Novelty Assessment Report

Paper: Online Pseudo-Zeroth-Order Training of Neuromorphic Spiking Neural Networks

PDF URL: https://openreview.net/pdf?id=6ZietpbPoB

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2026-01-07

Abstract

Brain-inspired neuromorphic computing with spiking neural networks (SNNs) is a promising energy-efficient computational approach. However, successfully training deep SNNs in a more biologically plausible and neuromorphic-hardware-friendly way is still challenging. Most recent methods leverage spatial and temporal backpropagation (BP), not adhering to neuromorphic properties. Despite the efforts of some online training methods, tackling spatial credit assignments by alternatives with competitive performance as spatial BP remains a significant problem. In this work, we propose a novel method, online pseudo-zeroth-order (OPZO) training. Our method only requires a single forward propagation with noise injection and direct top-down signals for spatial credit assignment, avoiding spatial BP's problem of symmetric weights and separate phases for layer-by-layer forward-backward propagation. OPZO solves the large variance problem of zeroth-order methods by the pseudo-zeroth-order formulation and momentum feedback connections, while having more guarantees than random feedback. Combining online training, OPZO can pave paths to on-chip SNN training. Experiments on neuromorphic and static datasets with both fully connected and convolutional networks demonstrate the effectiveness of OPZO with competitive performance compared with spatial BP, as well as estimated low training costs.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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Core Task Landscape

This paper addresses: **biologically plausible training of spiking neural networks**

A total of **50 papers** were analyzed and organized into a taxonomy with **25 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Learning Rule Design and Theoretical Foundations**
- **Network Architecture and Structural Design**
- **Training Efficiency and Optimization Techniques**
- **Domain-Specific Applications and Implementations**
- **Theoretical Analysis and Comparative Studies**
- **Interdisciplinary Perspectives and Emerging Paradigms**

Complete Taxonomy Tree

- biologically plausible training of spiking neural networks Survey Taxonomy
- Learning Rule Design and Theoretical Foundations
  - Gradient-Based and Backpropagation Alternatives
  - Spatiotemporal Gradient Adjustment Methods (2 papers)
    - [9] Backpropagation with biologically plausible spatiotemporal adjustment for training deep spiking neural networks (Shen, 2022) View paper
    - [11] Bioleaf: A bio-plausible learning framework for training of spiking neural networks (Yang Yukun, 2021) View paper
  - Zeroth-Order and Feedback-Based Approximations ★ (3 papers)
    - [0] Online Pseudo-Zeroth-Order Training of Neuromorphic Spiking Neural Networks (Anon et al., 2026) View paper
    - [12] BioGrad: Biologically Plausible Gradient-Based Learning for Spiking Neural Networks (Tang, 2022) View paper
    - [22] Approximating back-propagation for a biologically plausible local learning rule in spiking neural networks (Amar Shrestha, 2019) View paper
  - Local and Unsupervised Learning Mechanisms
  - Hebbian and Spike-Timing-Dependent Plasticity (3 papers)
    - [6] Biologically plausible unsupervised learning for self-organizing spiking neural networks with dendritic computation (Geng Zhang, 2025) View paper
    - [13] A biologically plausible speech recognition framework based on spiking neural networks (Jibin Wu, 2018) View paper
    - [39] Biologically plausible learning algorithms (Mutalik, 2019) View paper
  - Self-Organizing and Active Learning Approaches (2 papers)
    - [4] Bio-inspired Active Learning method in spiking neural network (Qiugang Zhan, 2022) View paper
    - [16] Adaptive structure evolution and biologically plausible synaptic plasticity for recurrent spiking neural networks (Wenxuan Pan, 2023) View paper
  - Reinforcement Learning and Model-Based Methods (3 papers)
  - [20] Towards biologically plausible model-based reinforcement learning in recurrent spiking networks by dreaming new experiences (Cristiano Capone, 2024) View paper
  - [21] Biologically plausible solutions for spiking networks with efficient coding (Koren, 2022) View paper
  - [41] Energy-aware bio-inspired spiking reinforcement learning system architecture for real-time autonomous edge applications (Joshua Ifeanyi Okonkwo, 2024) View paper
  - Online and Continual Learning Frameworks (2 papers)

