

# Wei Fang's CV [\[Homepage\]](#) [\[GitHub\]](#) [\[Google Scholar\]](#)

## About

Name: Wei Fang

Email: [fangwei123456g@gmail.com](mailto:fangwei123456g@gmail.com), [fwei@pku.edu.cn](mailto:fwei@pku.edu.cn)

## Education and Working Experience

2015.9-2019.6	Tsinghua University, Department of Automation, bachelor
2016.9-2019.6	Tsinghua University, School of Economics and Management, the second bachelor's degree
2019.9-2024.6	Peking University, School of Computer Science, Ph.D., advised by Professor <a href="#">Yonghong Tian</a>
2024.9-Now	Peking University, School of Electronic and Computer Engineering, Research Assistant Professor

## Publications

My research focuses on the deep learning algorithms of Spiking Neural Networks (SNNs), which is an inter-discipline of computational neuroscience, machine learning, deep learning, recurrent neural networks (RNNs), quantized neural networks, and neuromorphic computing. In general, deep SNNs can be regarded as special RNNs with activations quantized as 0 and 1. They have the advantages of high biologically plausible, event-driven, and sparse computation, and show extremely high power-efficiency in neuromorphic chips.

**Citations: 1407, h-index: 10, i10-index: 10.**

### First-author Publications

**[ICCV 2021][485 Citations]** [Incorporating Learnable Membrane Time Constant to Enhance Learning of Spiking Neural Networks](#)

Introduction: This paper models the spiking neurons to a general formulation and proposes the Parametric LIF neuron. Then both the weights of synapses and the neuronal dynamics can be trained in deep SNNs with the Parametric LIF neuron. The proposed method achieves STOA accuracy on three static and three neuromorphic datasets. Meanwhile, the spiking neuron model, the parameterization of neuronal dynamics, and network structure, and the data processing method of the neuromorphic datasets, are widely adopted by other researchers, which brings high citations for this paper.

**[NeurIPS 2021][363 Citations]** [Deep Residual Learning in Spiking Neural Networks](#)

Introduction: Based on the view of the identity mapping and gradients, this paper explains the reason why the Spiking ResNet gets worse performance in SNNs, and proposes the Spike-Element-Wise (SEW) ResNet. The recorded gradient data are consistent with the theoretical analysis that the Spiking ResNet suffers from vanishing/exploding problems, while the SEW ResNet gets stable gradients. The experiment results on ImageNet validate that the SEW ResNet obtains performance gain by adding layers, while the accuracy of Spiking ResNet degenerates with the increase of depth. This is also the first time that deep SNNs with more than 100 layers have been trained successfully. The SEW residual connection and the SEW ResNet have been the backbones of deep SNNs, and are applied in many new structures, such as Spikformer, SpikeGPT, and SpikeBERT.

**[Science Advances] [79 Citations]** [SpikingJelly: An Open-source Machine Learning Infrastructure Platform for Spike-based Intelligence](#)

Introduction: Spiking neural networks (SNNs) aim to realize brain-inspired intelligence on neuromorphic chips with high energy efficiency by introducing neural dynamics and spike properties. As the emerging spiking deep learning paradigm attracts increasing interest, traditional programming frameworks cannot meet the demands of the automatic differentiation, parallel computation acceleration, and high integration of processing neuromorphic datasets and deployment. In this work, we present the SpikingJelly framework to address the aforementioned dilemma. We contribute a full-stack toolkit for pre-processing neuromorphic datasets, building deep SNNs, optimizing their parameters, and deploying SNNs on neuromorphic chips. Compared to existing methods, the training of deep SNNs can be accelerated 11 $\times$  and the superior extensibility and flexibility of SpikingJelly enable users to accelerate custom models at low costs through multilevel inheritance and semiautomatic code generation.

With the full-stack solution provided by SpikingJelly for building, training, and deploying SNNs, the boundaries of deep SNNs have been

extended from toy dataset classification to applications with practical utility, including human-level performance classification, network deployment, and event data processing. Beyond the classic machine learning tasks, several frontier applications of deep SNNs have also been reported, including a spike-based neuromorphic perception system consisting of calibratable artificial sensory neurons, a neuromorphic computing model running on memristors and the design of an event-driven SNN hardware accelerator. All the above evidence indicates that the advent of SpikingJelly will accelerate the boom of the spiking deep learning community.

This research is recommended by **Nature Computational Science** in the Research Highlight article [A Full-stack Platform for Spiking Deep Learning](#).

