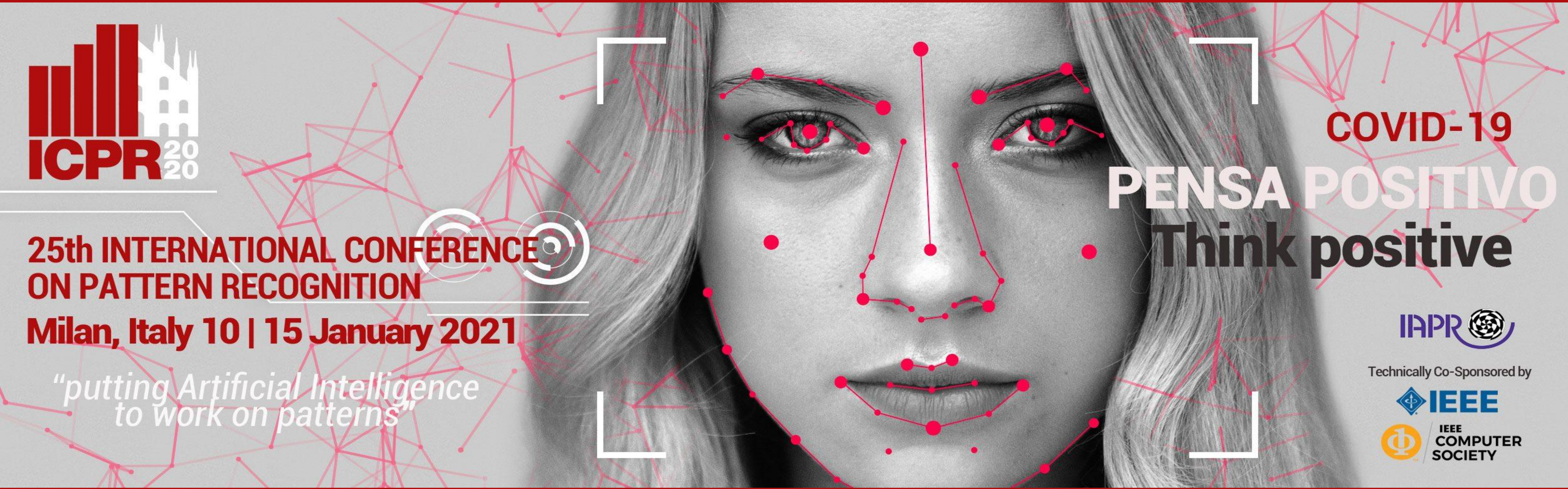

SPA: Stochastic Probability Adjustment for System Balance of Unsupervised SNNs

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Speaker: Xingyu Yang

Speaker Biography

- Xingyu Yang
- I'm pursuing the M. Degree in electronic science and technology with the School of Electronic Information and Engineering from Sun Yat-sen University, Guangzhou, China, in 2018.
- My research interests include Deep Learning-based Medical Image Analysis, Spiking Neural Networks, neuromorphic computing hardware, brain-like chips.

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.

- *Keywords*—Spiking neural network, Stochastic model, Unsupervised learning, Brownian process

Related Work

- Diehl, Peter U., and Matthew Cook. “Unsupervised learning of digit recognition using spike-timing-dependent plasticity.” Frontiers in computational neuroscience 9 (2015): 99.
- Saunders, Daniel J., et al. "Locally connected spiking neural networks for unsupervised feature learning." Neural Networks 119 (2019): 332-340.
- M. Meng, X. Yang, S. Xiao and Z. Yu, "Spiking Inception Module for Multi-layer Unsupervised Spiking Neural Networks," 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020.
- This paper

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Brownian-like Adjustment

Stochastic Probability Adjustment with Brownian-like process

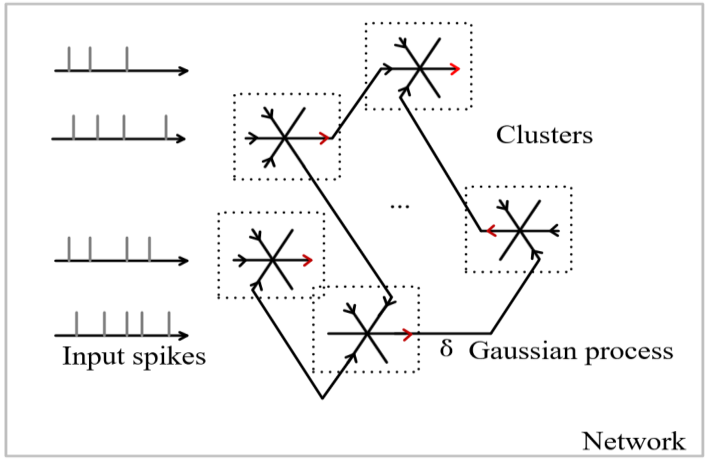


Fig. 2. SNN mapped into probability space (Ω, A, P) and synapses clusters

Step:

1) Create clusters with at least one neuron and their connected synapses. The release of synaptic transmitter follows a Gaussian distribution which is the first stochastic process. Each neuron's type (i.e., excitatory or inhibitory) is determined by Boolean value 0 or 1.