- [26] Online Training Through Time for Spiking Neural Networks (Xiao Ming-qing, 2022) View paper
  - [45] NADOL: Neuromorphic architecture for spike-driven online learning by dendrites (Shuangming Yang, 2023) View paper
- Network Architecture and Structural Design
  - Neural Circuit Evolution and Topology Optimization (2 papers)
  - [3] Brain-inspired neural circuit evolution for spiking neural networks (Guobin Shen, 2023) View paper
  - [49] Bio-inspired evolutionary model of spiking neural networks in ionic liquid space (Ensieh Iranmehr, 2019) View paper
  - Transformer and Attention-Based SNN Architectures (2 papers)
  - [10] Attention Spiking Neural Networks (Man Yao, 2023) View paper
  - [23] Spike-driven transformer v2: Meta spiking neural network architecture inspiring the design of next-generation neuromorphic chips (Yao Man, 2024) View paper
  - Dendritic Computation and Neuron Model Extensions (1 papers)
  - [7] Ternary Spike: Learning Ternary Spikes for Spiking Neural Networks (Chen, 2023) View paper
- Training Efficiency and Optimization Techniques
  - Initialization and Convergence Optimization (2 papers)
  - [31] Fluctuation-driven initialization for spiking neural network training (Julian Rossbroich, 2022) View paper
  - [37] Going Deeper With Directly-Trained Larger Spiking Neural Networks (Deng Lei, 2021) View paper
  - Data Augmentation and Regularization (1 papers)
  - [17] Neuromorphic Data Augmentation for Training Spiking Neural Networks (Yuhang Li, 2022) View paper
  - Transfer Learning and Domain Adaptation (1 papers)
  - [19] Effective Transfer Learning Algorithm in Spiking Neural Networks (Qiugang Zhan, 2021) View paper
- Domain-Specific Applications and Implementations
  - Robotics and Control Applications (2 papers)
  - [1] Brain-inspired learning rules for spiking neural network-based control: a tutorial (Choongseop Lee, 2025) View paper
  - [24] A survey of robotics control based on learning-inspired spiking neural networks (Zhenshan Bing, 2018) View paper
  - Speech and Audio Processing (1 papers)
  - [43] Neuromorphic Speech Recognition With Photonic Convolutional Spiking Neural Networks (Shui-Ying Xiang, 2023) View paper
  - Vision and Image Recognition (2 papers)
  - [34] Computational modeling of color perception with biologically plausible spiking neural networks (Hadar Cohen Duwek, 2022) View paper
  - [46] A 10 000-Inference/s Bio-Inspired Spiking Vision Chip Based on an End-to-End SNN Embedding Image Signal Enhancement (Xu Yang, 2025) View paper
  - Medical and Healthcare Applications (2 papers)
  - [32] Integrating Complexity and Biological Realism: High-Performance Spiking Neural Networks for Breast Cancer Detection (Agnieszka, 2025) View paper
  - [33] Neuromorphic deep spiking neural networks for seizure detection (Yikai Yang, 2023) View paper
  - Natural Language Processing and Sentiment Analysis (2 papers)
  - [5] Biologically plausible learning for NLP using spiking neural network (T Hossain, 2025) View paper
  - [27] Neuromorphic Sentiment Analysis Using Spiking Neural Networks (Raghavendra K. Chunduri, 2023) View paper
  - Neuromorphic Hardware and Privacy-Preserving Computing (3 papers)
  - [42] Lead federated neuromorphic learning for wireless edge artificial intelligence (Helin Yang, 2022) View paper
  - [44] A self-training spiking superconducting neuromorphic architecture (Schneider Ml, 2025) View paper
  - [47] Towards Privacy-Preserving Federated Neuromorphic Learning via Spiking Neuron Models (Bing Han, 2023) View paper
- Theoretical Analysis and Comparative Studies
  - Survey and Tutorial Papers (5 papers)
  - [2] A review of learning in biologically plausible spiking neural networks (A. Taherkhani, 2020) View paper
  - [8] Towards biologically plausible learning in neural networks (JesÃºs GarcÃa FernÃ¡ndez, 2021) View paper
  - [25] Research on SNN Learning Algorithms and Networks Based on Biological Plausibility (Bingqiang Huo, 2025) View paper
  - [29] Biologically Plausible Learning with Spiking Neural Networks (Daniel Niederlechner, 2021) View paper
  - [40] Training Spiking Neural Networks Using Lessons From Deep Learning (Eshraghian, 2023) View paper
  - Neural Coding and Representation Studies (1 papers)
  - [36] Neural coding in spiking neural networks: A comparative study for robust neuromorphic systems (Wenzhe Guo, 2021) View paper
  - Robustness and Adversarial Analysis (1 papers)
  - [14] Neuromorphic computing paradigms enhance robustness through spiking neural networks (Jianhao Ding, 2025) View paper
  - ANN-SNN Conversion and Hybrid Approaches (1 papers)
  - [35] When bio-inspired computing meets deep learning: Low-latency, accurate, & energy-efficient spiking neural networks from artificial neural networks (Datta, 2023) View paper
  - Benchmark and Framework Evaluations (2 papers)
  - [15] Efficient Biologically-Plausible Training of Spiking Neural Networks with Precise Timing (Richard Boone Ph.D., 2021) View paper
  - [50] A comprehensive multimodal benchmark of neuromorphic training frameworks for spiking neural networks (Wang Xin-hu, 2025) View paper
- Interdisciplinary Perspectives and Emerging Paradigms
  - Neuroscience-AI Integration and Brain-Inspired Computing (3 papers)
  - [18] Brain-inspired spiking neural networks (Khadeer Ahmed, 2020) View paper
  - [38] Bio-Inspired Approaches for Deep Learning: From Spiking Neural Networks to Hebbian Plasticity (Lagani, 2023) View paper
  - [48] Learning in Biologically Plausible Neural Networks (Xu, 2022) View paper
  - Neuromorphic Hardware Technologies and Implementations (2 papers)
  - [28] Contemporary implementations of spiking bio-inspired neural networks (Andrey Schegolev, 2024) View paper
  - [30] Memristorsâ□□From inâ□□memory computing, deep learning acceleration, and spiking neural networks to the future of neuromorphic and bioâ□□inspired computing (Adnan MehoniÄ□, 2020) View paper

