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

Yiting Dong∗
School of Future Technology,
University of Chinese Academy of Sciences
Institute of Automation,
Chinese Academy of Sciences
dongyiting2020@ia.ac.cn

Dongcheng Zhao∗
Institute of Automation,
Chinese Academy of Sciences
zhaodongcheng2016@ia.ac.cn

Yang Li
School of Artificial Intelligent,
University of Chinese Academy of Sciences
Institute of Automation,
Chinese Academy of Sciences
liyang2019@ia.ac.cn

Yi Zeng†
School of Future Technology,
University of Chinese Academy of Sciences
School of Artificial Intelligent,
University of Chinese Academy of Sciences
Institute of Automation,
Chinese Academy of Sciences
yi.zeng@ia.ac.cn

Abstract

The backpropagation algorithm has promoted the rapid development of deep learning, but it relies on a large amount of labeled data, and there is still a large gap with the way the human learns. The human brain can rapidly learn various concept knowledge in a self-organized and unsupervised way, which is accomplished through the coordination of multiple learning rules and structures in the human brain. Spike-timing-dependent plasticity (STDP) is a widespread learning rule in the brain, but spiking neural network trained using STDP alone are inefficient and performs poorly. In this paper, taking inspiration from the short-term synaptic plasticity, we design an adaptive synaptic filter, and we introduce the adaptive threshold balance as the neuron plasticity to enrich the representation ability of SNNs. We also introduce an adaptive lateral inhibitory connection to dynamically adjust the spikes balance to help the network learn richer features. To accelerate and stabilize the training of the unsupervised spiking neural network, we design a sample temporal batch STDP which update the weight based on multiple samples and multiple moments. We have conducted experiments on MNIST and FashionMNIST, and have achieved state-of-the-art performance of the current unsupervised spiking neural network based on STDP. And our model also shows strong superiority in small samples learning.

1 Introduction

Simulating and designing a machine that thinks like a human is the ultimate goal in the of artificial intelligence. The vast majority deep learning models rely on backpropagation algorithms, which

∗Equal contribution
†Corresponding author

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require a large amount of labeled data to adjust parameters. However, the cost of obtaining labeled data is expensive, and the backpropagation algorithm has a series of constraints such as weight transport problem [Lillicrap et al. 2016] and requires accurate gradient derivation, which are 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 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 are more biologically plausible and energy efficient, and has been widely used in various fields [Fang et al. 2021, Zhao et al. 2022, 2021].

Training an efficient and robust spiking neural network is the key problem that many researchers have been paying attention to. Due to the non-differentiable characteristics of the spiking neural network, it is difficult to directly use the backpropagation algorithm for training, which greatly restricts the development of the SNNs. 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 a well-trained ANNs to convert them to the 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 researches introduce the surrogate gradient to make the backpropagation algorithm can be directed used in the training of SNNs [Lee et al. 2016, Wu et al. 2018, 2019, Shen et al. 2021], however the backpropagation algorithm is implausible.

Many researchers take inspirations from the learning process in the human brain and design some biologically plausible learning rules to the training of SNNs. The synaptic plasticity of neurons is the neurological basis of learning and memory in the brain [Bi and Poo 1998]. Spike Timing Dependent Plasticity (STDP) is a common learning rule 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. Many researchers built spiking neural networks based on STDP training [Querlioz et al. 2013] tried a two-layer fully connected SNN using a simplified unsupervised approach of STDP [Diehl and Cook 2015] used an STDP unsupervised method with two layers of activation and inhibition. [Kheradpisheh et al. 2018] used hand-designed DoG filters for feature extraction, STDP to train convolutional layers and SVM as classifier. The convolution kernels of each layer are designed individually. Only the training in the intermediate convolutional layers is unsupervised. 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.
SNNs trained based on STDP still performs poor, 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 parameters settings can easily lead to disordered spikes, making it difficult to transfer useful information. The human brain is not regulated by a single learning rule [Abbott and Regehr 2004]. The brain dynamically coordinates different learning rules and connections to achieve rapid learning and inference. In mammals, short-term synaptic plasticity is another important learning rule. It lasts for a short time and adaptively controls the activity of different firing frequencies, so as to better control the information transmission in different layers [Zucker and Regehr 2002], [Citri and Malenka 2008], [Tauffer and Kumar 2021]. Taking inspiration from 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 the transmission. The adaptive lateral inhibition 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 temporal batched processing, which greatly accelerates the training process. The experimental results on MNIST and FashionMNIST show that our algorithm achieves the best performance of the current unsupervised spiking neural network trained with STDP.