2) To distinguish the differences between different clusters, the activities of different clusters are the second stochastic process where we use Brownian-like motion to adaptively adjust variances and movements.

3) The third stochastic process is a statistical OUP, which could predict network evolution.

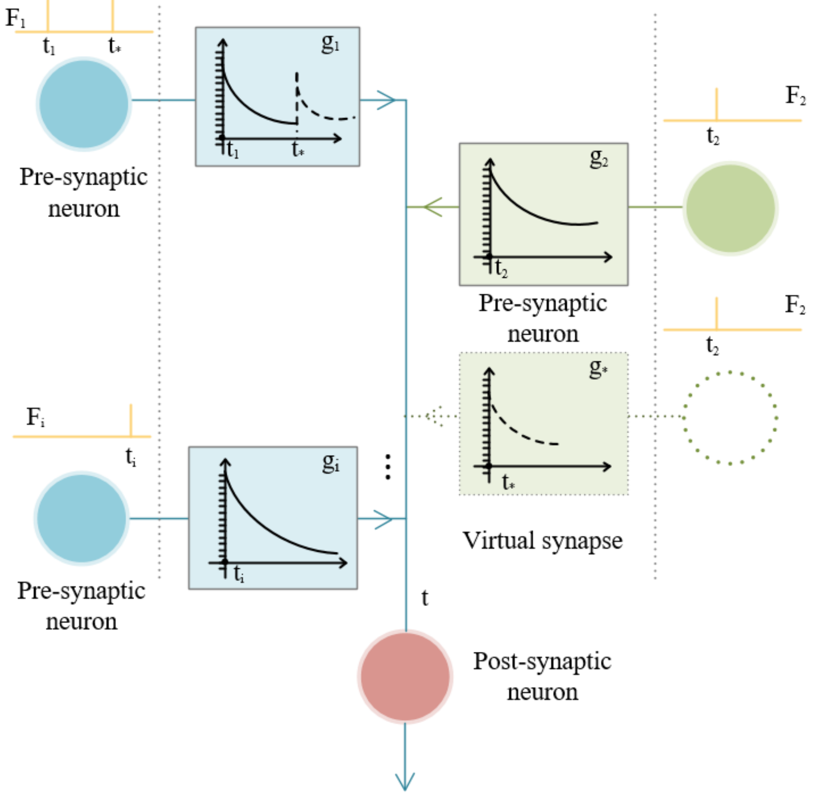


Fig. 3. Real synapses and virtual synapses on timeline, and the post-synaptic potential change is caused by the superposition of multiple independent pre-synapses.

