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Autonoumous Learning Paradigm for Spiking Neural Networks

Junxiu Liu[1*], Liam J. McDaid[1], Jim Harkin[1], Shvan Karim[1], Anju P. Johnson[2], David M. Halliday[2], Andy M. Tyrrell[2], Jon Timmis[2], Alan G. Millard[2], and James Hilder[2]

[1] School of Computing, Engineering and Intelligent Systems, Ulster University, Northern Ireland, United Kingdom, BT48 7JL
{*j.liu1,lj.mcdaid,jg.harkin,haji_karim-s}@ulster.ac.uk
[2] Department of Electronic Engineering, University of York, York, United Kingdom, YO10 5DD
{anju.johnson,david.halliday,andy.tyrrell,jon.timmis, alan.millard,james.hilder}@york.ac.uk

Abstract. Compared to biological systems, existing learning systems lack the ability to learn autonomously, especially in changing and dynamic environments. This paper addresses the issue of autonomous learning by developing a self-learning spiking neural network (SNN) and demonstrating its autonomous learning capability using a simple robot controller application. Our proposed learning rule exploits an inherit property of the existing Spike-Timing-Dependent Plasticity (STDP) rule in that if the instantaneous presynaptic frequency decreases, then for a conventional Hebbian window the STDP rule potentiates. Conversely if the instantaneous frequency increases the STDP rule depresses: the opposite is true for anti-Hebbian window. This paper will also show that obstacle avoidance is achievable using a conventional Hebbian learning window while object tracking can be learned using an anti-Hebbian learning window. Hence the proposed learning paradigm is novel in that it does not require external supervisions for either these tasks. The proposed learning paradigm also uses a previously explored astrocyte neuron interaction where a periodic Slow Inward Current (SIC) from an astrocyte can potentiate a postsynaptic neuron for a period of time: this time window can be used to strengthen/weaken synaptic pathways. An obstacle avoidance task is used for the performance analysis and results show that the SNN based robot controller has autonomous learning capabilities under the dynamic conditions.

Keywords: SNN, learning, plasticity windows, robots

1 Introduction

Spiking neural networks (SNNs) are a third generation networks which closely resemble their biological counterparts. SNNs comprise of neurons and synapses where the former releases a transient voltage spike when excited. When action potentials arrive at the presynaptic terminal, the membrane potential of the postsynaptic neuron increases under the stimuli and a spike event occurs when the postsynaptic potential exceeds a threshold level. SNNs have good temporal data processing capability and are used in many applications such as the pattern recognition [1], data analytics [2], fault-tolerant computing [3,4] and robotic control [5,6]. Various learning algorithms have been proposed for SNNs and the choice of algorithm is critically dependant of the application domain. Most SNN applications use some form of supervision for the learning phase where the learning data is preselected from a dataset. However, the requirement for a supervised approach constrains the design, development and deployment of the SNN systems, especially for applications operating within a dynamic environment, e.g. robots [7].

The Spike-Timing-Dependent plasticity (STDP) [8] and Bienenstock, Cooper, and Munro (BCM) [9] learning rules are two commonly used learning rules for SNNs. A combined STDP/BCM learning rule, termed BSTDP, has be demonstrated in an SNN-based robotic controller application to implement learning, e.g. in the approach of [7] the spiking astrocyte neural network used BSTDP to implement both learning and self-repair in the robotic applications. However, it required supervisory signals to achieve the correct input/output mapping. In this paper we address the issue of autonomous learning. This paper revisits earlier work and proposes a novel autonomous learning strategy which uses the Hebbian/anti-Hebbian learning approach where the novelty is a decision capability that can potentiate or depress as a function of instantaneous previous synaptic spike frequency. Furthermore, we draw on the concept of an SIC which is a postsynapitc stimulus current released by astrocytes: note that SIC model used in this work is a high level abstraction of the biological SIC function. This approach avoids the complexity involved in modelling many astrocyte processes. This autonomous learning strategy is demonstrated on a simple SNN robotic controller.

The rest of the paper is organized as follows. Section 2 describes the autonomous learning strategy and section 3 presents simulation results which demonstrate the proposed autonomous learning concept for obstacle avoidance. Section 4 concludes the paper.

2 Autonomous learning principle

This section presents an SNN that demonstrates a plausible autonomous learning paradigm.

