

Two Methods to Improve the Efficacy of ReSuMe

Jing Yang

School of Management, Zhuhai, Beijing Normal University, Zhuhai, 519087, China

Keywords: Resume, Synapse, Ensemble, Spiking neuron.

Abstract. Neuron learning is the basis of the more complex learning of neuron network. Resume is the one of the most popular used supervised learning algorithm for spiking neurons. It corresponds to the Widrow-Hoff rule and its weights adjustment is derived from the spike-based Hebbian processes. Although it makes quite success the learning accuracy decreases quickly when the desired output spike train gets longer. This paper analyzes two important factors related to the learning convergence of Resume. And we proposed two methods based on them to improve the efficacy of Resume. The experimental results show that the two improved algorithms both can achieve better performance.

Introduction

Spiking neuron (SN) is a kind of biological nervous based neuron which transmits information via spike trains. The supervised learning method for SNs is a very important part in its research area^[1]. The goal of supervised SN learning is to train SN to reproduce arbitrary spike trains in response to given synaptic stimuli (input spiking trains). There are different methods to train SN. Gutig et al.^[2] proposed a supervised learning method for SNs named as tempotron which can solve pattern recognition and classification problems. Spike-timing-dependent-plasticity (STDP)^[3] is a learning mechanism based on biological neurons. There are some leaning methods^[4] realizing the supervised leaning by using STDP. In this paper, we choose ReSuMe^[5] as the research mainly because it is widely used and has relatively good performance. As to the supervised learning of SNNs SpikeProp^[6] is based on gradient descent and extended the BP algorithm to SNNs. Xu and el.^[7] proposed a gradient descent based algorithm which can realize the multi-spike learning.

In this paper, we propose two novel methods to improve the efficacy of ReSuMe. The arrangement of the paper is as follows. The SN model and ReSuMe are briefly introduced in Section 2. Section 3 explains the two main influence factors of ReSuMe learning and gives two improved-ReSuMe algorithms. In Section 4 some experiments are conducted to demonstrate the efficiency of the new methods. Finally a conclusion is drawn in Section 5.

SN Modal and ReSuMe Algorithm

SRM Modal

SN has different models, such as leaky integrate-and-fire model (LIF), Hodgkin-Huxley model (HH) and spike response model (SRM)^[8]. In this paper the commonly used SRM model is taken as our research model whose internal state can be expressed intuitively. In this model, the inputs of a SN are spikes transmitted from presynaptic neurons via numerous synapses. When the internal state of the neuron, namely, membrane potential exceeds the neuron threshold ϑ the neuron fires an output spike at that time. The following equation is the internal state expression.

$$u(t) = \sum_{i=1}^N \sum_{\substack{t_i^{(f)} \in F_i \\ t_i^{(f)} > t_i^{(fr)} + R_a}} w_i \mathcal{E}(t - t_i^{(f)}) + \eta(t - t_i^{(fr)}) \quad (1)$$

where N is the number of input synapses of the neuron, $F_i = \{t_i^{(1)}, t_i^{(2)}, \dots, t_i^{(F_i)}\}$ is the spike train fired by the i th synapse and $t_i^{(fr)}$ is the time of the most recent output spike of the neuron prior to the

current time t , w_i is the weight of the i th synapse and $\varepsilon(t)$ is the spike response function expressed as

$$\varepsilon(t) = \begin{cases} \frac{t}{\tau} e^{\frac{1-t}{\tau}} & \text{if } t > 0 \\ 0 & \text{if } t \leq 0 \end{cases} \quad (2)$$

where τ is the time decay constant. If the neuron fires at time t its internal state will drop quickly to zero and the input spikes are futile in the period of $(t, t + R_a)$. This is called the absolute refractory period whose length is controlled by R_a . After this period the internal state of the neuron increases slowly and keeps lower than ϑ . This is called the relative refractory period which is interpreted by $\eta(t - t_i^{(fr)})$ in Eq. 3. The function $\eta(t)$ is expressed as follow and τ^R is the time decay constant.

$$\eta(t) = \begin{cases} -2\vartheta e^{-\frac{t}{\tau^R}} & \text{if } t > 0 \\ 0 & \text{if } t \leq 0 \end{cases} \quad (3)$$

