Synaptic Plasticity and Separative Responses in Liquid State Machine for Time Series Classification

Infrastructure and Formal Definition

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Outline

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Introduction

Background

Spiking Neuron Networks (SNNs) are often referred to as the 3^{rd} generation of neural networks. Highly inspired from natural computing in the brain and recent advances in neurosciences, they derive their strength and interest from an accurate modeling of synaptic interactions between neurons, taking into account the time of spike firing.[3, 2, 1]

Motivation

- The model is more biological plausible than Artificial Neural Network to simulate the mechanism of brain-like Computing.
- Not only traditional learning rules but also Many bio-inspired learning rules are available for SNN without the limitation of the vanishing gradient.
- Information is processed by spikes in SNN, which is consider as Energy effective and Hardware friendly.

Introduction

Challenges

The main challenge is to discover efficient learning rules that might take advantage of the specific features of SNNs while keeping the nice properties (general-purpose, easy-to-use, available simulators, etc.) of traditional models.

Introduction

Challenges

- SNN is non-differentiable for back-propagation in supervised learning.
- The mechanism of unsupervised Learning rules (such as Hebbian rule) are not very reasonable and effective for classification.
- Hyper-parameters are difficult to determine and the quantity is much more than traditional model.
- The lack of large-scale simulators such as Tensorflow(the neuron in human brain)

Outline

Spiking Neural Model

Formal Definition

Spike train

A chain of action potentials emitted by a single neuron is called a spike train. The spike train of a neuron i is denoted as the sequence of firing times:

$$S_i(t) = \sum_f \delta(t - t_i^{(f)}) \tag{1}$$

Spiking Neural Model

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$$S_i(t) = \sum_f \delta(t - t_i^{(f)}) \tag{1}$$

where $\delta(\tau - t_i)$ is Dirac function and $\int_t^{t+\Delta t} \delta(\tau - t_i)\, d\tau = 1$

Spiking Neural Model

Formal Definition

Postsynaptic Potentials(PSP)

At $t = 0$ the presynaptic neuron j fires its spike. For $t > 0$, we see at the electrode a response of neuron i,

$$u_i(t) - u_{rest} =: \epsilon_{ij}(t) \tag{2}$$

where $\epsilon_{ij}(t)$ defines the postsynaptic potential (PSP).

Spiking Neural Model

Formal Definition

Spike Response Model(zero order) (SRM_0)

$$u_i(t) = \eta(t - \hat{t}_i) + \sum_i \sum_f w_{ij} \cdot \epsilon_{ij}(t - t_j^{(f)}) + u_{rest} \tag{3}$$

where $\eta(t - t_i^f)$ is the trajectory of the membrane potential, u_{rest} is resting potential(By an appropriate shift of the voltage scale, we can always set $u_{rest} = 0$.)

$$t^{(f)} : \quad u(t^{(f)}) = \vartheta \quad and \quad \frac{du(t)}{dt}\Big|_{t=t(f)} > 0 \tag{4}$$

Spiking Neural Model

Formal Definition

Formal Pulse

In the limit of $\Delta t \to 0$ the square pulse approaches a Dirac δ function;The negative spike-after potential in Eq. (2.3) is thus a simple model of neuronal refractoriness.

$$\eta(t - t_i^f) = \begin{cases} 1/\Delta t & for \quad 0 < t - t_i^f < \Delta t \\ -\eta_0 \, exp(-\frac{t-t_i^f}{\tau}) & for \quad 0 < \Delta t < t - t_i^f \end{cases} \tag{5}$$

Spiking Neural Model

Specific Model

Leaky Integrate-and-Fire Model

The basic circuit of an integrate-and-fire model consists of a capacitor C in parallel with a resistor R driven by a current $I(t)$.

$$\tau_m \frac{du}{dt} = -u(t) + RI(t) \tag{6}$$

$$I(t) = \sum_t C * (exp(-\frac{t}{\tau_1}) - exp(-\frac{t}{\tau_2})) * \delta(t - t_i^{(f)}) \tag{7}$$

