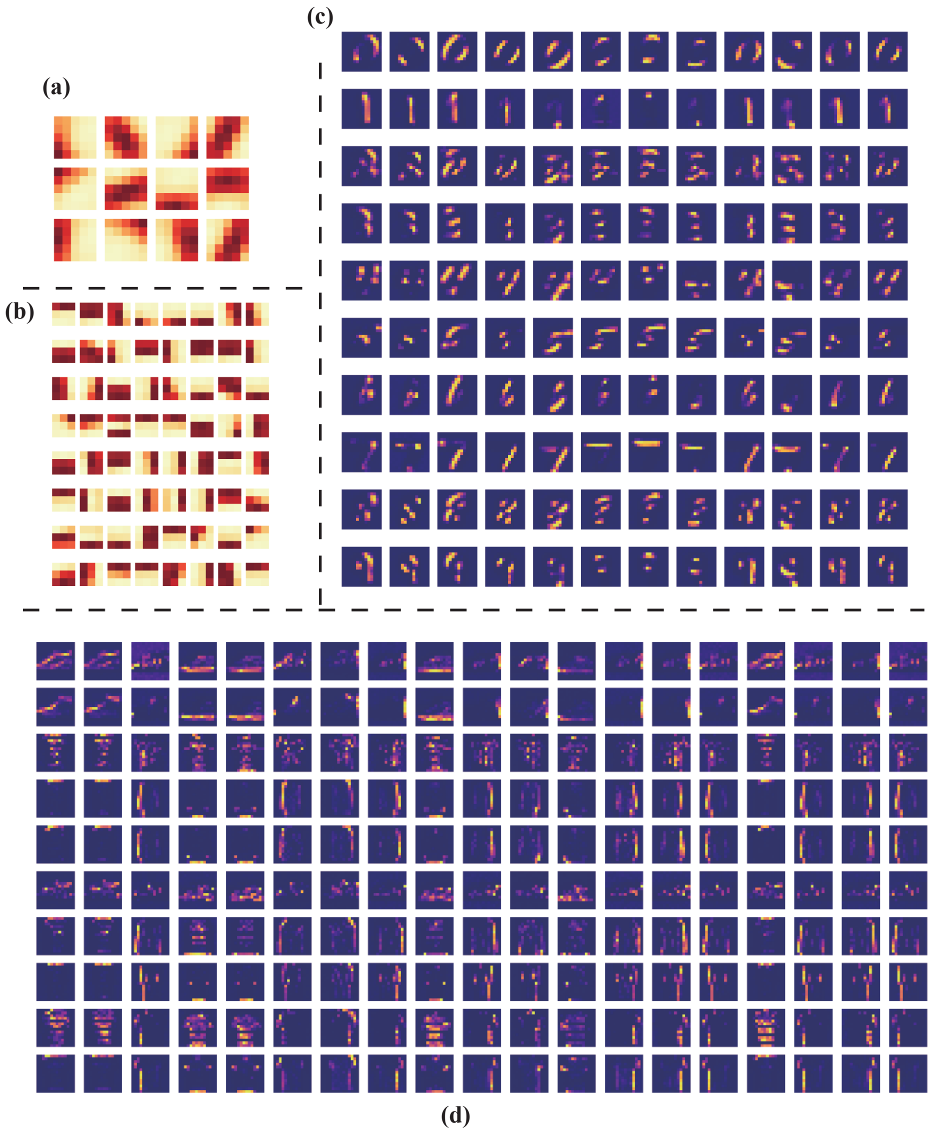

Figure 6: Visualization of the weights of the model. (a) represents the convolutional layers trained on MNIST. It contains 12 channels, and we visualize the weights of each kernel. (b) Convolutional layer trained on FashionMNIST. It contains 64 kernels. (c) Fully connected layer on MNIST. We randomly selected 10 neurons from the corresponding categories. The corresponding weights are visualized. Each of these rows shows one category, (d) Fully connected layer on the FashionMNIST dataset. We visualized a portion of these weights, where each row represents the weight of neurons corresponding to a category.

The convolutional kernels capture simple features such as edges, lines. With the introduction of our adaptive lateral inhibitory connections, our network does not have a large number of repeated features. Figure 6 c and d show 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 simple features, the different numbers can be easily classified. While FashionMNIST is more complex, it is not easy to distinguish similar objects such as Shirts and T-Shirt. In future work, we will consider introducing more biologically plausible rules to improve the performance of our model.

6. Conclusion

Spiking neural networks (SNNs) trained with STDP alone are inefficient and hardly achieve a high performance of SNN. In this paper, we design an adaptive synaptic filter and introduce the adaptive threshold balance to enrich the representation ability of SNNs. We also introduce an adaptive lateral inhibitory connection to help the network learn richer features. 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-STDP, we have achieved current state-of-the-art performance for unsupervised STDP-trained SNNs on MNIST and FashionMNIST. Further, we tested on the more complex CIFAR10 dataset, and the results fully illustrate the superiority of our algorithm. Since we consider more of the unsupervised learning rules, it does not obtain significant improvement when it is extended to deep networks. In future work, we intend to consider more learning methods of the human brain, such as dopamine-based regulation of the reward mechanism. Also, We will introduce more brain-like structures, such as global feedback connections.

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