Leveraging Time for Sparse Spiking Forward-Forward Algorithm

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The Forward-Forward (FF) [1] algorithm has recently emerged as a promising alternative to error backpropagation as it's layer-wise contrastive loss enables to rely on local weight updates only. The algorithm consists of forward passes only in the network of positive and negative data, the former are intended to maximize a layer-wise "goodness" function while the later should in contrast minimize it. However, the standard definition of this goodness as the sum of neuron activations inherently promotes dense firing, especially for positive examples, making existing rate-coded Spiking Forward-Forward (C-SFF) [2] suboptimal in terms of sparsity and energy-efficiency.
To address this limitation, we introduce a Time-To-First-Spike (TTFS) variant of the C-SFF algorithm, in which neurons are allowed to fire only once. Instead of relying on spiking activity we devised a custom time-based "goodness" such that learning depends on the spike timing rather than the firing rate. Once trained, the network should respond quickly when submitted to positive examples while negative examples should elicit a delayed response. This new theoretical framework which shifts from the intensity of the activity towards its timing benefits from this intrinsically temporally sparse regime while preserving a local and backpropagation-free learning rule. Furthermore, the proposed framework naturally accommodates trainable synaptic delays, which provide additional degrees of freedom to shape the temporal response of the network also benefiting from the differentiability of spike times [3].
Experiments on the MNIST dataset using latency encoding and a single fully connected spiking layer of 2000 leaky integrate-and-fire (LIF) neurons with exponentially decaying synapses, demonstrate a reduction in spike count by a factor 10 while maintaining a comparable test error to rate-based counterparts (see Table 1).

Algorithm	**Test Error**	**Spike Count** (spike/example)	
		Positive Examples	**Negative Examples**
TTFS-C-SFF (2000 LIF) ours	3.6%	34 ± 6	10 ± 4
Rate-C-SFF(2000 ALIF) [2]	2.9%	246 ± 28	205 ± 32

Table 1: Comparison between TTFS-C-SFF and the rate-coded C-SFF on MNIST with a single layer of 2000 neurons.

While the current rate-based implementation achieves slightly better accuracy, it relies on more complex neuronal dynamics and architectural features (lateral inhibition, top-down connections, adaptative LIF (ALIF) neurons). In contrast, our approach highlights the potential of time-based representations for efficient and scalable learning in spiking neural networks. Preliminary results further show that training synaptic delays alone (above 93% test accuracy on MNIST) with our algorithm can also be used as an alternative to weights training, suggesting new directions for temporally-driven learning in neuromorphic systems.

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[1] G. Hinton, arXiv, 2022.

[2] A. G. Ororbia, Science Advances, 10, 43, 2024.

[3] J. Göltz et al, Nature Communications, vol. 16, no 1, p. 8245, 2025.