SPA: Stochastic Probability Adjustment for System Balance of Unsupervised SNNs

Xingyu Yang; Mingyuan Meng; Shanlin Xiao; Zhiyi Yu;

Sun Yat-sen University

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Abstract

Spiking neural networks (**SNNs**) receive widespread attention because of their low-power hardware characteristic and brain-like signal response mechanism, but currently, the performance of SNNs is still behind Artificial Neural Networks (ANNs). We build an information theory-inspired system called **Stochastic Probability Adjustment** (SPA) system to reduce this gap. The SPA maps the synapses and neurons of SNNs into a probability space where a neuron and all connected pre-synapses are represented by a cluster. The movement of synaptic transmitter between different clusters is modeled as a **Brownian-like stochastic process** in which the transmitter distribution is adaptive at different firing phases. We experimented with a wide range of existing unsupervised SNN architectures and achieved consistent performance improvements. The improvements in classification accuracy have reached **1.99%** and **6.29%** on the MNIST and EMNIST datasets respectively.

Introduction

SNNs consist of input spike generators, computing units (i.e. spiking neurons), connection synapses, and output decoding. SNNs are promising to achieve ultra-low power consumption because each spiking neuron in SNNs works asynchronously in an event-driven manner like the human brain[1][2]. In contrast to ANNs processing continuous signals in deep learning, spiking neurons are similar to biological neurons so that SNNs process discrete signals.

$$\Delta\boldsymbol{\omega}_{\boldsymbol{i}} = \begin{cases} \boldsymbol{A}^{+} \cdot \boldsymbol{exp}(\boldsymbol{f}(\boldsymbol{x})) \\ -\boldsymbol{A}^{-} \cdot \boldsymbol{exp}(\boldsymbol{f}(\boldsymbol{x})') \end{cases}$$

For SNNs' training, unlike widely used supervised learning using a loss function to measure the difference between actual output and target output (i.e. label), unsupervised SNNs let neurons adjust their own synaptic weights according to their spiking activities, which is similar to the process of real neurons in the human brain. The most used unsupervised learning rule for SNN is the mentioned **STDP** rule, which is based on Hebb rule. In addition, researchers should not only focus on the learning methods of a neural network system, because the architecture of a network is also very important for creating a more advanced artificial intelligence system. Some scholars have suggested that the architecture of a neural network itself might be more important than how it learns[3]. Here, by 'architecture' we mean spiking neuron models, synapse models, and connection topology.

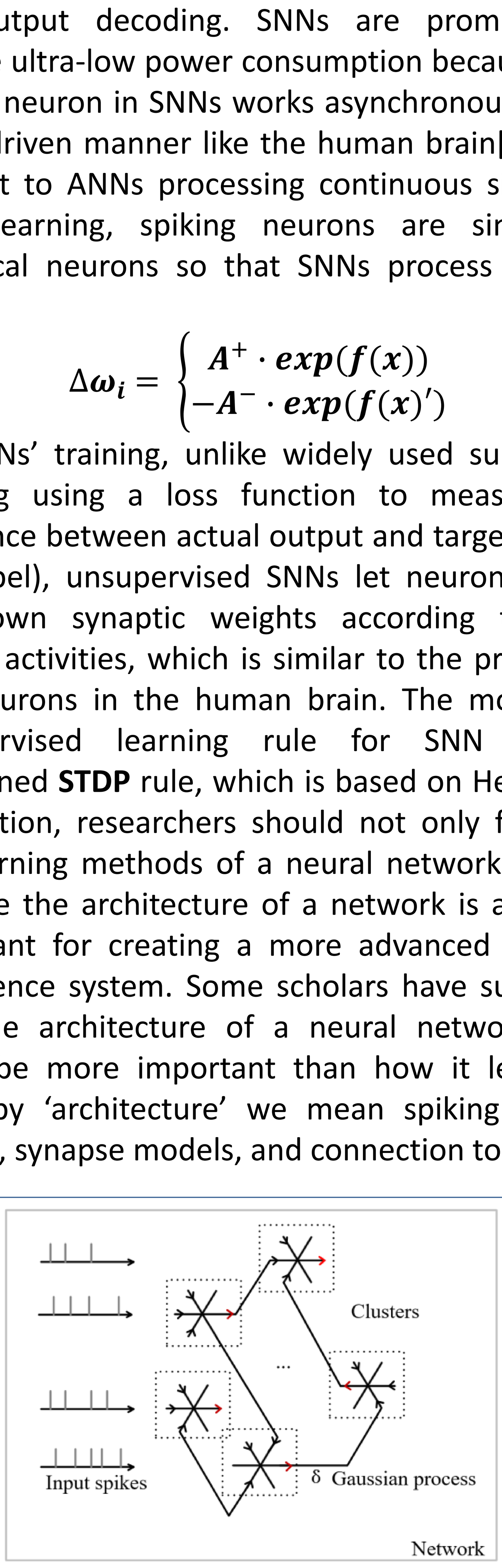

Fig 1. SNN mapped into probability space (Ω, A, P) and synapses clusters.