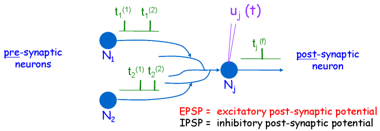
After $t^{(f)}$, the potential is reset to a new value $u_r < \vartheta$

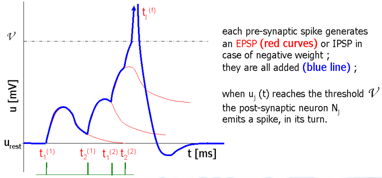
$$\begin{aligned} t^{(f)} : \quad & u(t^{(f)}) = \vartheta \\ \lim_{t \to t^{(f)}; t > t^{(f)}} & u(t) = u_r \end{aligned} \tag{8}$$

Spiking Neural Model

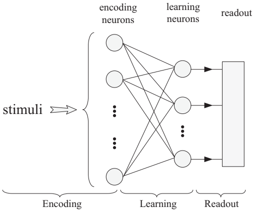
Specific Model

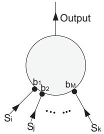
Leaky Integrate-and-Fire Model





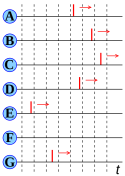
Encoding and Decoding





Encoding : P(response | stimulus)

Decoding : P(stimulus | response)



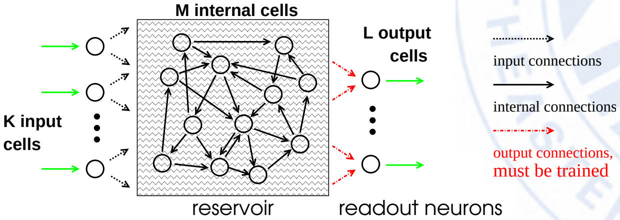
	count	latency	rank
A	1	5	3
B	1	6	5
C	1	7	6
D	1	5	4
E	1	1	1
F	0	–	–
G	1	3	2

Numeric examples:	count code	binary code	timing code	rank order
left (opposite) figure $n = 7, T = 7ms$	3	7	≈ 19	12.3
Thorpe et al. [164] $n = 10, T = 10ms$	3.6	10	≈ 33	21.8

Number of bits that can be transmitted by n neurons in a T time window.

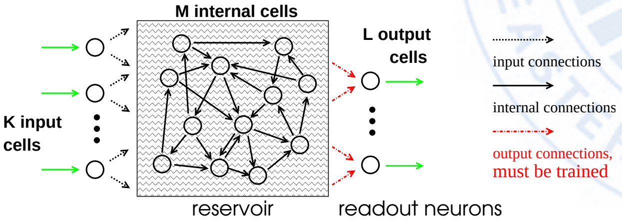
Liquid State Machine

Liquid State Machine(LSM) has emerged as a computational model that is more adequate than the Turing machine for describing computations in biological networks of neurons. LSM is a model for real-time computations on continuous streams of data.[4, 5]



Liquid State Machine

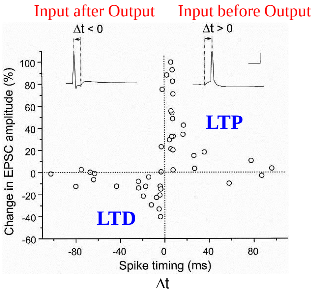
- A layer of K neurons with input connections toward the reservoir.
- A recurrent network of M neurons, interconnected by a random and sparse set of weighted links: the so-called reservoir, that is usually left untrained.
- A layer of L readout neurons with trained connections from the reservoir.

