

Synchrony-Based Coding Enhances Robustness in Spiking Multimodal Retrieval Models

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: Does replacing temporal coding with synchrony-based coding in spiking multimodal models enhance robustness against adversarial perturbations in cross-modal retrieval metrics. 17 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Learning with Spike Synchrony in Spiking Neural Networks. Research question: Does replacing temporal coding with synchrony-based coding in spiking multimodal models enhance robustness against adversarial perturbations in cross-modal retrieval metrics?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.3/10.

3 Results

15 papers retrieved. 17 claims extracted; 0 independently verified. Quality review score: 2.3/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
SSDP was evaluated on static image datasets including Fashion-MNIST, CIFAR-10, CIFAR-100, and ImageNet.	×	0.05
SSDP was evaluated on event-driven neuromorphic vision datasets N-MNIST and CIFAR10-DVS.	×	0.04
SSDP was evaluated on auditory high temporal datasets SHD and SSC.	×	0.06
The Proposed SpikingResformer-L achieved a Top-1 classification accuracy of $79.35\% \pm 0.36\%$ on ImageNet-1K.	×	0.05
The Proposed SpikingResformer-L has 60.38M parameters and 8.89G MACs.	×	0.02
Spikingformer-8-768 achieved a Top-1 classification accuracy of 74.81 on ImageNet-1K.	×	0.05
Spike-driven Transformer-8-768 achieved a Top-1 classification accuracy of 76.32 on ImageNet-1K.	×	0.04
DHSRNN+SSDP achieved an accuracy of $89.1\% \pm 0.21\%$ on the SHD dataset.	×	0.02
DHSNN+SSDP achieved an accuracy of $82.86\% \pm 0.26\%$ on the SSC dataset.	×	0.02
The Proposed SpikingResformer-Cifar achieved an accuracy of $96.24\% \pm 0.29\%$ on CIFAR-10.	×	0.01
The Proposed SpikingResformer-Cifar achieved an accuracy of $79.48\% \pm 0.27\%$ on CIFAR-100.	×	0.01
Transformer-4-384 achieved an accuracy of 96.73 on CIFAR-10.	×	0.01
Transformer-4-384 achieved an accuracy of 81.02 on CIFAR-100.	×	0.01
The synchrony gate $\lambda_{b,j,i}$ equals 1 if and only if both the presynaptic neuron i and postsynaptic neuron j emit at least	×	0.04
Recording only first-spike times requires $O(BC)$ memory, whereas recording all spike times requires $O(BCT)$ memory.	×	0.02
In the proposed method, silent units are assigned a first-spike time equal to T (the simulation window length).	×	0.04
Using binary spike flags focuses the update on co-activation rather than raw firing rates.	×	0.03

References

- <http://arxiv.org/abs/2405.18770v6>
- <http://arxiv.org/abs/2505.14841v2>
- <http://arxiv.org/abs/2104.09369v1>