ReSuMe Algorithm

The learning algorithm of spiking neuron is the most important part in the research of spiking neuron. The adjustment formula of ReSuMe for an SN is based on the interaction between two spike-timing – dependent plasticity (STDP) processes which are well-recognized physiological phenomena. There are two parts of weight adjustment, strengthening and weakening. A synaptic weight should be strengthened when there is a desired output t_d^f during the running time and the weight should be weakened when the neuron fire an actual output spike t_o^f . These two processes are defined by the following two equations:

$$\Delta w_i = \alpha + \beta \sum_{t_i^s < t_d^f} W(t_d^f - t_i^s) \quad (4)$$

$$\Delta w_i = -[\alpha + \beta \sum_{t_i^s < t_o^f} W(t_o^f - t_i^s)] \quad (5)$$

where α is a constant which makes the weight change in any cases, β is the learning rate and $W(\cdot)$ is the learning window function. In this paper the learning window is selected as the STDP form which is expressed as

$$W(s) = \begin{cases} +A_+ e^{-\frac{s}{\tau_+}} & \text{if } s > 0 \\ 0 & \text{if } s \leq 0 \end{cases} \quad (6)$$

where A_+ is a constant and τ_+ is the time decay constant.

Two Methods to Improve ReSuMe

Two Main Influence Factors of ReSuMe

It has been demonstrated that ReSuMe enables efficient learning of arbitrary spike trains. However, the learning accuracy will decrease when length of the desired spike train gets longer. The following figure shows the results of a set of experiments in which the neuron has 400 synapses, the input spike train is generated according to a homogeneous Poisson process with rate=10 Hz and so does the

output spike train with rate=100Hz, the max learning epoch is 1000. We can see that the learning is barely successful when the length of the spike train is more than 1000.

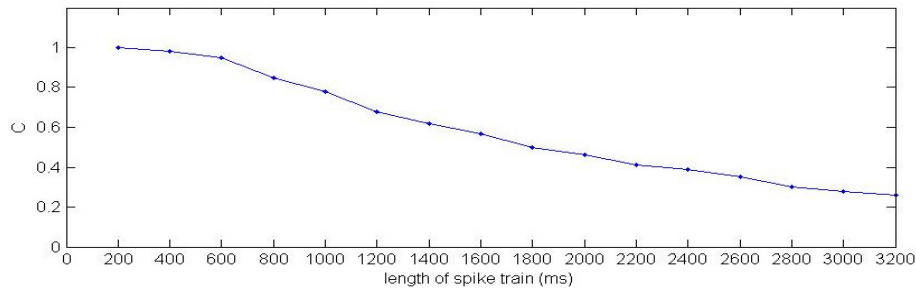


Figure 1. Learning accuracy of ReSuMe to different length of output spike train.

Apparently the length of desired output spike train could be the main reason for the failure of learning. That can also be explained from the weights adjustment process of ReSuMe. As we know, ReSuMe is a local learning algorithm. At each round of weight adjustment, all the synapse' weights are adjusted according to Eq. 4 or 5. If it's a strengthen round the adjustment will lead to the neuron's internal state get bigger both at the current time and the former running times. That would destroy the results of the former weaken rounds. So if there are lots of desired output spikes strengthen round and weaken round would happen alternately and that leads to the failure of the learning.

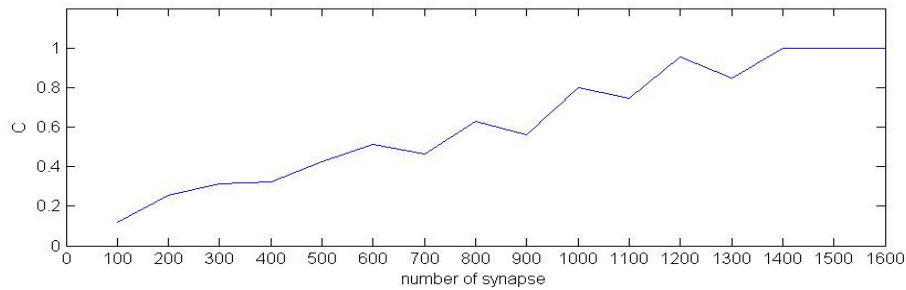


Figure 2. Learning accuracy of ReSuMe to different number of synapse.