2 Backgrounds

2.1 Neuron Model

![Image of neuron model]

Figure 2: Features of the convolutional layers trained with only STDP, the same features are marked with the same color. SNNs trained only with STDP cannot properly regulate the information transmitted by the spikes, which will lead to sparse or frequent spikes.

The leaky integral-and-fire (LIF) neurons are most commonly used computational model in the SNNs. LIF neurons receives the pre-synaptic spikes as the input currents and accumulates it 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 \( u_{\text{reset}} \), here we set \( u_{\text{reset}} = 0 \). The details are shown in Equation (1):

\[
\tau \frac{du(t)}{dt} = -u(t-1) + Ri_{\text{exc}}(t), \quad \text{if } u(t) < u_{\text{thresh}}(t)
\]

\[
s(t) = 1 \quad u(t) = 0, \quad \text{if } u(t) > u_{\text{thresh}}(t)
\]

where \( u(t) \) is the membrane potential. \( u_{\text{thresh}}(t) \) is the threshold for this neuron at time \( t \). \( \tau \) is the time constant. \( i_{\text{exc}}(t) \) is the input current at time \( t \), \( s(t) \) denotes the spikes from pre-synaptic neuron \( j \). \( R \) is resistance. We denote \( \lambda = 1 - \frac{1}{\tau} \).

\[
i_{\text{exc}}(t) = \sum_j w_{ij}(t) s_j(t)
\]

In order to facilitate the calculation, we convert the differential formula into a discrete representation as shown in Equation (3) where \( C \) is capacitance. We set \( C = 1 \).

\[
u(t) = (1 - \frac{1}{\tau})u(t-1) + \frac{1}{C} i_{\text{exc}}(t)
\]
2.2 STDP Algorithm

In this paper, we adopt the commonly used unilateral STDP:

\[
\Delta w_j = \sum_{f=1}^{N} \sum_{n=1}^{N} W(t_f^j - t_n^j)
\]

\[
W(\Delta t) = A^+ e^{\frac{-\Delta t}{\tau}} - x_{offset} \quad if \quad \Delta t > 0
\]

where \( \Delta w_j \) is the modification of the synapse \( j \), \( W(\Delta t) \) is the STDP function. \( x_{offset} \) is the threshold to determine whether the weights are potentiated or depressed. As can be seen in Equation 4, the weight is only determined by the time-interval of the pre- and post-synaptic spikes. Since the algorithm lacks a global guided signal, the neuron can not judge whether it is a suitable time for spiking. When the spike activities of the network is sparse, sufficient features cannot be learned; when the firing frequency is large, it will damage the effective information representation, as shown in Figure 2. While the SNNs only have two states of spiking and non-spiking, and when a large number of neurons in the same layer are in the same state, the weights of the network will learn a large number of repeated features, which greatly damages the performance of the network.

As shown in the Figure 2, we train a convolutional neural network with only STDP, and there are a lot of repeated features in the convolutional layer.

3 Methods

In order to alleviate the problems mentioned above, we design an adaptive synaptic filter which takes inspiration from the short-term synaptic plasticity, adaptive spiking threshold, and the adaptive inhibitory connections to better control the spikes of the net. As a result, the representation abilities of the SNNs are enriched and the feature extraction ability are better improved.

3.1 Adaptive Synaptic Filter

There are various states in the ANNs based on the real-valued output, which can transmit a lot of rich information, so as to update the weights well. While SNNs have only two states of spiking and non-spiking, which leads to that when the currents received in the same layer in the network are relatively similar, a large number of neurons in this layer will be in the same state. When the network’s spikes are too sparse, it’s difficult for the network to transmit useful information, making it hard to converge, and when the network’s spikes are too frequent, it will carry a lot of useless information, which will destroy the network’s feature representation. Therefore, we consider to avoid the network receiving the similar information inputs. The short-term synaptic plasticity can affect the short-term information processing of synapses, and can generate a filter function for information processing by increasing or decreasing the efficiency of synapses [Scott et al., 2012], [Rotman et al., 2011]. Taking inspiration from this, we construct an adaptive synaptic filter(ASF) based on the input current, which will amplify the difference between the input currents and make the information transfer in the network richer. The details are shown in Equation 5.