2.1 Autonomous learning strategy

We consider as a demonstrator an SNN-based robotic controller deployed in an obstacle avoidance application. In the present case our SNN controller senses one input and learns over time to respond with an appropriate output action to avoid an obstacle. To put this in context we will consider a robot moving in a forward direction with an obstacle placed in its path. We also assume that the sensor input data is mapped to a linear spike train and the actuator output neurons drive the robot in either the forward direction or to motion a left turn (the left turn was chosen arbitrarily). Hence our SNN controller has one presynaptic neuron and two postsynaptic actuator neurons: the proposed autonomous learning algorithm will learn to respond with either a forward or left turn motion. A key signalling pathway is the slow inwards current (SIC) emitted by an excited astrocyte cell [10]. Because astrocyte interacts with many neurons we assume that the SIC continually stimulates both postsynaptic neurons, which propels the robot initially towards the obstacle. When the robot becomes in proximity to the object, the sensor becomes active and the presynaptic neuron fires. However, because of morphology we assume that astrocyte processes are of different lengths with different associated delays and therefore the SIC signal will cause only one of the actuator neurons to become active for a period of time followed by the other: none of the two actuator neurons are active at the same time. In the current case this will cause the two postsynaptic neurons to enter into a "toggling action" where one actuator neuron becomes active for a period of time followed by the other and then this process repeats. Hence each pathway between the presynaptic neuron and the postsynaptic neurons will be periodically strengthened or weakened. If the activity of one of the postsynaptic neuron causes the instantaneous presynaptic firing frequency Δf_{pre} to increase then the synaptic pathway will be depressed: in the present case the SNN based controller is learning an obstacle avoidance task and consequently motion towards an object needs to be avoided. Our simulations will show that a conventional Hebbian learning window in conjunction with STDP will train an SNN to implement obstacle avoidance without the need for a learning signal. Consequently for obstacle avoidance we require that for $\Delta f_{pre} > 0$ the weights associated with active actuator neurons are depressed and potentiated only for $\Delta f_{pre} < 0$. This condition is satisfied by adopting a conventional Hebbian learning window. Conversely the SNN will learn an object tracking task using an anti-Hebbian learning window. In the present case the former is adopted and a Hebbian window is selected.

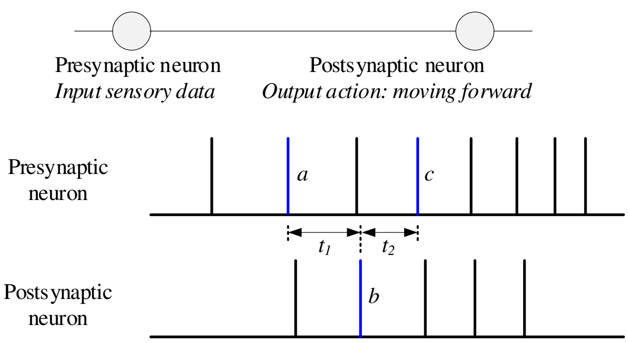

Fig. 1. Temporal changing between the input sensory spikes and output spikes for obstacle avoidance where the output neuron is to move forward.

Fig. 1 shows a synaptic connection between the input sensory neuron and output actuator neuron (forward motion). Each time the postsynaptic neuron fires, the robot will move forward decreasing the distance to the obstacle which increases the input sensory neuron spike frequency. Therefore, the inter spike interval (ISI) decreases, as shown in Fig. 1. Spikes at times a, b and c show a steadily reducing ISI where the time period between spike a and b is greater than the time period between spike b and c, $t_1 > t_2$ and $\Delta f_{pre} > 0$. The proposed rule effectively uses the sign of Δf_{pre} to implement either potentiation if Δf_{pre} is negative or depression if Δf_{pre} is positive. Note that in the present case our approach uses all correlations between pre and post firing times that are within the plasticity window except for the presynaptic spike time that causes the postsynaptic response to cross the firing threshold. This spike time when correlated with postsynaptic firing tends to favour weight potentiation strongly and swamps out other correlations within the plasticity. Therefore, to avoid this and make learning more sensitive to ISI we only consider before and after spike correlations.

2.2 Models

The STDP learning rule with different kernel structures can be used for synaptic long-term potentiation (LTP) or long-term depression (LTD). Based on the Hebbian STDP learning rule, LTP occurs when the presynaptic neuron fires before the postsynaptic firing, whereas LTD occurs when the temporal firing order is reversed [11]. STDP based learning is described by

$$\delta w^i_{syn}(\Delta t) = \begin{cases} A_0 exp(\dfrac{\Delta t}{\tau_+}), & \Delta t \leq 0 \\ -A_0 exp(\dfrac{\Delta t}{\tau_-}), & \Delta t > 0 \end{cases} \tag{1}$$

