SiLIF: Structured State Space Model Dynamics and Parametrization for Spiking Neural Networks

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Abstract

Multi-state spiking neurons [1, 3] combine sparse binary activations with rich second-order nonlinear recurrent dynamics, making them a promising alternative to standard deep learning models. However, gradient propagation through these dynamics often leads to instabilities that hinder scalability and performance. Inspired by the stable training and strong performance of state space models (SSMs) [2] on long sequences, we introduce two SSM-inspired Leaky Integrate-and-Fire (SiLIF) neuron models. The first extends the two-state adaptive LIF (adLIF) [1] neuron with a learnable discretization timestep and logarithmic reparametrization, while the second additionally incorporates the initialization scheme and structure of complex-state SSMs, enabling oscillatory regimes. Our two SiLIF models achieve new state-of-the-art performance among spiking neuron models on both event-based and raw-audio speech recognition datasets. We further demonstrate a favorable performance-efficiency trade-off compared to SSMs, even surpassing them while using half the computational cost through the use of synaptic delays.

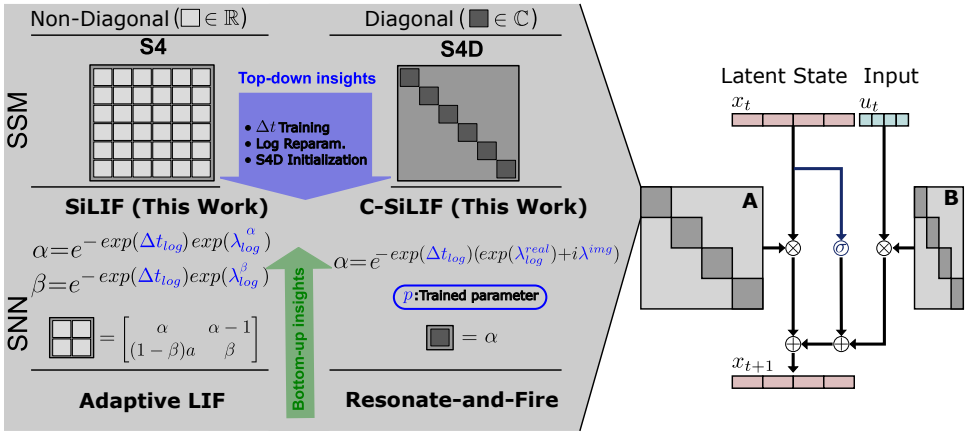

Figure 1: Proposed method to obtain the SiLIF and C-SiLIF models.

References

[1] Alexandre Bittar and Philip N. Garner. A surrogate gradient spiking baseline for speech command recognition. *Frontiers in Neuroscience*, 16, 2022.

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