\[
\delta_{asf}(i_{exc}^{(t)}) = \frac{u(t)^{thresh}_{asf} \sum_{i,j} w_{ij}^{(t)} s_{ij}^{(t)}}{1 + e^{-\alpha_{asf} \sum_{i,j} w_{ij}^{(t)} s_{ij}^{(t)} + \beta_{asf}}} = \frac{u(t)^{thresh}}{1 + e^{-\alpha_{asf} \sum_{i,j} w_{ij}^{(t)} s_{ij}^{(t)} + \beta_{asf}}}
\]

3.2 Adaptive Threshold Balance

As well as, since the spiking neurons only communicate with the binary spike sequences, a lot of information is lost in the network information transmission. As the intrinsic plasticity of neurons, the adaptive threshold balance can reduce the loss during the transmission, allowing neurons to express more precise information [Wilent and Contreras, 2005], [Huang et al., 2016]. We design an adaptive threshold balance(ATB) mechanism for neurons. In the convolutional layer, the threshold will be adaptively adjusted according to the input, and the maximum current in the input will be selected as
I >> V_{threshold}

I << V_{threshold}

Adaptive Synaptic Filter

Adaptive Threshold Balance

Sample 1 Sample 2 Sample 3 Sample 4

(a) Adaptive Synapse Filter (ASF) and Adaptive Threshold Balance (ATB)

(b) Adaptive Lateral Inhibition Connection (ALIC)

Figure 3: The adaptive synaptic filter helps to regulate the inputs, and the adaptive threshold balance helps to regulate the outputs. The adaptive lateral inhibition connection helps to suppress the same state to avoid learning repeat features.

For the fully connected layer, to prevent a single neuron dominating, we increase with threshold $u_{\text{plus}}^{(t)}$ once the neuron fires spikes, and when the $\theta^{(t)}_{\text{plus}}$ reaches $\gamma$, it decreases the difference from $\gamma$. The details are shown in Equation 7.

\[ u_{\text{thresh}}^{(t)} = \theta_{\text{init}} + \theta^{(t)}_{\text{plus}} \]
\[ \frac{d\theta_{\text{plus}}}{dt} = \alpha_{\text{plus}} \sum_{b,t} \hat{S}_{ij}^{(t)} - (\theta_{\text{thresh}}^{(t-1)} - \gamma) \quad \text{if} \quad \theta_{\text{thresh}}^{(t-1)} > \gamma \] (7)

3.3 Adaptive Lateral Inhibitory Connection

The traditional STDP-based network only updates the weights according to the time interval of the pre- and post-synaptic neurons. When there are a large number of similar states in the same layer, weights of multiple neurons will converge to the similar direction. The input directly affects the states of neurons. As a result, we introduce an adaptive lateral inhibitory connection (ALIC) between the same layer. A neuron that reaches the spiking threshold is chosen, and it will select those neurons that may reach the same spiking state as itself for inhibition dynamically. In this paper, the connection is designed to choose those neurons with larger input currents for inhibition, because larger input are
more likely to generate spikes. The details are shown as follows:

\[\text{inh}_j^{(t)} = \alpha_{\text{inh}} \left( \max_{b,c,w,h} s_j^{(t)} \right) \]

\[= \alpha_{\text{inh}} \left( \sum_{i,j} w_{ij}^{(t)} s_j^{(t)} \right) \]

(8)

3.4 STB-STDP

Most of the existing STDP-based SNNs use a single sample every time for training, and the weights are updated at each moment, which greatly slows down the convergence speed of the model. And the single-sample, single-moment update will lead to instability in the optimization direction. Therefore, we propose a sample temporal batch STDP (STB-STDP) to update the weights based on multiple samples and moments, as shown in Equation 9:

\[\frac{dw_j^{(t)}}{dt} = N_{\text{batch}} \sum_{m=0}^{T_{\text{batch}}} \sum_{n=0}^{N} W(t_f^{m,n} - \delta_{j}^{m,n}) \]

where \(N_{\text{batch}}\) is the batchsize of the input, \(T_{\text{batch}}\) is the batch of time step. After the weights update, we will normalize the weights as shown in Equation 10 and 11. In order to stabilize the input and output between layers, we add a spike normalization module between each layer. It collects spikes and control them at the highest frequency of 1. This controls the input range of the spikes.