Methods and Materials

Stochastic Probability Adjustment (SPA) system composed of adaptive spiking neuron models and stochastic synapse models with Gaussian distributed synaptic transmitter. Our system can be used in a wide range of unsupervised SNN frameworks and improve their classification performance. The adaptive adjustments of SPA are as follows:

1) Adaptive selection of the synapse model. A single synapse has both the characteristics of excitatory and inhibitory synapses. The required type (i.e excitatory or inhibitory) and distribution of synapses are determined by a Boolean selection of 0 and 1;

2) The reception rate of transmitter self-adapts using Brownian-like random process[4], thereby mitigating the influence of neuron voltage;

3) The overall stochastic SPA system and it's closed-loop control methods.

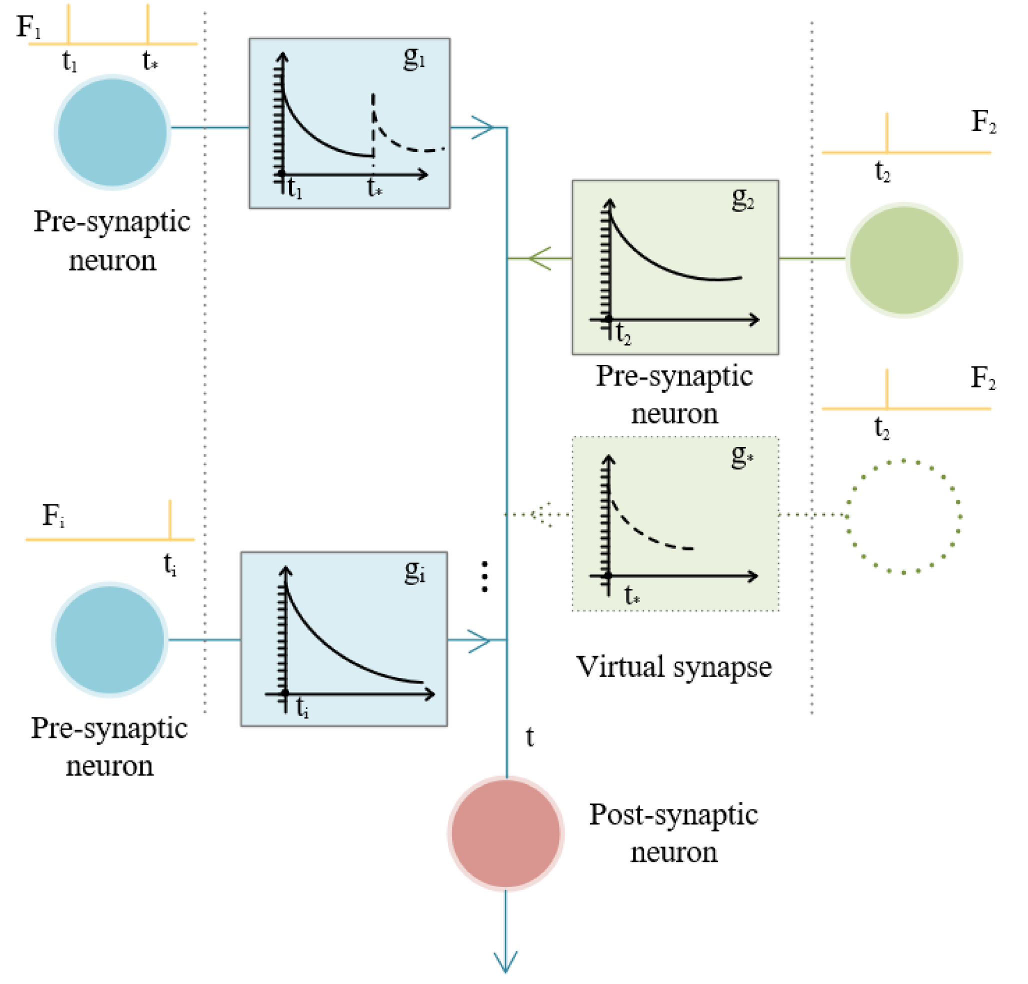

Fig 2. Real synapses and virtual synapses on timeline, and the post-synaptic potential change is caused by the superposition of multiple independent pre-synapses.

Results

MNIST: The proposed SPA method improves the training accuracy by 0.68%, 1.68%, and 1.99% on the SNN architectures of [5], [6], and [7], and improves the testing accuracy by 0.36%, 0.78%, and 0.99% respectively. The training accuracy reached 96.20%, 97.44%,98.01% and the testing accuracy reached 95.36%, 95.85, 96.63% with SPA respectively. The speed comparison is shown in Table I.

EMNIST: With SPA, the training/testing accuracy increases by 4.49%/2.79% in [6], and the training/testing accuracy increases by 6.29%/1.86% in [7].