where $\delta w^i_{syn}(\Delta t)$ is the i^{th} synaptic weight to be updated, Δt is the time difference between post and presynaptic spikes, A_0 is the height of STDP learning window, τ_+ and τ_- are the widths of the plasticity window. In addition, the postsynaptic neuron was modelled using the Leaky Integrate and Fire (LIF) approach, due to its simplistic nature, and this neuron model is expressed as

$$\tau_m \frac{dv}{dt} = -v(t) + R_m \sum_{i=1}^{n} I^i_{syn}(t), \tag{2}$$

where τ_m and v are the time constant and membrane potential respectively, R_m is the membrane resistance, $I^i_{syn}(t)$ is the current injected to the neuron membrane at synapse i, and the firing threshold voltage is 9 mV. The neuron model also includes a refractory period of 2 ms, and the current injected to the neuron from the i^{th} synapse, $I^i_{syn}(t)$, is calculated by

$$I^i_{syn}(t) = r_I * w^i_{syn}(t) + I_s, \tag{3}$$

where r_I is the synaptic current production rate, I_s is the SIC signal from astrocyte, $w^i_{syn}(t)$ is the synaptic weight of the i^{th} synapse, which is modulated by the STDP learning rule, i.e.

$$w^i_{syn}(t) = w^i_{syn}(t-1) + \delta w^i_{syn}. \tag{4}$$

Note that I_s is the SIC signal and because the formulation of a biologically plausible model for this current takes into account many factors, we will assume for simplicity an SIC spike of duration 1 ms. Additionally, since SIC currents correlate with neuron activities, but on a slow time scale, we choose arbitrary an SIC interspike interval of 1/6 of the presynaptic spike frequency.

3 Results

In this section a simple robotic demonstrator is used to showcase the proposed autonomous learning algorithm where the data was collected using the Psi swarm robot developed by the York Robotics Laboratory, University of York, UK [12]. An infrared sensor placed at the front of the robot provided the sensory input data for the SNN-based controller. This data was converted to a linear spike train which modelled the presynaptic neuron: a rate-based encoding scheme is used where the distance between the mobile robot and obstacle (or object), d, is proportional to the reciprocal of input spike train frequency, $1/f_{pre}$. Fig. 2 shows the SNN structure for the obstacle avoidance task, where two output neurons are synaptically connected to the input of a sensory neuron. The input neuron senses the output of the front sensor and, in response, the output neurons A and B will, when active, motion the robot to move forward and turn left.

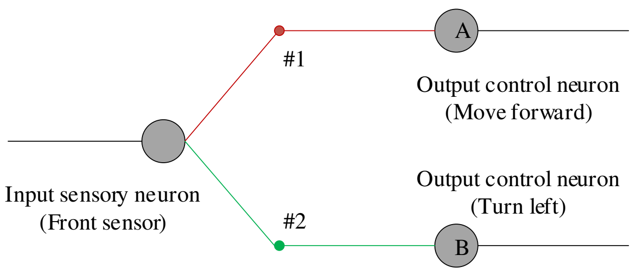

Fig. 2. Synaptic connections between the input and output neurons.

The output actuator neurons are periodically firing due to the astrocyte signal SIC. Also, we initiate the learning process with neuron A (forward motion) becoming active before neuron B, as shown in Fig. 3(c): neuron A is active for 3 seconds followed by neuron B for a further 3 seconds and this process continually repeats. In the time period when neuron A is active, the synaptic pathway (#1) is depressed from an initial synaptic weight of 20, see Fig. 3(f). Under the input