\[N_{\text{fc}}, N_{\text{conv}}\] is the number of neurons, and \(A_{\text{fc}}, A_{\text{conv}}\) is scale factor to control normalization. For fully connected layer:

\[\frac{dw_j^{(t)}}{dt} = w_j^{(t)} - A_{\text{fc}} \frac{N_{\text{fc}} w_j^{(t)}}{\sum_j w_j^{(t)}} \]

(10)

For convolutional layer:

\[\frac{dw_{ij}^{(t)}}{dt} = w_{ij}^{(t)} - A_{\text{conv}} \frac{w_{ij}^{(t)} - \sigma^{(t)}}{\left( \sum_j |w_{ij}^{(t)} - \sigma^{(t)}| \right)^{\frac{1}{2}} } \]

where \(\sigma^{(t)} = \frac{\sum_{i,j} w_{ij}^{(t)}}{N_{\text{conv}}} \)

(11)

4 Experiments

To demonstrate the effectiveness of our model, we conduct experiments on the commonly used datasets, MNIST LeCun et al. [1998] and FashionMNIST Xiao et al. [2017]. All the experiments are based on the structure consists of a convolutional layer followed by a 2*2 max pooling layer, a spiking normalization layer, and a fully connected layer. Since our model is an unsupervised network, we adopt the same voting strategy as in Diehl and Cook [2015] of the output of the final layer for category prediction. And the parameters of the network is trained layer-wisely. Where \(A_{\text{fc}} = 0.01, A_{\text{conv}} = 1, \alpha_{\text{inh}} = 1.625, \theta_{\text{init}} = 10, \alpha_{sfa} = 0.4, \beta_{sfa} = 0.4, \beta_{\text{thresh}} = 8, \alpha_{\text{plus}} = 0.001, \lambda = 0.99, \beta_{\text{offset}} = 1, x_{\text{offset}} = 0.3. \)

4.1 Experimental Results

MNIST is a digital handwriting recognition dataset, which is widely used as a benchmark for evaluating model performance in recognition and classification tasks. The dataset contains a total of 60,000 training set samples and 10,000 test set samples. The size of each sample is 28*28 pixels. In the experiments, the examples in MNIST was normalized, using direct encoding and without any form of data augmentation and preprocessing. For MNIST dataset, we set the kernelsize of the convolutional layer to 5. To verify the superiority of our model, we compare the results with other famous STDP-based SNN models. Un-Supervised denotes the formal layer is trained unsupervised, while the final decision layer is trained with supervised information. As shown in Table 1, Our model achieves 97.9% accuracy. Compared with Diehl and Cook [2015], which only uses the STDP, our
model improves nearly 3%. Our model has surpassed all the unsupervised STDP-based SNNs and even some SNNs with supervised information.

FashionMNIST is more complex compared with MNIST within cloths and shoes as the samples. The shape and data size are the same with MNIST. The kernel size for the convolutional layer is set with 3. As can be seen in the Table 2, our model achieves 87.0% accuracy, and has surpassed most of the STDP-based SNNs. Although the performance of GLSNN is higher than ours, it introduces global supervised connections, while our network has no supervision information.

Table 2: The performance on FashionMNIST dataset compared with other STDP-based SNNs.

| Model          | Learning Method                          | Type       | Accuracy |
|----------------|------------------------------------------|------------|----------|
| FSpiNN         | STDP                                     | Unsupervised | 68.8%    |
| Rastogi et al. | A-STDP                                   | Unsupervised | 75.9%    |
| Hao et al.     | Sym-STDP                                 | Supervised  | 85.3%    |
| VPSNN          | Equilibrium Propagation + STDP           | Supervised  | 83.0%    |
| CBSNN          | VPSNN + Curiosity                        | Supervised  | 85.7%    |
| GLSNN          | Global Feedback + STDP                   | Supervised  | 89.1%    |
| Ours           | ASF + ATB + ALIC + STB-STDP              | Unsupervised | 87.0%    |

And the details of the classification results of MNIST and FashionMNIST are shown in the confusion matrix of Figure 4.

Figure 4: The confusion matrix of our model on MNIST and FashionMNIST test dataset.
Figure 5: The top is the performance of our model on MNIST and FashionMNIST with different number of convolutional kernels and voting neurons. The bottom is the test accuracy of our model with and without the modules we design.

