DeepTAGE: Deep Temporal-Aligned Gradient Enhancement for Optimizing Spiking Neural Networks

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Motivation

As time steps increase, membrane potential distributions in SNNs shift away from the firing threshold, resulting in diminished gradient magnitudes and unbalanced training processes.

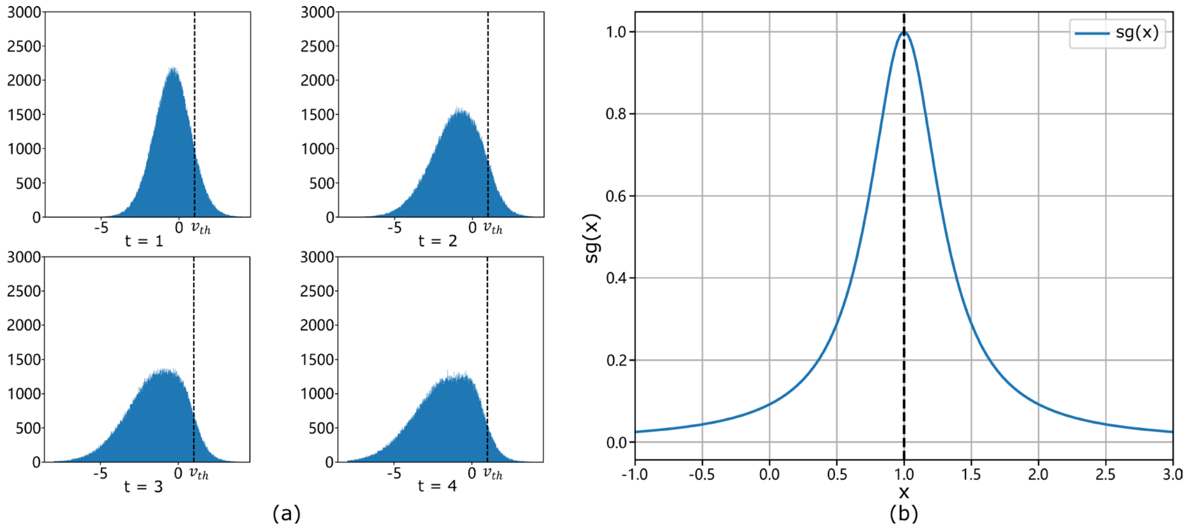

Fig1. Visualization of membrane potential dynamics and surrogate gradient function in the spiking ResNet-19.

Our main contributions

Temporal-Aligned Gradient Enhancement.
The surrogate gradient is adapted based on membrane potential distribution for improved backpropagation.
Spatio-Temporal Deep Supervision.
Deep supervision is applied at multiple stages and time steps to reduce gradient vanishing and improve convergence.
Experimental Validation.
Extensive experiments show significant improvements over existing SNN methods on multiple benchmarks.

Methodology

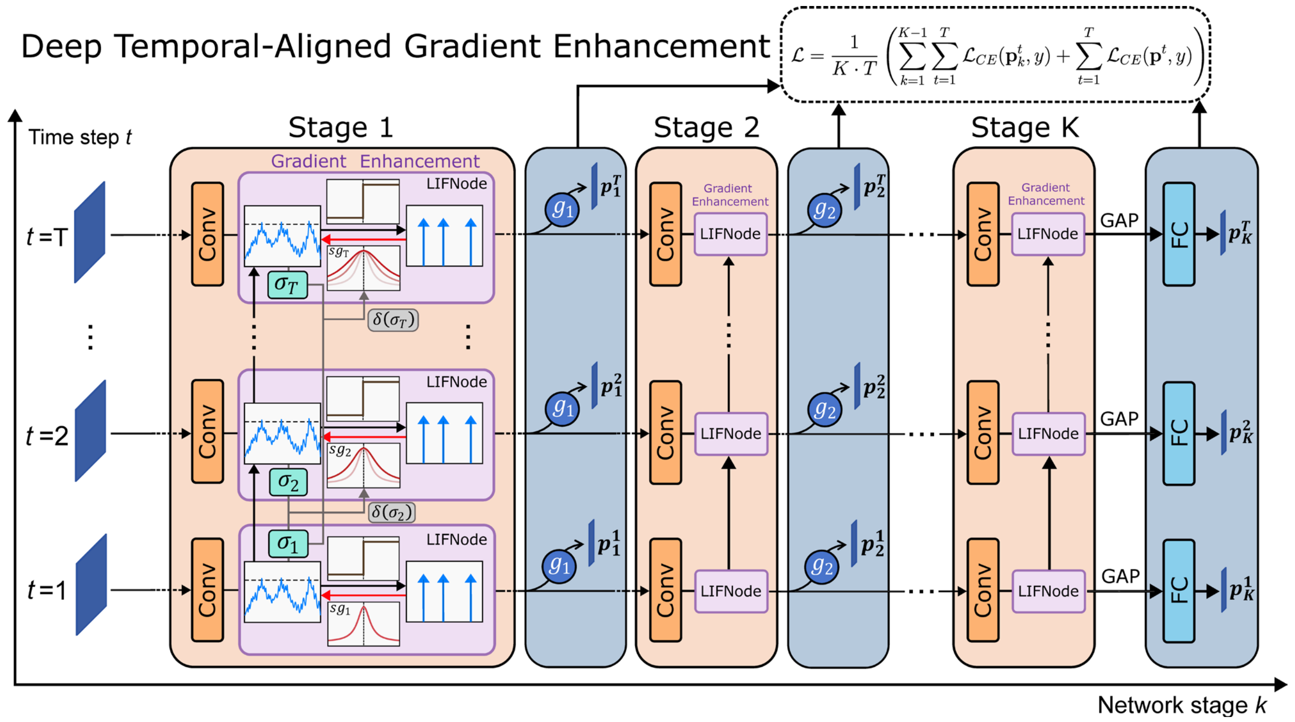

Fig2. The overall framework of our Deep Temporal-Aligned Gradient Enhancement method.

