (t_{post}) was adapted externally. The potentiation parameter t_{pre} can also be adapted while learning and these adaptations can be made dependent on the network state rather than via external programming. These potential modifications will be explored in future studies.

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