**[NeurIPS 2023] [14 Citations] [Parallel Spiking Neurons with High Efficiency and Ability to Learn Long-term Dependencies](#)**

Introduction: Vanilla spiking neurons in Spiking Neural Networks (SNNs) use charge-fire-reset neuronal dynamics, which can only be simulated serially and can hardly learn long-time dependencies. We find that when removing reset, the neuronal dynamics can be reformulated in a non-iterative form and parallelized. By rewriting neuronal dynamics without reset to a general formulation, we propose the Parallel Spiking Neuron (PSN), which generates hidden states that are independent of their predecessors, resulting in parallelizable neuronal dynamics and extremely high simulation speed. The weights of inputs in the PSN are fully connected, which maximizes the utilization of temporal information. To avoid the use of future inputs for step-by-step inference, the weights of the PSN can be masked, resulting in the masked PSN. By sharing weights across time-steps based on the masked PSN, the sliding PSN is proposed to handle sequences of varying lengths. We evaluate the PSN family on simulation speed and temporal/static data classification, and the results show the overwhelming advantage of the PSN family in efficiency and accuracy.

### Other Publications

Papers	Publishers	Author Rank	Citations
<a href="#">Optimal ANN-SNN Conversion for High-accuracy and Ultra-low-latency Spiking Neural Networks</a>	ICLR 2022	2	162
<a href="#">Exploring Loss Functions for Time-based Training Strategy in Spiking Neural Networks</a>	NeurIPS 2023	2	7
<a href="#">Optimal ANN-SNN Conversion with Group Neurons</a>	ICASSP 2024	2	
<a href="#">Pruning of Deep Spiking Neural Networks through Gradient Rewiring</a>	IJCAI 2021	3	49
<a href="#">State Transition of Dendritic Spines Improves Learning of Sparse Spiking Neural Networks</a>	ICML 2022	3	27
<a href="#">Training Spiking Neural Networks with Event-driven Backpropagation</a>	NeurIPS 2022	3	35
<a href="#">A Unified Framework for Soft Threshold Pruning</a>	ICLR 2023	3	13
<a href="#">Self-architectural Knowledge Distillation for Spiking Neural Networks</a>	Neural Networks	4	1
<a href="#">Spike-based Dynamic Computing with Asynchronous Sensing-Computing Neuromorphic Chip</a>	Nature Communications	8	

### Academic Service

Journal Reviewer: IEEE Transactions on Cognitive and Developmental Systems, IEEE Transactions on Neural Networks and Learning Systems, IEEE Transactions on Pattern Analysis and Machine Intelligence, Neural Networks

Conference Reviewer: CVPR, ICCV, NeurIPS, ICLR

### Projects

[SpikingJelly: an open-source deep learning framework for Spiking Neural Networks \(SNNs\)](#)

- 1200+ stars, 220+ forks, 520+ issues/pull requests
- There are more than 210 [publications](#) using SpikingJelly, including ICCV 4, IJCAI 3, NeurIPS 9, CVPR 5, ICLR 4, AAAI 6,

ICML 2, ECCV 3, TMLR 1, ACM MM 1, PR 1, Nature Communications 2, IEEE Transactions 14

#### [Python JPEG Encoder](#)

- This project starts from scratch to create a standardized JPEG file

#### [Tello GUI Controller](#)

- A GUI controller based on Qt5 for the DJI Tello UAV.

#### **Contributions to other open-source projects**

- [Lava DL](#) (a library of deep learning tools for deep event-based networks under Intel's leadership): fix the bug of WgtScaleBatchNorm, block.AbstractInput
- [Awesome Model Quantization](#)(Collections about model quantization): fix the errors of paper URLs

### **Awards**

---

- Outstanding Students of the Year of National Engineering Laboratory for Video Technology, Peking University, in 2021
- Outstanding developers of the OpenIntelligence (OpenI) community in 2020, 2021, and 2022
- The first prize of the fourth China Software Open Source Innovation Competition
- Merit Student of Peking University in the academic year of 2021-2022
- College Scholarship (Schlumberger Scholarship) of School of Computer Science, Peking University in the academic year of 2021-2022
- Merit Student of Peking University in the academic year of 2022-2023
- College Scholarship (Ubiquant Scholarship) of School of Computer Science, Peking University in the academic year of 2022-2023
- "Shi Qingyun Academician's Excellent Thesis Award" in 2023 (only two papers will be selected from the students in School of Intelligence Science and Technology, School of Computer Science and School of Mathematical Sciences in Peking University)
- Annual Top 10 students of the National Engineering Laboratory for Video Technology (rank first)
- Outstanding Graduate of Peking University, 2024
- Outstanding Graduate of Beijing, 2024
- Outstanding Doctoral Dissertation Award, Peking University, 2024

Note: Data in this CV are as of 2024.07.11