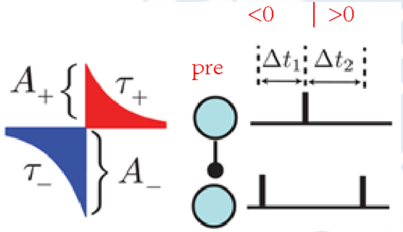


Synaptic Plasticity

Spiking-Timing Dependent Plasticity(STDP)

$$\Delta w = \begin{cases} A_{+} exp(-\Delta t/\tau_{+}) & if \Delta t \geq 0 \\ -A_{-} exp(-\Delta t/\tau_{-}) & if \Delta t < 0 \end{cases} \quad (9)$$





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Synaptic Competition in STDP

Synaptic Competition is the significant mechanism of plasticity. The post-synaptic neurons have greater opportunity to response the spiking pattern of the winner in pre-synaptic neuron.[6]

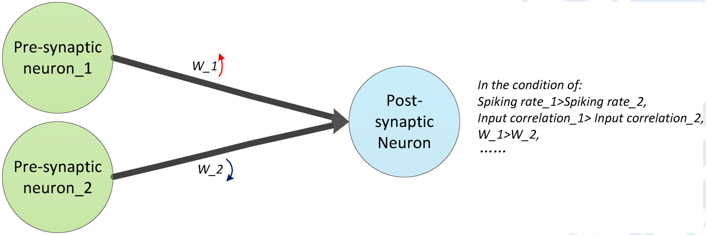

Fig. 1: Synaptic Competition in Neural Plasticity

Synaptic Competition in STDP

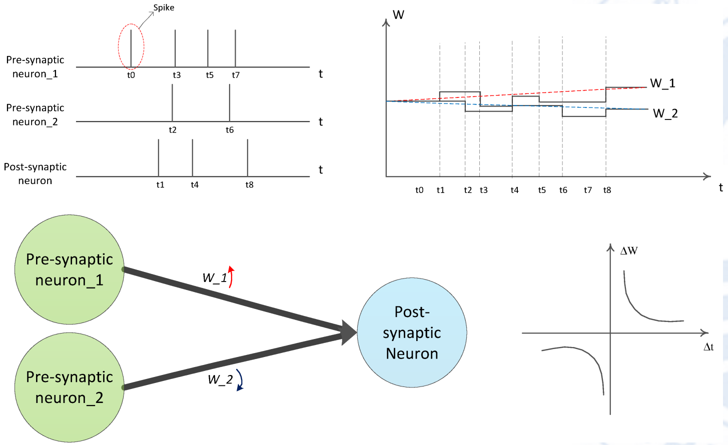

Fig. 2: Illustration of Competition in Neural Plasticity

Separative Responses in Reservoir

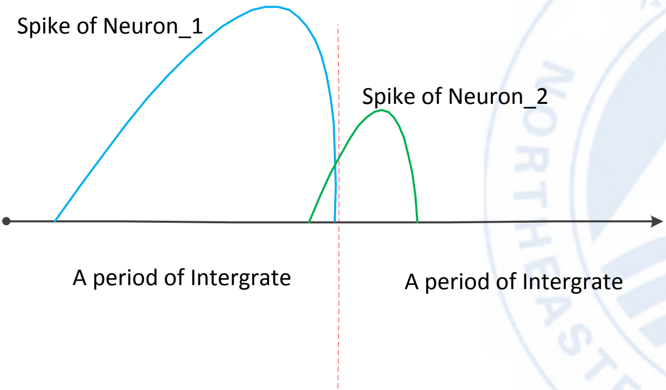

Fig. 3: Illustration of Separative Responses in Reservoir

Training internal synapses of Reservoir with STDP

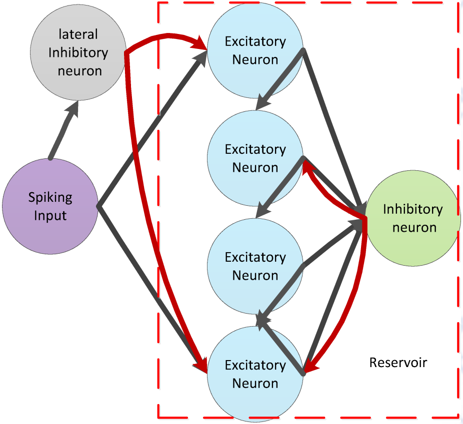

Fig. 4: LSM model with lateral inhibitory neuron

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Spike Trains classification

Simulations Setting

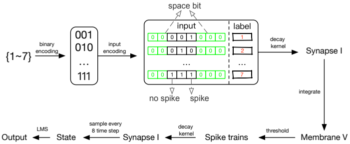

Fig. 5: Spike Trains Classification

Patterns:

[[1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
[1, 1, 0, 1, 1, 0, 0, 1, 0, 1],
[1, 0, 1, 1, 0, 0, 1, 0, 1, 0],
[0, 1, 0, 1, 0, 1, 0, 1, 0, 1],
[0, 0, 1, 1, 0, 0, 1, 0, 1, 0],
[0, 1, 0, 1, 1, 0, 1, 1, 0, 1],
[0, 1, 1, 1, 0, 0, 1, 1, 1, 0],
[0, 1, 1, 0, 1, 0, 1, 0, 1, 1],
[1, 1, 0, 0, 1, 0, 1, 1, 1, 0],