Narrative

Core task: biologically plausible training of spiking neural networks. The field organizes around several complementary perspectives. Learning Rule Design and Theoretical Foundations explores how to derive training algorithms that respect biological constraints, including gradient-based alternatives and feedback mechanisms that avoid the implausibilities of standard backpropagation. Network Architecture and Structural Design examines neuron models, dendritic computation, and connectivity patterns inspired by cortical circuits. Training Efficiency and Optimization Techniques addresses practical concerns such as convergence speed, memory usage, and online learning regimes. Domain-Specific Applications and Implementations demonstrate these methods on tasks ranging from vision and speech recognition to robotics control, while Theoretical Analysis and Comparative Studies provide rigorous benchmarks and performance guarantees. Interdisciplinary Perspectives and Emerging Paradigms bring insights from neuroscience, evolutionary algorithms, and novel hardware substrates, creating a rich landscape that balances biological fidelity with computational performance.

Within the gradient-based alternatives, a particularly active line of work focuses on zeroth-order and feedback-based approximations that sidestep the need for precise error backpropagation. Online Pseudo Zeroth Order[0] exemplifies this direction by proposing efficient pseudo-gradient estimates suitable for online learning scenarios. Nearby efforts such as BioGrad[12] and Approximating Backpropagation Local[22] similarly seek local update rules that approximate global objectives without violating biological constraints like weight transport or symmetric connectivity. These methods contrast with approaches in other branches that rely on more structured architectural priors or hybrid training schemes. A central tension across the field is whether to prioritize strict biological realism—potentially sacrificing some performance—or to adopt pragmatic approximations that retain key neuromorphic properties while achieving competitive accuracy. Online Pseudo Zeroth Order[0] navigates this trade-off by maintaining local computations and online adaptability, positioning itself among works that emphasize scalability and real-time learning over exact gradient fidelity.

Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

1. BioGrad: Biologically Plausible Gradient-Based Learning for Spiking Neural Networks

Authors: Tang, Guangzhi, Kumar Neelesh, Guangzhi Tang, Polykretis, et al. (11 authors total) | **Year/Venue**: 2022 | **URL**: View paper

Abstract

Spiking neural networks (SNN) are delivering energy-efficient, massively parallel, and low-latency solutions to AI problems, facilitated by the emerging neuromorphic chips. To harness these computational benefits, SNN need to be trained by learning algorithms that adhere to brain-inspired neuromorphic principles, namely event-based, local, and online computations. Yet, the state-of-the-art SNN training algorithms are based on backprop that does not follow the above principles. Due to its limited...

Relationship Analysis

Both papers belong to the Zeroth-Order and Feedback-Based Approximations category, addressing biologically plausible training without symmetric weight transport. While the original paper (OPZO) uses pseudo-zeroth-order formulations with noise injection and momentum feedback connections for online training, BioGrad employs multi-compartment neurons with eligibility traces and a periodic sleep phase to align feedback weights, achieving functional equivalence to backpropagation through a different architectural and learning mechanism.

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2. Approximating back-propagation for a biologically plausible local learning rule in spiking neural networks

Authors: Amar Shrestha, Haowen Fang, Qing Wu, Qinru Qiu | **Year/Venue**: 2019 | **URL**: View paper

Abstract

Asynchronous event-driven computation and communication using spikes facilitate the realization of spiking neural networks (SNN) to be massively parallel, extremely energy efficient and highly robust on specialized neuromorphic hardware. However, the lack of a unified robust learning algorithm limits the SNN to shallow networks with low accuracies. Artificial neural networks (ANN), however, have the backpropagation algorithm which can utilize gradient descent to train networks which are locally ...

Relationship Analysis

Both papers belong to the 'Zeroth-Order and Feedback-Based Approximations' category, seeking biologically plausible alternatives to standard backpropagation in SNNs by avoiding symmetric weight transport. The original paper proposes online pseudo-zeroth-order (OPZO) training using noise injection and momentum feedback connections to estimate gradients without spatial BP, while the candidate paper approximates backpropagation using spiking neurons themselves and extends it to a local STDP-like learning rule. The key difference is that OPZO uses zeroth-order optimization with direct feedback signals, whereas the candidate maintains a backpropagation-like structure but implements it through spiking neuron dynamics.

Contributions Analysis

Overall novelty summary. The paper proposes OPZO, a training method for spiking neural networks that uses noise injection and direct top-down signals for spatial credit assignment, avoiding symmetric weight transport and separate forward-backward phases. It sits in the 'Zeroth-Order and Feedback-Based Approximations' leaf, which contains only three papers total, indicating a relatively sparse research direction within the broader field of biologically plausible SNN training. This leaf focuses specifically on methods that replace explicit gradient backpropagation with noise-based or feedback mechanisms, distinguishing it from the more populated gradient-adjustment approaches in the sibling leaf.

The taxonomy reveals that OPZO's parent branch, 'Gradient-Based and Backpropagation Alternatives', contains two main directions: spatiotemporal gradient adjustment methods and zeroth-order/feedback approaches. The sibling leaf on gradient adjustment includes techniques that still compute explicit gradients but modify their flow, whereas OPZO's leaf emphasizes avoiding gradient computation entirely. Neighboring branches in 'Learning Rule Design' include local Hebbian mechanisms and reinforcement learning methods, which differ fundamentally by relying on unsupervised correlation-based rules or reward signals rather than supervised error-driven updates. The taxonomy's scope notes clarify that OPZO belongs here because it uses feedback signals without explicit gradient backpropagation, not in the Hebbian category.