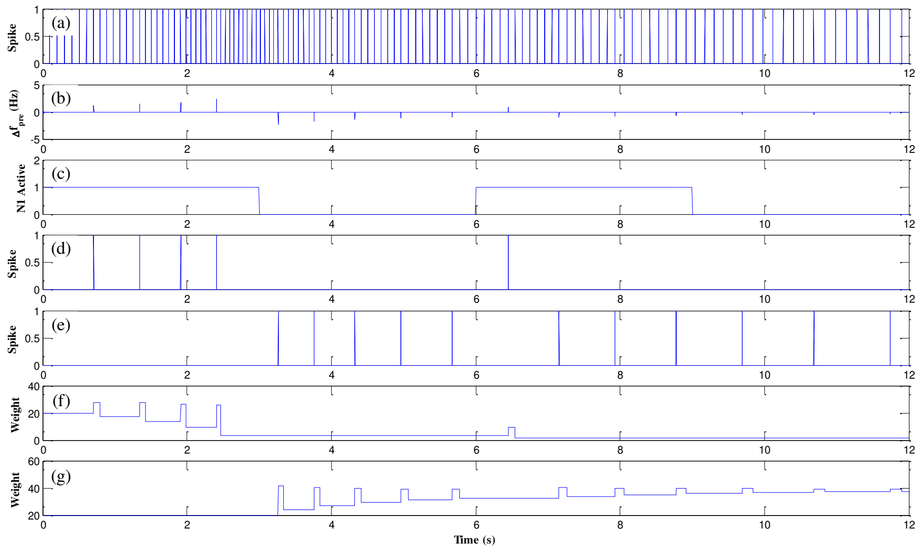

Fig. 3. SNN activities between input sensor neuron and output action neurons. (a). Input spike train. (b). Δf_{pre}. (c). Neuron A active status where 1 represents active and value 0 represents inactive. (d, e). Spikes of output neuron A and B. (f, g). Synapse #1 and #2 weights.

stimuli, the postsynaptic neuron fires at $\sim$ 0.6 sec as shown in Fig. 3(d), then the robot moves forward to the obstacle and Δf_{pre} is positive, see Fig. 3(b). An STDP window with equally balanced LTP and LTD kernel structure is used for the learning. When the output neuron A continues to fire from $\sim$ 0.6 second, the robot continually moves towards the obstacle and the frequency of input sensory spike train increases. This leads to the LTD, as shown by Fig. 3(f). Each time neuron A is stimulated the synaptic pathway #1 is further depressed and eventually pathway (#1) becomes inactive and postsynaptic neuron A ceases to fire ($\sim$ 6.5 sec in Fig. 3(d)). This we define as autonomous learning as weight depression does not require the external supervision.

Now consider the connection between input sensor and output neuron B (left turn motion) when synaptic pathway #2 is active due to SIC. The initial weight for the synapse #2 is also set to 20 (see Fig. 3(g)). The synaptic pathway #2 is active between 3 and 6 sec. Under the input stimuli, the output neuron B fires at $\sim$3.4 sec, i.e. the robot turns slightly to the left and therefore away from the obstacle. Thus, the frequency of input sensory spike train decreases (negative Δf_{pre} in Fig. 3(b)). Note the same plasticity window is used in all pathways. The weight of synapse #2 starts to be potentiated, as shown by Fig. 3(g) and as the synaptic weight increases, the SNN continues to promote a left turning motion, see the output spikes in Fig. 3(e). As the robot turns to the left moving away from the obstacle, Δf_{pre} approaches zero, learning ceases and the synaptic weights stabilize, see Fig. 3(g). Results demonstrate the autonomous learning process favours strengthening the pathway to neuron B, which is a left turning motion, and the weight associated with this pathway is potentiated accordingly. Note that during the initial learning phase, one of the actuator neurons is active for a period of time followed by the other due to the delays in the SIC spikes. However, after a period of learning, only one actuator neuron will be active (left turn motion) due to the potentiated synaptic weight, and the other actuator neuron becomes inactive as the associated synaptic weight is depressed. Compared to other approaches such as [7], the proposed method can learn and adapt to the surrounding environmental conditions based on the STDP kernel structures. Therefore, the proposed learning approach does not require an input to output mapping table and thus points to a possible future direction for SNN metaplasiticity.

4 Conclusion

A novel autonomous learning strategy for SNNs has been presented which uses the STDP with kernel structures. It exploits an inherit property of STDP where if $\Delta f_{pre} < 0$, the STDP rule potentiates for conventional Hebbian window. Conversely if the $\Delta f_{pre} > 0$ the STDP rule depresses: the opposite is true for anti-Hebbian window. This novel learning strategy, demonstrated using an obstacle avoidance task, used a conventional Hebbian learning window. However, the SNN could be reconfigured to learn an object tracking task using an anti-Hebbian learning window. Another novel feature of the proposed learning paradigm is an astrocyte associated SIC. The SIC potentiates postsynaptic actuator neurons periodically and in each time window weight potentiation/depression occurs. Results of an SNN under an obstacle avoidance robotic task show that the proposed paradigm is able to learn autonomously within a dynamic environment. The authors recognise that the proposed SNN demonstrator requires much refinement to allow scaling to a useful SNN. Despite this our SNN fragment does demonstrate a new approach to autonomous learning. Furthermore, this approach could be taken further but would require a significant body of research involving experimentalists to determine the time course of SICs and other associated secondary messengers. However, with current data on astrocyte process morphology it may be possible to model delays but this would in itself be a challenge well beyond the scope of this paper. Overcoming this challenge in future work would permit scaling the network to a more useful SNN controller with the capability to continually learn more complex input/output patterns and operate in a real-world environment.

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