4.2 Result Analysis

First we explore the effect of different parameter settings on network performance. We change the number of kernels in the convolutional layer and the number of neurons in the voting layer. As shown in the Figure 5, the more the number of voting neurons is set, the higher the performance. Because more voting neurons will provide more predictions about the input samples, then combining with all the predictions, the network will produce a more precise result. For the setting of the number of convolutional kernels, the more is not the better. For MNIST, the best performance is achieved when the number of kernels is set to 12, while for FashionMNIST, more convolutional kernels need to be set due to its complexity, and the optimal performance is achieved when the number of kernels is set to 64.

To fully illustrate the impact of each module of our model on the results, we conduct the ablation studies. As shown in Figure 5, when only STDP rule is introduced, the network performs worst. And when the introduction of our adaptive module, the performance if gradually improved.

Table 3: The performance of our model compared with ANN on MNIST dataset with different training samples.

| samples | 200   | 100   | 50    | 10    |
|---------|-------|-------|-------|-------|
| ANN     | 79.77%| 71.40%| 68.72%| 47.12%|
| Ours    | 81.45%| 75.44%| 72.88%| 51.45%|
|         | 1.68% | 4.04% | 4.16% | 4.33% |
Also, to better illustrate the power of our model on small sample training, we conduct experiments with very few training samples on the MNIST dataset, ranging from 200 to 100 to 50, and to the most extreme case, 10 training samples. That’s to say only one sample per class. We compare ANN with the same structure, which is trained using a supervised backpropagation algorithm, and the last layer directly output the results.

As can be seen in the Table 3, as the number of training samples gradually decreases, the performance gap of our model and ANN gradually increases. When there are only 10 training samples, our model exceeds ANN by 4.43%. It fully illustrate that our model requires only a few samples to achieve high performance compared with ANNs that require a large amount of labeled training data.

4.3 Visualization

To illustrate the feature extraction capability of our model, we visualize weights of different layers. Figure 6 a and b shows the weight of the convolutional layer on the MNIST and FashionMNIST dataset separately. As can be seen, the convolutional kernels capture the simple features such as the edge. With the introduction of our adaptive lateral inhibition connections, our network does not exist a large number of repeated features. Figure 6 a and b shows the weight of the fully connected layer, according to the label assigned to the neuron, we visualize the weight of ten categories, and each row represents a category. It can be seen that the fully connected layer automatically combines the features of the convolutional layers to form higher-level semantic representations. For MNIST, with the combination of the simple features, the different number can be easily classified. While FashionMNIST is more complex, and it is difficult to distinguish the similar objects such as Shirt and T-Shirt. In future work, we will consider introducing more biologically plausible rules to improve the performance of our model.

Figure 6: The weight visualization of the convolutional layer and the fully connected layer of our model on MNIST and FashionMNIST dataset.
5 Conclusion

This paper analyzes the problems existing in the traditional unsupervised spiking neural network based on STDP training, and finds that only based on STDP will lead to weak information transmission, and will extract a large number of repeated features, which greatly damages the performance of the SNNs. Inspired by short-term synaptic plasticity, we design an adaptive synaptic filter combined with the adaptive spiking threshold as neuron plasticity, which greatly improves the information transfer of SNNs. This paper introduces an adaptive lateral inhibition connection, which enables the network to extract richer features. In order to accelerate and stabilize the STDP-based SNNs, we propose a batch STDP, which utilizes multiple samples and multiple moments to update the weights of the network. We have achieved the current state-of-the-art performance for unsupervised STDP training SNNs on MNIST and FashionMNIST. We also conduct the experiments on the small samples training, our SNN far exceeds the ANNs trained by the supervised backpropagation, which fully demonstrates the superiority of our model.

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**Checklist**

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] See Section 1.
   (b) Did you describe the limitations of your work? [Yes] See Section 5.
   (c) Did you discuss any potential negative societal impacts of your work? [No]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See supplemental material.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4 for basic setup.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No]

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [No] We adopt public datasets.
(c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
   We upload our code in supplemental material.
(d) Did you discuss whether and how consent was obtained from people whose data you’re
    using/curating? [No]
(e) Did you discuss whether the data you are using/curating contains personally identifiable
    information or offensive content? [No]

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if
       applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review
       Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount
       spent on participant compensation? [N/A]