An Unsupervised STDP-based Spiking Neural Network Inspired By Biologically Plausible Learning Rules and Connections

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Abstract

The backpropagation algorithm has promoted the rapid development of deep learning, but it relies on a large amount of labeled data and still has a large gap with how humans learn. The human brain can quickly learn various conceptual knowledge in a self-organized and unsupervised manner, accomplished through coordinating various learning rules and structures in the human brain. Spike-timing-dependent plasticity (STDP) is a general learning rule in the brain, but spiking neural networks (SNNs) trained with STDP alone is inefficient and perform poorly. In this paper, taking inspiration from short-term synaptic plasticity, we design an adaptive synaptic filter and introduce the adaptive spiking threshold as the neuron plasticity to enrich the representation ability of SNNs. We also introduce an adaptive lateral inhibitory connection to adjust the spikes balance dynamically to help the network learn richer features. To speed up and stabilize the training of unsupervised spiking neural networks, we design a samples temporal batch STDP (STB-STDP), which updates weights based on multiple samples and moments. By integrating the above three adaptive mechanisms and STB-

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STDP, our model greatly accelerates the training of unsupervised spiking neural networks and improves the performance of unsupervised SNNs on complex tasks. Our model achieves the current state-of-the-art performance of unsupervised STDP-based SNNs in the MNIST and FashionMNIST datasets. Further, we tested on the more complex CIFAR10 dataset, and the results fully illustrate the superiority of our algorithm. Our model is also the first work to apply unsupervised STDP-based SNNs to CIFAR10. At the same time, in the small-sample learning scenario, it will far exceed the supervised ANN using the same structure.

Keywords:
Spiking Neural Network, Unsupervised, Plasticity Learning Rule, Brain Inspired Connection

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1. Introduction

Simulating and designing a machine that thinks like a human is the ultimate goal of artificial intelligence. The vast majority of deep learning models rely on backpropagation algorithms, which require a large amount of labeled data to adjust parameters. However, obtaining labeled data is expensive. The backpropagation algorithm has a series of constraints, such as weight transport problem Lillicrap et al. (2016), and requires accurate gradient derivation, which is quite different from the learning process in the human brain. The human brain learns rapidly by relying on unsupervised local learning rules. Meanwhile, the traditional artificial neurons are far from the real spiking neurons which are rich in spatiotemporal dynamics Maass (1997). Spiking neurons receive input current and accumulate membrane potential, transmitting information through discrete spike sequences when the membrane potential exceeds the threshold. The spiking neural networks (SNNs) are more biologically plausible and energy efficient and have been widely used in various fields Fang et al. (2021); Zhao et al. (2022, 2021).

Training an efficient and robust spiking neural network is a critical problem many researchers have been paying attention to. Due to the non-differentiable characteristics of the spiking neural network, it is challenging to directly use the backpropagation algorithm for training, which significantly restricts the development of the SNNs. Many researchers take inspiration from the learning process in the human brain and design some biologically plausible learning rules to train SNNs. The synaptic plasticity of neurons is the neurological

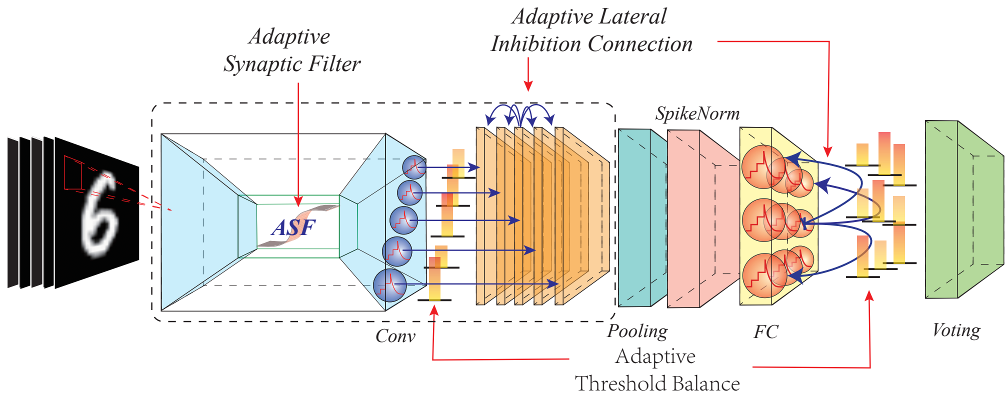

Figure 1: The backbone of our model, which introduces the adaptive synaptic filter, the adaptive threshold balance, and the adaptive lateral inhibitory connection to improve the information transmission and feature extraction of STDP-based SNNs.

basis of learning and memory in the brain Bi and Poo (1998). Spike Timing Dependent Plasticity (STDP) is a common learning rule that exists in multiple areas of the brain and plays a vital role in the brain's perception and learning process. STDP influences the strength of synapses through the temporal relationship of pre- and postsynaptic spikes.

SNNs trained based on STDP still perform poorly due to the local optimization rule without global guided error compared with the backpropagation algorithm. This will lead to a lack of coordination and self-organization within and between layers of the model. Different parameter settings can easily lead to disordered spikes, making it challenging to transfer useful information. The human brain is not regulated by a single learning ruleAbbott and Regehr (2004). The brain dynamically coordinates multiple learning rules and connections for rapid learning and inference. In mammals, short-term synaptic plasticity (STP) is another essential learning rule. It lasts for a short time and adaptively controls the activity of different firing frequencies to regulate the information transmission better in a different layerZucker and Regehr (2002); Citri and Malenka (2008); Tauffer and Kumar (2021). Inspired by this, this paper designs an adaptive synaptic filter to help amplify the difference of the input current for better information transmission. Also, the adaptive spiking threshold is designed as the neuron plasticity to reduce the information loss during transmission. The adaptive lateral inhibition