Among the three contributions analyzed across twenty-eight candidate papers, the pseudo-zeroth-order formulation examined eight candidates with none providing clear refutation, while the OPZO training method with momentum feedback examined ten candidates, also without refutation. The biologically plausible on-chip training framework examined ten candidates and found one that appears to provide overlapping prior work. This suggests that the core algorithmic innovations appear relatively novel within the limited search scope, while the on-chip training framing may have more substantial precedent. The analysis explicitly covers top-K semantic matches and citation expansion, not an exhaustive literature review.

Based on the limited search of twenty-eight candidates, the work appears to occupy a sparsely populated research direction with modest prior overlap. The core pseudo-zeroth-order formulation and momentum feedback mechanisms show no clear refutation among examined candidates, though the on-chip training motivation has at least one overlapping prior work. The taxonomy structure suggests this is an emerging area within biologically plausible SNN training, though definitive novelty claims would require broader literature coverage beyond the semantic search scope employed here.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Pseudo-zeroth-order formulation for neural network training

Description: The authors introduce a formulation that separates the model function from the loss function, maintaining a zeroth-order approach for the model while leveraging first-order gradients of the loss. This decoupling enables more informative error signals compared to standard zeroth-order methods, reducing variance while preserving the black-box property of the model.

This contribution was assessed against **8 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. A Stochastic Vanishing Viscosity Approach for Eikonal Equations

URL: View paper

Brief Assessment

Stochastic Vanishing Viscosity[65] focuses on solving Eikonal equations using stochastic methods, not neural network training or zeroth-order optimization for machine learning models.

2. Relizo: Sample reusable linear interpolation-based zeroth-order optimization

URL: View paper

Brief Assessment

Relizo[58] focuses on zeroth-order optimization through linear interpolation and query reuse for general optimization problems, not on decoupling model and loss functions for neural network training as in the original paper's pseudo-zeroth-order formulation.

3. Gradient-free learning based on the kernel and the range space

URL: View paper

Brief Assessment

Kernel Range Space[62] focuses on gradient-free learning through kernel-and-range space manipulation for linear systems, not on decoupling model and loss functions in zeroth-order optimization for neural networks.

4. Revising recurrent neural networks to eliminate numerical derivatives in forming Physics-Informed loss terms with respect to time

URL: View paper

Brief Assessment

Eliminating Numerical Derivatives[60] focuses on revising RNN architectures for physics-informed loss terms with respect to time, not on decoupling model and loss functions for zeroth-order optimization in general neural network training.

5. Training radial basis neural networks with the extended Kalman filter

URL: View paper

Brief Assessment

Extended Kalman Filter[61] focuses on derivative-free training methods for radial basis neural networks using decoupled extended Kalman filters, not on decoupling model and loss functions for zeroth-order optimization with first-order loss gradients.

6. Homogenization of Composites using the Derivative-Free Loss Method for Neural Networks

URL: View paper

Brief Assessment

Derivative Free Loss[64] applies derivative-free methods to composite material homogenization, not to neural network training with decoupled model and loss functions for reducing gradient variance.

7. Gradient-free policy architecture search and adaptation

URL: View paper

Brief Assessment

Gradient Free Policy[59] focuses on gradient-free policy architecture search for autonomous driving using evolutionary methods, not on decoupling model and loss functions for neural network training with zeroth-order optimization.

8. Optimization Design of Adaptive Loss Function Using Evolutionary Neural Networks

URL: View paper

Brief Assessment

Adaptive Loss Function[63] focuses on optimizing loss functions using evolutionary neural networks for derivative-free optimization, not on decoupling model and loss functions for zeroth-order gradient estimation in neural network training.

