

connection of different input samples is introduced to the spiking neurons of the same layer, which improves the self-organization ability of the model and enables the network to learn more abundant representations. Also, this paper extends the original STDP with sample temporal batched processing, which significantly accelerates the training process. To summarize, our key contributions are:

1. We propose the adaptive synaptic filter, adaptive lateral inhibitory connection, and the adaptive threshold balance to assist the training of unsupervised STDP-based SNNs, which significantly improves the representation ability of SNNs, alleviates the problem of repetitive features, and compensates for the input-output mismatch between layers.
2. We extend the original STDP by integrating multiple samples and different moments into a batch (STB-STDP), which significantly speeds up and stabilizes the training process.
3. Experimental results on MNIST and FashionMNIST show that our algorithm achieves the state-of-the-art performance of unsupervised spiking neural networks. At the same time, the performance of SNNs in complex scenarios is improved, allowing unsupervised SNNs to show excellent performance in CIFAR10 and small-sample training scenarios.

2. Related Work

The training of spiking neural networks is currently divided into three categories, conversion-based, backpropagation-based, and brain-inspired algorithm learning rules based.

By exploring the relationship between the spike activation and the artificial activation function, the real value of the artificial neural networks (ANNs) can be approximated to the average firing rates of SNNs. As a result, an alternative way is explored to add constraints on the weights of well-trained ANNs to convert them to SNNs Diehl et al. (2015); Li et al. (2021); Han and Roy (2020). Although these converted methods make SNNs show excellent performance in more complex network structures and tasks, it does not fundamentally solve the training problems of SNNs. Other researchers introduce the surrogate gradient to make the backpropagation algorithm can be directed used in the training of SNN Lee et al. (2016); Wu et al. (2018, 2019); Shen et al. (2021). However, as said before, the backpropagation algorithm is implausible and far from how the brain learns.

Since STDP is a ubiquitous learning rule in the brain, many researchers trained spiking neural networks based on STDP. Querlioz et al. (2013) tried a two-layer fully connected SNN using a simplified unsupervised approach of STDP. Diehl and Cook (2015) used an unsupervised STDP method with two layers of activation and inhibition. Notably, despite two layers, only one has trainable parameters. Kheradpisheh et al. (2018) used hand-designed DoG filters for feature extraction, STDP to train convolutional layers, and SVM as the classifier. The convolution kernels of each layer are designed individually. Only the training in the intermediate convolutional layers is unsupervised. However, due to the local optimization property of STDP, it tends to perform poorly on deep networks, so many researchers have tried to introduce supervisory signals to guide STDP tuning based on the global feedback connections Zhao et al. (2020), equilibrium propagation Zhang et al. (2018), backpropagation Liu et al. (2021), and the dopamine-modulated Hao et al. (2020). Some methods combine STDP with backpropagation for hybrid training. Such as Liu et al. (2021) and Lee et al. (2018a), they both first performed STDP training to extract weights with better generalization. The training of supervised backpropagation is then performed to obtain better performance.

Lateral inhibition is usually used to help neurons achieve mutual competition mechanism Heitzler and Simpson (1991); Amari (1977); Blakemore et al. (1970). The lateral inhibition mechanism has been tried to be added to the training of spiking neural networks. Diehl and Cook (2015) tried to use a static lateral inhibition mechanism, so that the firing neurons can inhibit other non-spiking neurons by reducing the membrane potential. Cheng et al. (2020) help the spiking neural network to have stronger noise-robustness by introducing lateral inhibitory connections.

3. Backgrounds

3.1. Neuron Model

The leaky integral-and-fire (LIF) neurons Dayan and Abbott (2005) are the most commonly used computational model in the SNNs. LIF neurons receive the pre-synaptic spikes as the input currents and accumulate them on the decayed membrane potential. When the membrane potential reaches the threshold, the neuron releases a spike with the membrane potential reset to the resting potential u_{reset} . Here we set $u_{reset} = 0$. The details are shown in

Equation 1:

$$\begin{aligned} s = 0 \quad \tau \frac{du}{dt} &= -u + Ri, & \text{if } u < u_{thresh} \\ s = 1 \quad u &= 0, & \text{if } u \geq u_{thresh} \end{aligned} \quad (1)$$

where u is the membrane potential. u_{thresh} is the threshold for this neuron. τ is the time constant. i is the input current. We denote $i = \sum_j w_{ij} s_j$. s is the spikes from pre-synaptic neuron. w_{ij} is the strength of synapses. R is resistance.

In order to facilitate the calculation, we convert the differential formula into a discrete representation as shown in Equation 2, where C is capacitance, which we set equal to 1.

$$\begin{aligned} s^{(t)} = 0 \quad u^{(t)} &= (1 - \frac{1}{\tau})u^{(t-1)} + \frac{1}{C}i^{(t)}, & \text{if } u^{(t)} < u_{thresh}^{(t)} \\ s^{(t)} = 1 \quad u^{(t)} &= 0, & \text{if } u^{(t)} \geq u_{thresh}^{(t)} \end{aligned} \quad (2)$$

where $u^{(t)}$ is the membrane potential at the time t . $u_{thresh}^{(t)}$ is the threshold for this neuron at the time t . $i^{(t)}$ is the input current at the time t .

3.2. STDP Algorithm

In this paper, we improved the commonly used unilateral STDP. For conventional STDP, as seen in Equation 3, the modification of weights is determined by the time interval of the pre- and post-synaptic spikes. The larger the time gap, the less correlated the two spikes are and the less affected the synaptic weights.

$$\begin{aligned} \Delta w_j &= \sum_{f=1}^N \sum_{n=1}^N W(t_i^f - t_j^n) \\ W(\Delta t) &= A^+ e^{\frac{-\Delta t}{\tau_+}} - x_{offset} \quad \text{if } \Delta t > 0 \end{aligned} \quad (3)$$

where Δw_j is the modification of the synapse j , $W(\Delta t)$ is the STDP function. For unilateral STDP, focus only on the presynaptic spikes before the firing of the postsynaptic spikes, which makes the synapse strength continue to grow Lee et al. (2018a). So x_{offset} is to determine whether the modification are potentiated or depressed.