System Flowchart

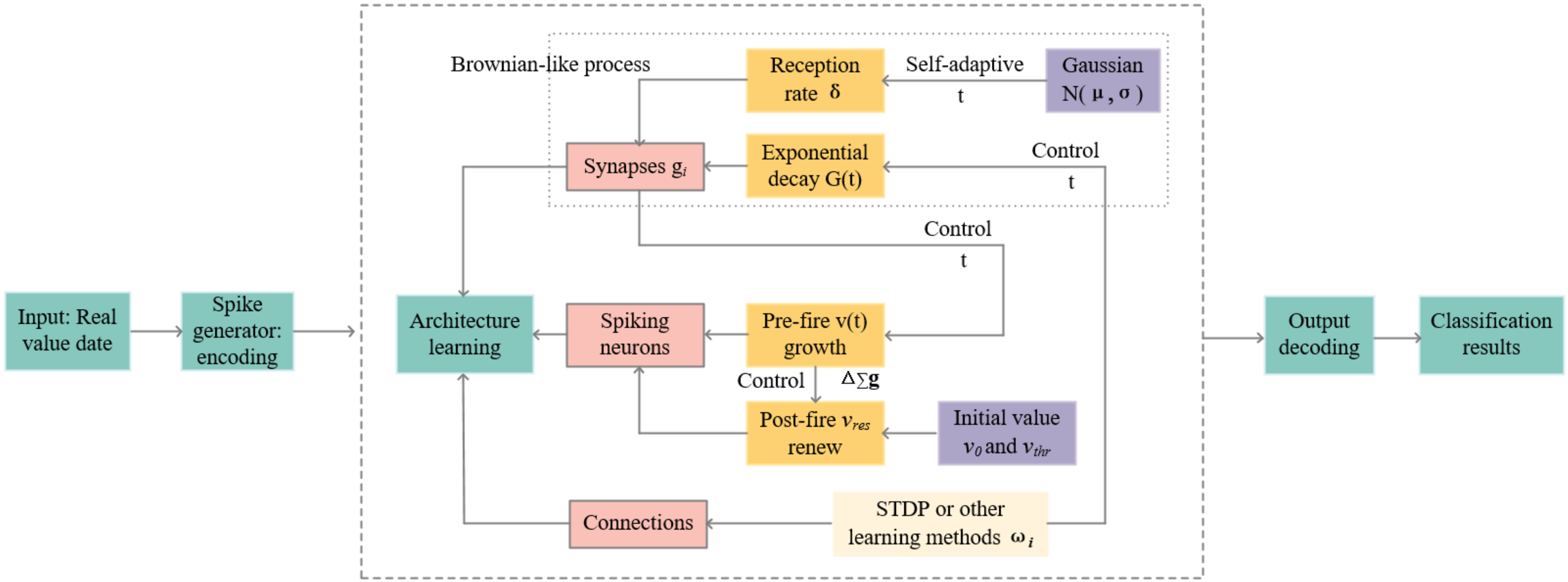
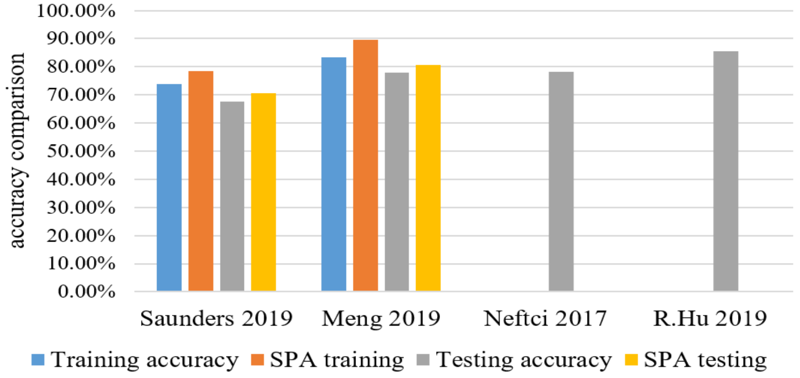


Fig. 5. The overall SNN balance system flowchart, where the mapping stochastic model is in the external dashed box, the specific stochastic process is in the internal dashed box. The control process includes self-adaptive adjustment and controlled adjustment.

Comparison

Paper	Description	Scales (neurons number)	Training samples/convergence	SPA samples	Training accuracy	SPA training results	Testing accuracy	SPA testing results
Diehl et al. 2015 [14]	2-layer unsupervised SNN	6400	60000×15times	**60000**	95.52%	**96.20%**	95.00%	**95.36%**
Saunders et al. 2019 [15]	2-layer unsupervised LC-SNN	9000	60000	**60000**	95.76%	**97.44%**	95.07%	**95.85%**
Meng et al. 2019 [16]	3-layer unsupervised SNN	10000	60000	**60000**	96.02%	**98.01%**	95.64%	**96.63%**

Paper	Training method	Training accuracy	SPA training accuracy	Testing accuracy	SPA testing accuracy
Diehl et al. 2015 [14]	Unsupervised STDP	58.68%	/	low	/
Saunders et al. 2019 [15]	Unsupervised STDP	73.92%	**78.41%**	67.68%	**70.47%**
Meng et al. 2019 [16]	Unsupervised STDP	83.30%	**89.59%**	79.86%	**81.72%**



Paper	Training samples	Scales	Origin testing accuracy	SPA results
Diehl et al. 2015 [14]	60000	100	82.9%	**86.62%**
		400	87.0%	**92.28%**
		1600	91.9%	**94.60%**
She et al. 2019 [25]	60000	1000	92.2%	/

Paper	SPA or not	Average training time (s / image)	Spikes intensity (spikes / per image)
Diehl et al. 2015 [14]	No	7.26±1	6~20
	Yes	7.48±1	4~16
Saunders et al. 2019 [15]	No	13.68±1	12~35
	Yes	13.24±1	11~30
Meng et al. 2019 [16]	No	13.32±1	35~60
	yes	13.16±1	16~50

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. 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. Besides, our method is similar to an adaptive generalized Wiener-random process, and the Wiener process method possibly can be combined with stochastic encoding in digital circuits to improve the performance. Combining neuroscience and computer science is already a key point of machine learning [28], especially for SNNs.

Thank You!