Contribution 2: OPZO training method with momentum feedback connections

Description: The authors develop the online pseudo-zeroth-order (OPZO) training method that uses only one forward pass with noise injection and direct top-down feedback via momentum-based connections. These connections are updated using one-point zeroth-order estimation of the Jacobian expectation, addressing the high variance problem of traditional zeroth-order approaches while maintaining computational efficiency.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Convergence of first-order algorithms with momentum from the perspective of an inexact gradient descent method

URL: View paper

Brief Assessment

Inexact Gradient Descent[70] focuses on first-order optimization algorithms with momentum for general smooth functions, not on zeroth-order training methods for spiking neural networks with single forward pass and noise injection as in the original paper.

2. Tensor-compressed back-propagation-free training for (physics-informed) neural networks

URL: View paper

Brief Assessment

Tensor Compressed Training[72] focuses on tensor-train decomposition for variance reduction in zeroth-order optimization, not on momentum feedback connections for spatial credit assignment in spiking neural networks. The technical approaches and application domains differ fundamentally.

3. A consensus-based global optimization method with adaptive momentum estimation

URL: View paper

Brief Assessment

Consensus Based Momentum[68] focuses on consensus-based optimization for general high-dimensional functions, not on neuromorphic SNN training with zeroth-order methods and momentum feedback connections for spatial credit assignment.

4. Distributed gradient-free and projection-free algorithm for stochastic constrained optimization

URL: View paper

Brief Assessment

Distributed Gradient Free[66] focuses on distributed stochastic zeroth-order optimization for multi-agent systems with Frank-Wolfe framework, not neuromorphic SNN training with momentum feedback connections for spatial credit assignment.

5. Boosting One-Point Derivative-Free Online Optimization via Residual Feedback

URL: View paper

Brief Assessment

Residual Feedback Boosting[67] focuses on online optimization with time-varying objective functions using residual feedback between consecutive time steps, not on neural network training with momentum-based feedback connections for spatial credit assignment in SNNs.

6. Hardware Aware Robust Compression of Neural Networks

URL: View paper

Brief Assessment

Hardware Aware Compression[75] focuses on neural network compression techniques (pruning, quantization) for hardware deployment, not on training methods using zeroth-order optimization with momentum feedback connections for spiking neural networks.

7. Enhancing zeroth-order fine-tuning for language models with low-rank structures

URL: View paper

Brief Assessment

Zeroth Order Low Rank[69] focuses on fine-tuning large language models using low-rank gradient estimators for memory efficiency, not on training spiking neural networks with momentum feedback connections for neuromorphic computing.

8. Zo-adamu optimizer: Adapting perturbation by the momentum and uncertainty in zeroth-order optimization

URL: View paper

Brief Assessment

Zo-adamu[71] focuses on adapting momentum in zeroth-order optimization for LLM fine-tuning via perturbation-based gradient estimation, not on neuromorphic SNN training with direct top-down feedback connections for spatial credit assignment.

9. Zo-adamm: Zeroth-order adaptive momentum method for black-box optimization

URL: View paper

Brief Assessment

Zo-adamm[74] focuses on zeroth-order optimization for black-box problems using adaptive momentum methods (AdamM), not on neuromorphic SNN training with momentum feedback connections for spatial credit assignment as in the original paper.

10. Gradient-free method for heavily constrained nonconvex optimization

URL: View paper

Brief Assessment

Heavily Constrained Nonconvex[73] focuses on constrained optimization with penalty methods for handling multiple constraints, not on training neural networks with momentum-based feedback connections for spatial credit assignment.

Contribution 3: Biologically plausible on-chip training framework for SNNs

Description: By combining the pseudo-zeroth-order approach with online training methods, OPZO achieves a form similar to three-factor Hebbian learning with direct top-down modulations. This framework avoids the biological implausibility of spatial backpropagation (symmetric weights, separate forward-backward phases) and is designed to be compatible with neuromorphic hardware for on-chip SNN training.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Neuro-inspired computing chips

URL: View paper

Brief Assessment

Neuro Inspired Chips[56] discusses neuromorphic computing hardware technologies but does not present methods for biologically plausible online training of SNNs. The candidate focuses on hardware architectures rather than training algorithms that avoid spatial backpropagation.