As to the second influence factor of ReSuMe we consider the number of synapse. The above figure 2 shows the learning accuracy of ReSuMe to different number of synapse and the desired output spike train is 1000. One can find that although the accuracy doesn't always grow with the increase of the number of synapses there does have a growth trend. For the weight adjustments of ReSuMe the number of synapse decides the number of adjustable parameters. So enough synapses would improve the learning success rate.

Ensemble-ReSuMe (E-ReSuMe)

Ensemble is a popular method to solve complex problems and it's a composite model combining a set of individual learners. There are two types of ensemble system: pure ensemble systems, which solve the problem by a set of different learners, and modular ensemble systems, which break down the original problem into several sub-problems and each learner solves one sub-problem. As the most influential factor of ReSuMe is the length of spike train a possible method is to use modular ensemble systems. The output spike train should be divided into several segments and each segment is learned by one sub-neuron. Thus each segment has less output spikes than the original output spike train. Besides that, it's better to make the desired spike train sparse. So the division is to select one output spike for each sub spike train in turn. The following figure shows division of the original spike train. When each sub-neuron completes the learning it has to combine all the sub-neuron's output into one output. The combination method is to put all the output spikes together and arrange them in order of time. If there are duplicated spikes only one should be kept in the final result.

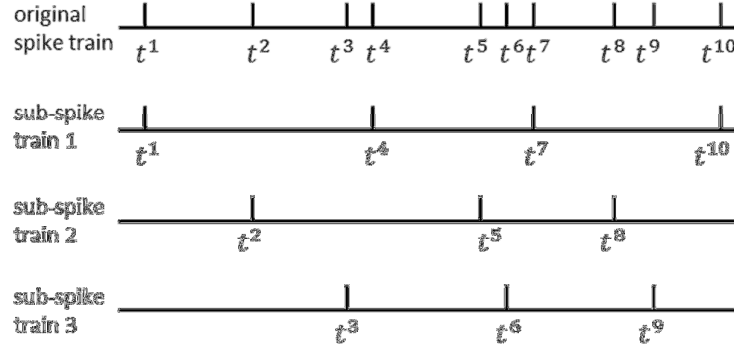


Figure 3. Division of spike train.

Artificial Synapse-ReSuMe (A-ReSuMe)

As to the second factor of ReSuMe learning a possible solution is to add some artificial synapses to the neuron. For a spiking neuron with n synapses all the input spike train is denoted by $S = \{s_1, s_2, \dots, s_n\}$ and $s_i = \{t_i^1, t_i^2, \dots, t_i^{n_i}\}$, n_i is the number of the i th synapse's input spike. If we add a time delay d to each spike time and that would make a new spike train. Taking s_i as an example, the new spike train is denoted by $s_i^{new} = \{t_i^1 + d, t_i^2 + d, \dots, t_i^{n_i} + d\}$. So the original input of the neuron is turned to $s^{new} = \{s_1, s_2, \dots, s_n, s_1^{new}, s_2^{new}, \dots, s_n^{new}\}$ and the number of the synapse is doubled. If the doubled synapse can't bring satisfied learning accuracy a tripled synapse could be considered. That is to add two different time delays to the input spike train. However too many synapses will lead to another problem which is the increased time and space complexity.

Experiments

In this section, we conduct some experiments to verify the effectiveness of the two improved ReSuMe algorithms. The input and output spike trains are generated in the same way described in section 3.1. The max learning epoch of each learning round is 1000.

E-ReSuMe Experiments

In this part of experiments, the number of the input synapse is set to 400 and the length of the desired spike train is set from 1000 to 4000 with a step of 200. The following figure shows the results of E-ReSuMe with four different number of sub-neurons.

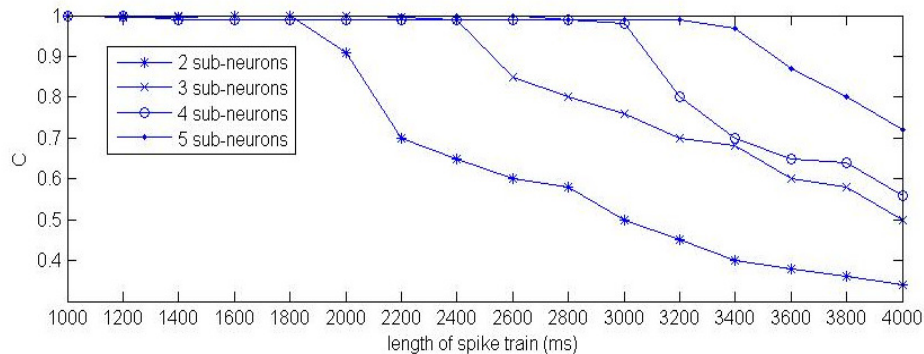


Figure 4. Performance of E-ReSuMe to different sub-neurons.

