the threshold, increasing firing frequency. The portion of current above the threshold will be lost due to the reset of the membrane potential. Therefore, a dynamic threshold method is needed so that the threshold can be adaptively changed according to the magnitude of the current. Due to neurons' inherent plasticity, the adaptive threshold can reduce the loss during transmission and facilitate the expression of more precise informationWilent and Contreras (2005); Huang et al. (2016). We introduce an adaptive threshold balancing (ATB) mechanism.

The convolutional and fully connected layers play different roles in the network. The convolutional layer extracts features, while the fully connected layer exhibits feature selectivity sensitive to different features. Therefore, we employ variable threshold methods at layers. For convolutional layers, ATB set threshold positively related to the maximum input current, as shown in Equation 7. where $u_{thresh}^{(t)}$ denotes the threshold of neuron at time t. β_{thresh} is a parameter controlling the threshold scale. The maximum current is selected from the maximum input value of all neurons in the convolutional layer. c, w, h represents the number of channels in the convolutional kernel and the size of the output, respectively. The input current of each neuron is obtained from the synaptic weights and the input spikes. ATB ensures that no information is lost due to excessive current. Meanwhile, it allows spikes to be transmitted for a limited time.

$$u_{thresh}^{(t)} = \beta_{thresh}\ (\max_{c,w,h} i^{(t)}) = \beta_{thresh}\ (\max_{c,w,h} \sum_{i,j} w_{ij}^{(t)} \hat{s}_{ij}^{(t)}) \tag{7}$$

For fully connected layers, ATB improves the method in Diehl and Cook (2015). Where $u_{thresh}^{t,j}$ denotes the threshold of the neuron j at time t. When a neuron fires a spike, we increase the threshold $\theta_{plus}^{t,j}$, making the next firing more difficult. When $\theta_{plus}^{t,j}$ reaches γ, all thresholds reduce the difference between maximum threshold and γ. As shown in Equation 8 . Where θ_{init} is the initial value. θ_{plus} is the increment of $u_{thresh}^{t,j}$. α_{plus} is a coefficient controlling the growth rate.

$$
\begin{aligned}
& u_{thresh}^{t,j} = \theta_{init} + \theta_{plus}^{t,j} \\
& \theta_{plus}^{t,j} = \theta_{plus}^{t-1,j} + \alpha_{plus} \sum_{b,t} \hat{s}_j^{(t)} - \theta_{bias}^{t,j} \\
& \theta_{bias}^{t,j} = \begin{cases} \max\limits_j u_{thresh}^{t-1,j} - \gamma & if \quad \max\limits_j u_{thresh}^{(t-1)} > \gamma \\ 0 & if \quad \max\limits_j u_{thresh}^{(t-1)} < \gamma \end{cases}
\end{aligned} \tag{8}
$$

In this manner, a dynamic balance is established, where each neuron is measured for relative sensitivity. When γ is reached, the whole shifts downward. All thresholds are limited within a range. Thus, the difference between the thresholds is indicative of the neuron's sensitivity. Neurons with higher thresholds have lower sensitivity. This dynamic balance prevents a single neuron from dominating and ensures that each neuron has an opportunity to fire.

4.3. Adaptive Synaptic Filter

With adaptive threshold balancing (ATB), the threshold is adjusted within the convolutional layers in order to match it to the current magnitude. However, current regulation for individual neurons will still assist the network in achieving a more stable performance.

The short-term plasticity (STP) of synapses affects short-term information processing at synapses, as shown in Figure 3 (b). By increasing or decreasing the signal transmission efficiency of synapses, it can provide filter functions for the processing of information Scott et al. (2012); Rotman et al. (2011). Inspired by this, we construct an adaptive synaptic filter (ASF) based on the input current. Details are shown in the Equation 9.

$$
\begin{aligned}
& \delta_{asf}(i^{(t)}) = \frac{u_{thresh}^{(t)}}{1 + e^{\sigma_t}} \\
& where \quad \sigma_t = -\alpha_{asf} \frac{i^{(t)}}{u_{thresh}^{(t)}} + \beta_{asf}
\end{aligned} \tag{9}
$$

δ_{asf} is the function of ASF, where $u_{thresh}^{(t)}$ denotes the threshold at time t. $i^{(t)}$ is the input current at time t. α_{asf} and β_{asf} are coefficients and control the function of the filter. The ASF adjusts the current through a nonlinear function, making the current more likely to concentrate near the threshold or resting potential. Concentrating current towards the threshold will result in more competition for the neuron. More competition will help avoid the dominance of neurons. And the current approach to resting potential will decrease the noise generated by low current strength neurons firing. Since ASF is calculated according to the threshold, ASF must be performed concurrently with ATB. We verify the effectiveness of ASF in section 5.3.

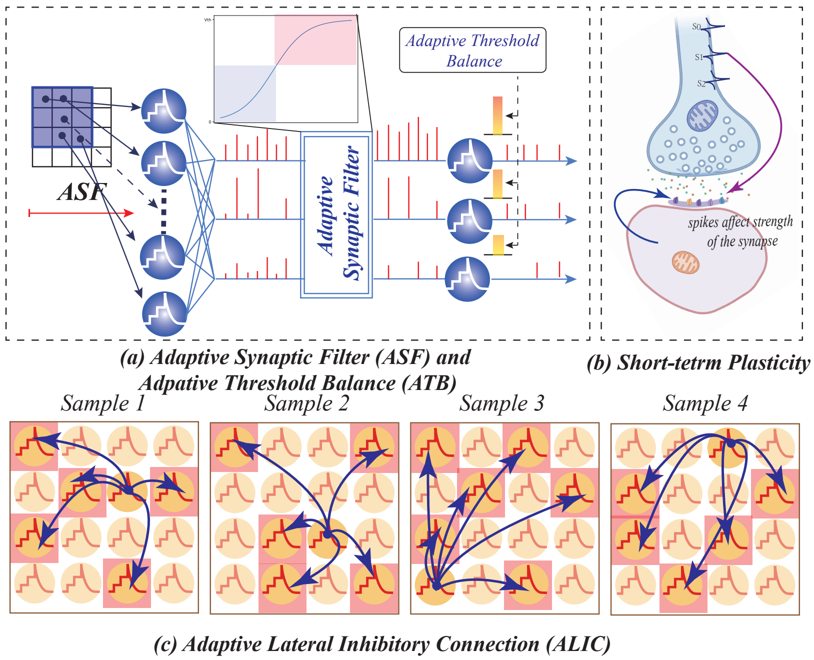

Figure 3: (a) The adaptive synaptic filter helps to regulate the inputs, and (b) the adaptive threshold balance helps to regulate the outputs. (c) The adaptive lateral inhibitory connection helps to suppress the same state to avoid learning repeat features.

4.4. STB-STDP

A majority of STDP-based SNN algorithms are trained with one sample at a time, with the weights being updated at every step of the training process. However, as with the backpropagation algorithm, combining a set of samples into batches for training can reduce the convergence instability caused by deviations in the distribution of each sample. Due to the batch processing of