2. Towards biologically plausible model-based reinforcement learning in recurrent spiking networks by dreaming new experiences

URL: View paper

Brief Assessment

Biologically Plausible Dreaming[20] focuses on model-based reinforcement learning with dreaming mechanisms in recurrent spiking networks, not on-chip training frameworks that avoid spatial backpropagation through pseudo-zeroth-order methods.

3. BrainScale, Enabling Scalable Online Learning in Spiking Neural Networks

URL: View paper

Brief Assessment

BrainScale[55] focuses on scalable online learning algorithms with linear memory complexity for large-scale brain simulation, not on biologically plausible alternatives to spatial backpropagation or neuromorphic hardware compatibility through three-factor Hebbian learning with direct top-down modulations.

4. Think local, act global: robust and real-time movement encoding in spiking neural networks using neuromorphic hardware

URL: View paper

Brief Assessment

Think Local Act Global[54] focuses on movement encoding using reservoir computing with the ResuMe learning rule on Loihi hardware, not on developing general biologically plausible training frameworks that avoid spatial backpropagation like OPZO's pseudo-zeroth-order approach with momentum feedback connections.

5. E-prop on SpiNNaker 2: Exploring online learning in spiking RNNs on neuromorphic hardware

URL: View paper

Brief Assessment

E-prop SpiNNaker[53] focuses on implementing the e-prop algorithm on neuromorphic hardware for keyword spotting tasks, not on developing a novel biologically plausible training framework that avoids spatial backpropagation like OPZO does.

6. Bio-inspired Active Learning method in spiking neural network

URL: View paper

Brief Assessment

Bio Inspired Active Learning[4] is not available for comparison as no full text context was provided for this candidate paper.

7. Ndot: Neuronal dynamics-based online training for spiking neural networks

URL: View paper

Brief Assessment

Ndot[51] focuses on forward-in-time learning using neuronal dynamics to capture temporal dependencies, not on addressing spatial backpropagation's biological implausibility through pseudo-zeroth-order methods with direct top-down modulation.

8. ETLP: event-based three-factor local plasticity for online learning with neuromorphic hardware

URL: View paper

Brief Assessment

ETLP[57] focuses on event-based three-factor local plasticity with projected labels for pattern recognition, while OPZO addresses spatial credit assignment through pseudo-zeroth-order optimization with momentum feedback connections, representing different technical approaches to on-chip learning.

9. Biologically-inspired training of spiking recurrent neural networks with neuromorphic hardware

URL: View paper

Brief Assessment

Biologically Inspired Hardware Training[52] focuses on implementing e-prop (a specific existing algorithm) on neuromorphic hardware with phase-change memory, rather than proposing a novel training framework like OPZO's pseudo-zeroth-order approach with three-factor Hebbian learning.

10. Online Training Through Time for Spiking Neural Networks

URL: View paper

Prior Art Analysis

Online Training Through Time[26] demonstrates that biologically plausible on-chip training for SNNs was achieved prior to the ORIGINAL paper. The candidate paper presents OTTT, which achieves three-factor Hebbian learning with direct top-down modulations without spatial backpropagation, avoiding symmetric weights and separate forward-backward phases. The candidate explicitly states that OTTT is 'in the form of three-factor hebbian learning rule' and is designed for 'online on-chip learning' on neuromorphic hardware, directly addressing the same biological plausibility concerns (symmetric weights, separate phases) that the ORIGINAL paper claims as novel contributions.

Evidence

Evidence 1 - **Rationale**: Both papers claim biological plausibility for on-chip training through three-factor learning rules with local updates and global signals, demonstrating that the candidate achieved this contribution first. - **Original**: built upon online training, opzo provides a more biologically plausible method friendly for potential on-chip training of snns - **Candidate**: we show that ottt is in the form of three-factor hebbian learning rule [37] and the weight can be updated locally with a global signal. the error signal δj[t] can be propagated in an error feedback path simultaneously with feedforward propagation, which is shown biologically plausible with high-freq...

Appendix: Text Similarity Detection

Textual similarity detection checked 30 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Enhancing zeroth-order fine-tuning for language models with low-rank structures

Detected in: Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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