[1, 0, 1, 1, 0, 1, 0, 0, 0, 1]]

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Spike Trains classification

Results

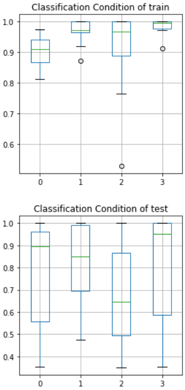

Fig. 6: Statistics AUC for 10 simulations in ST classification without STDP

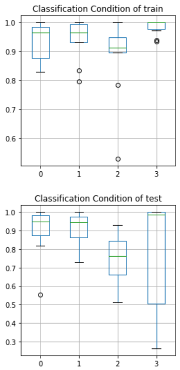

Fig. 7: Statistics AUC for 10 simulations in ST classification with STDP

Tri-function classification

Simulations Setting

The task is to predict which of three signal generating functions is currently active in producing a varying input signal. To generate a sample of the signal at a given timestep, one of the three following function types is used.

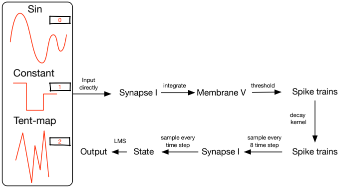

Fig. 8: Tri-function Classification

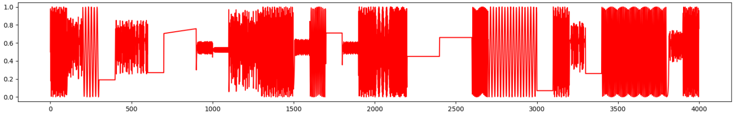

Fig. 9: Spike Trains Classification

Tri-function classification

Results

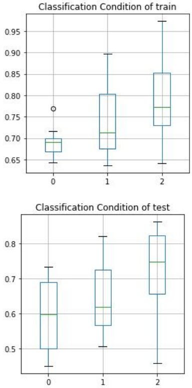

Fig. 10: Statistics AUC for 10 simulations in Tri classification without STDP

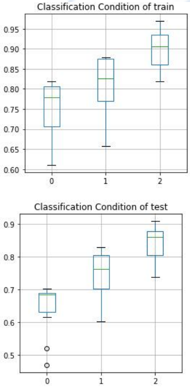

Fig. 11: Statistics AUC for 10 simulations in Tri classification with STDP

Outline

Discussion

- Training LSM is difficult due to the complicated recurrent structure.
- The primary hyper-parameter is the integral time constant τ, which should be suitable for the classification task.
- STDP can only change the synaptic weights, but the structure is fixed before training reservoir. In this case, the ability of STDP is limited.

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Thanks for Listening and Questions?

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