

Hybrid Neural Unit Bridging Artificial and Spiking Networks for Efficient Processing of Event-Based Data

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Brain-inspired computing has motivated the development of spiking neural networks (SNNs), which process information through sparse, event-driven spikes similar to biological neurons. While such models promise improved energy efficiency and temporal processing capabilities, they often remain difficult to train and integrate with the powerful learning mechanisms of conventional artificial neural networks (ANNs). Conversely, modern deep learning architectures provide highly effective optimization and representation learning but typically rely on dense, frame-based data and continuous activations, limiting their compatibility with event-driven sensing paradigms [1].

In this work, we propose a hybrid neural processing unit designed to bridge these two computational frameworks. The proposed unit performs forward computation through spike-based dynamics inspired by neuronal signaling while remaining fully compatible with gradient-based training methods used in standard deep learning. This hybrid design enables efficient event-driven computation while retaining the optimization advantages of ANN-based learning.

Event-based vision sensors, such as Dynamic Vision Sensors (DVS), provide a compelling application domain for such architectures by producing asynchronous streams of brightness changes rather than conventional image frames. Preliminary experiments achieve **97.5% accuracy on DVSGesture** and **93.2% on the SHD dataset**, placing the proposed hybrid architecture within the competitive range of current SNN approaches while using a lightweight model and efficient training (See Table 1). Preliminary experiments demonstrate the hybrid approach can effectively leverage the temporal and sparse characteristics of neuromorphic data while maintaining compact model complexity.

These results highlight the potential of leveraging biologically inspired principles and hybrid ANN–SNN architectures as a practical pathway toward scalable, brain-inspired machine learning systems capable of efficiently processing event-driven sensory data [2].

Table 1 Comparison of the proposed hybrid unit with typical SNN approaches on benchmarks.

Dataset	Model	Accuracy	Epochs to converge
DVSGesture [3]	State-of-the-art SNNs[4]	95-98%	150-500
	Hybrid Unit (Ours)	97.5%	60
SHD [5]	State-of-the-art SNNs[6]	90-95%	300-500
	Hybrid Unit (Ours)	93.2%	40

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