From the above figure we can find that the performance of E-ReSuMe increase a lot compared to the ReSuMe. The increase of the sub-neuron can bring better performance. However the time complexity shouldn't be ignored. For an ensemble of 5 sub-neurons, if no sub-neuron can achieve accuracy of 1 within the max epoch the time cost of E-ReSuMe would be five times to the original one.

A-ReSuMe Experiments

First, we take a neuron with 400 synapses as the learning neuron and the number of the desired output spike train is set from 1000 to 4000 with a step of 200. Four time delays $D=[2,3,4,5]$ are added to the original input spike train. So the number of the synapse is quintupled. The following figure shows the results of artificial synapse-resume and resume. One can find that the improved A-ReSuMe still can achieve learning accuracy of 1 when the length of desired spike train increases to 2800.

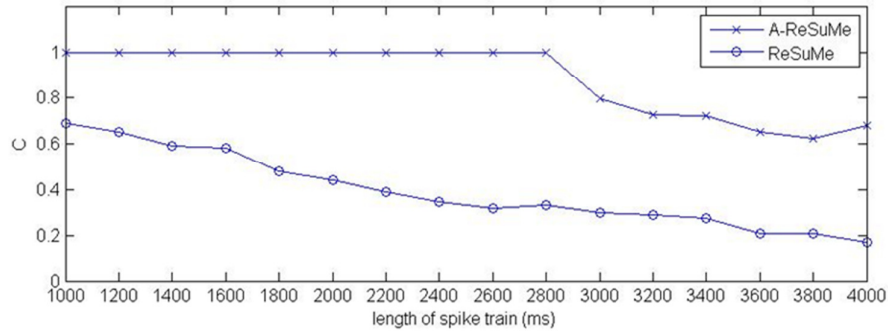


Figure 5. Comparison of A-ReSuMe and ReSuMe.

Summary

This paper focuses on the improvement of ReSuMe. Two main factors are discussed in the learning of ReSuMe. And the results show both the E-ReSuMe and the A-ReSuMe have better performance than the original ReSuMe. However the time complexity is boosted with the improvement of the accuracy. So our future work will focus on how to reduce the complexity of the algorithms.

Acknowledgement

This research was financially supported by the National Science Foundation of China under grants 61503031.

Reference

- [1] R. Gutig, To spike, or when to spike?, *Neurobiology*, 25, 2014, pp. 134-139.
- [2] R. Gutig, H. Sompolinsky, The tempotron: A neuron that learns spike timing-based decisions, *Nature Neuroscience* 9, 2006, pp. 420-428.
- [3] G.Q. Bi, M. m. Poo, Synaptic modifications in cultured hippocampal neurons: Dependence on spike timing, synaptic strength, and postsynaptic cell type, *Journal of Neuroscience*, 18, 1998, pp. 10464-10472.
- [4] R. Legenstein, D. Pecevski, W. Mass, A learning theory for reward-modulated spiketiming-dependent plasticity with application to biofeedback, *PLoS Computational Biology*, 4(10), 2008, pp. 1-27.
- [5] F. Ponulak, A. Kasinski, Supervised learning in spiking neural networks with resume: Sequence learning, classification and spike-shifting, *Neural Computation*, 22, 2010, pp. 467-510.
- [6] S.M. Bohte, J.N. Kok, J.A. La Poutre, Error-back propagation in temporally encoded networks of spiking neurons, *Neurocomputing*, 48, 2002, pp. 17-37.
- [7] Xu Y., Zeng X, Han L and Yang J, A supervised multi-spike learning algorithm based on gradient descent for spiking neural network. *Neural Networks*, 2013, pp. 99-113.
- [8] W. Gerstner, W.M. Kistler, *Spiking neuron models, Single neurons, populations, plasticity*, NY: Cambridge University Press, 2002.