Discussion

Inspired by neuroscience, we explained the relationship between the characteristics of neuron behaviors and parameters through algorithms, and established a model mapping SNNs into a probability space. Our main idea is an adaptive generalized Wiener-random process. Based on the experiments, our research can be further extended in many aspects. The next step may be sparse coding of neuron connections or self-learning of SNN architecture. After obtaining the precise characteristics of transmitter changing, we can try more transmitter modeling other than conductance.

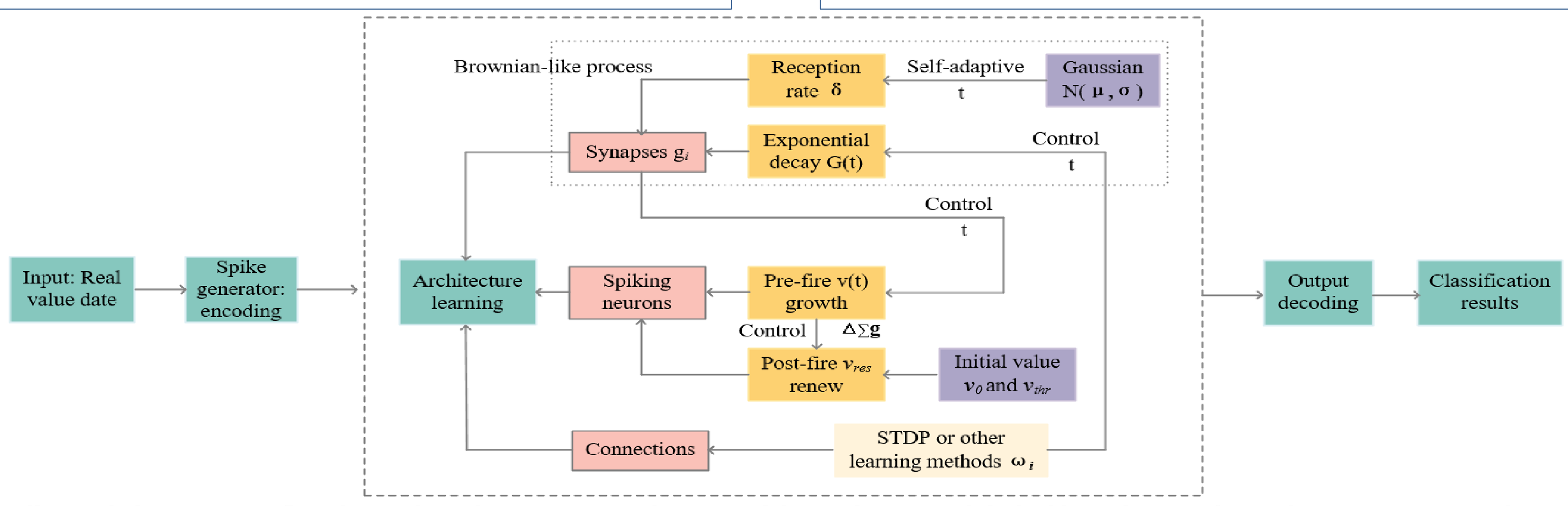

Fig 3. The overall SNN balance system flowchart, where the mapping stochastic model is in the external dashed box, the specific stochastic process is in the internal dashed box. The control process includes self-adaptive adjustment and controlled adjustment.

Paper	Training samples	Scales	Origin accuracy testing	SPA results
Diehl et al. 2015 [5]	60000	100	82.9%	86.62%
		400	87.0%	92.28%
		600	91.9%	94.60%
She et al. 2019 [8]	60000	1000	92.2%	/

Table I. COMPARISON OF TRAINING CONVERGENCE SPEED ON MNIST

Paper	Training accuracy	SPA training accuracy	Testing accuracy	SPA testing accuracy
Diehl et al. 2015	58.68%	/	low	/
Saunders et al.2019 [6]	73.92%	78.41%	67.68%	70.47%
Meng et al. 2019 [7]	83.30%	89.59%	79.86%	81.72%

Table II. RESULTS COMPARISON ON EMNIST WITH UNSUPERVISED LEARNING

Conclusions

We designed a stochastic adjustment system SPA for SNNs and designed a stochastic integration core which is similar to OPU for spiking neurons. This mechanism has produced improvements on different unsupervised SNN architectures. The experimental results show that, without more computations required, the maximum improvements of our method in training accuracy are 1.99% and 6.29% on the MNIST and EMNIST, and the improvements in testing accuracy can be up to 0.89% and 2.81% on the MNIST and EMNIST. In addition, we used the statistical properties of the stochastic integration process of the neurons in the mapping model, and used the computing cores in an equivalent differential form when calculating neuron parameters.

Contact

Author: Xingyu Yang

School of Electronic Information and Engineering, Sun Yat-Sen University

Email: yangxy@mail2.sysu.edu.cn

Phone: 24189833

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