DeepTAGE: We improves optimization gradients in SNNs with Temporal-Aligned Gradient Enhancement (TAGE) and Spatio-Temporal Deep Supervision (STDS).

- **TAGE.** The surrogate gradient is adapted based on membrane potential distribution, balancing gradients across time steps.
- **STDS.** Deep supervision is applied across multiple stages and time steps of the network to enhance the gradient flow on the back-propagation path.

Experiments

Table 1. Ablation studies of TAGE and STDS.

Dataset	Model	TAGE	STDS	Accuracy(%)
CIFAR100	Sew ResNet	✓		78.80
	Sew ResNet	✓	✓	81.39
DVS-CIFAR10	VGG-11	✓		79.60
	VGG-11	✓	✓	81.23

Visualization

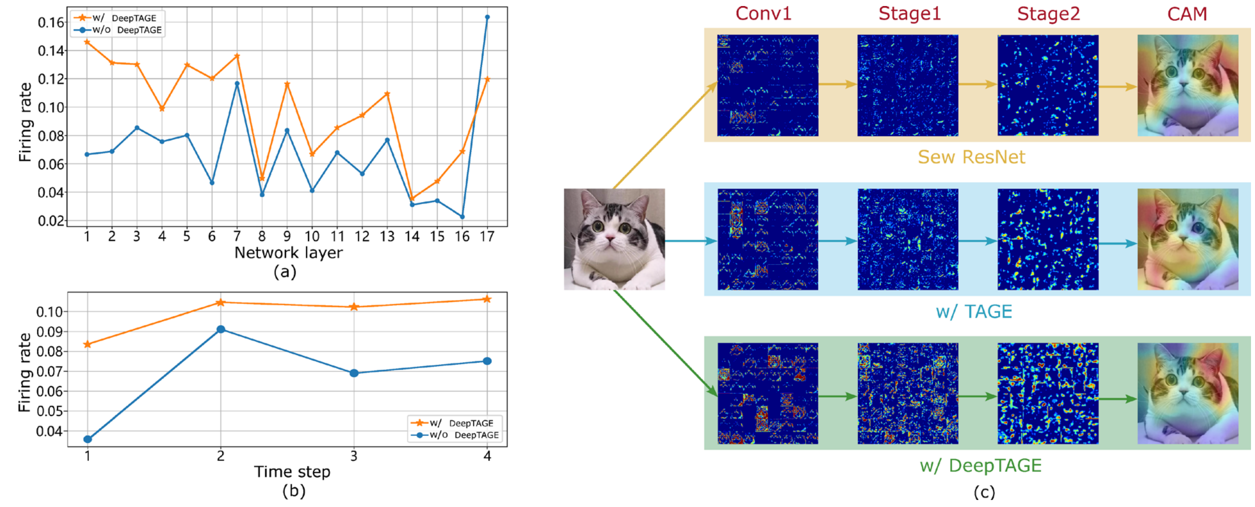

Fig3. Analysis of firing rates and feature activation maps using ResNet19 as the backbone.

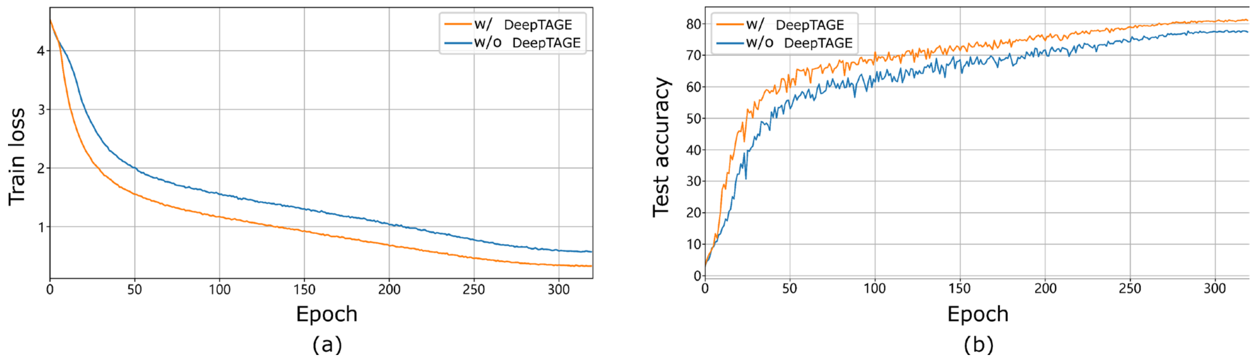

Fig4. Comparing the loss and accuracy of models with and without DeepTAGE.