**中文摘要：**

作为第三代神经网络模型，脉冲神经网络凭借其特有的时间动态特性及低能耗计算优势吸引了广泛的研究兴趣。该网络通过模仿大脑的神经脉冲传递机制，力求更接近生物神经系统的运作模式。因此，它不仅展现出了更高的生物学合理性，还能在专为其设计的神经形态芯片上实现显著的能效提升。本文深入研究了脉冲神经网络中生物合理的高效学习规则，特别是脉冲驱动学习方法和在线学习方法。这两种方法分别从节省梯度传播次数和节省中间状态存储的角度改进了脉冲神经网络中常用的沿时间步反向传播学习方法。本文的研究内容涵盖了深度脉冲神经网络的时序脉冲驱动学习方法反向传播性质分析、时序脉冲驱动学习方法中的损失函数分析、在线学习方法时序协方差漂移问题分析、以及脉冲驱动方法和在线学习方法在脉冲流分类任务上的联合应用。本文的创新点总结如下：

**第一，针对脉冲驱动学习方法训练深度网络的难题，提出了可以保留梯度规模的池化层和梯度一致的反向传播核函数，解决了脉冲驱动方法的梯度消失问题。**首先通过理论分析证明了基于时间的脉冲驱动学习策略在反向传播中，对于含有神经元的网络层能够保持梯度总和一致性，其次修正了平均池化层的反向传播方法以维持梯度之和不变性。同时，通过引入新的反向传播核函数，解决了脉冲时序梯度传播中的反向梯度问题。本方法在 Fashion-MNIST 和 CIFAR10 数据集上相比先前最优的脉冲驱动学习方法性能分别提升了 0.45% 和 1.04%，并成功应用于 CIFAR100 数据集的学习。相比沿时间步反向传播方法，在多个数据集上节省了约 75% 到 90% 的梯度传播次数。

**第二，针对脉冲驱动学习中损失函数缺乏时序特性的问题，提出了包含时序信息的损失函数和比例因子调整方法，提升了网络的时间动态编码能力。**通过理论分析发现了网络内频率编码与时间编码之间的潜在联系。基于均方计数损失梯度与脉冲数量不一致的问题提出了改善型计数损失，并将权重标准化过程中的比例因子调整至阈值。本方法在多个数据集上实现了发表时脉冲驱动方法的最佳学习效果，在 CIFAR10 和 CIFAR100 数据集上，与先前最优方法相比分别实现了 1.44% 和 6.53% 的准确率提高。

**第三，针对在线学习中稳定性与适应性的平衡问题，引入了在线脉冲重归一化和在线阈值稳定器，解决了在线学习中的时序协方差漂移问题。**通过引入在线脉冲重归一化和在线阈值稳定器，不仅确保了训练和推理时归一化参数的一致性，而且通过理论分析和实验验证了在线阈值稳定器可以有效稳定网络训练及控制神经元发放率。本方法为发表时脉冲神经网络在线学习中性能最佳的方法，在 Imagenet 数据集上相比先前方法在时间步减少 33% 的情况下取得了 1.35% 的准确率提升。相比沿时间步反向传播方法，在 4 个时间步和 30 个时间步时分别节省了约 40% 和 86% 的显存占用。

**第四，集成了脉冲驱动与在线学习方法，解决了网络融合中的架构与神经元模型不一致问题，搭建了基于脉冲神经网络的实时脉冲流识别系统。**采用脉冲驱动学习在 CIFAR100 数据集上得到的预训练模型，在 SpiReco 数据集上使用在线学习微调。实验结果表明，微调的性能明显优于直接训练，在 S-CIFAR 和 S-CALTECH 子数据集上分别取得了 1.47% 和 3.79% 的提升。此外，通过构建脉冲流识别展示系统，本文直观展示了脉冲神经网络处理脉冲流任务的实际能力。

综上所述，本文针对脉冲神经网络中脉冲驱动学习和在线学习这两种生物合理的高效学习规则展开了深入研究，对学习方法及网络进行性质分析的同时提出了改进方案。通过这些提出的新方法和技术，本文在多个标准数据集上取得了显著的性能提升，不仅推动了脉冲神经网络学习算法的发展，也为理解大脑的学习机制提供了新的视角。

**英文摘要**：

As the third generation of neural network models, Spiking Neural Networks (SNNs) have attracted widespread research interest due to their unique temporal dynamics and low-energy computing advantages. By mimicking the brain's mechanism of neural spike transmission, these networks strive to operate closer to the biological neural system. Hence, they not only exhibit higher biological plausibility but also achieve significant energy efficiency improvements on neuromorphic chips designed specifically for them.

This thesis delves into efficient biologically plausible learning rules within SNNs, particularly spike-driven and online learning methods. These two methods improve the commonly used backpropagation through time (BPTT) learning method in SNNs by reducing the number of gradient propagation steps and saving intermediate state storage, respectively. The research covered in this thesis includes analysis of properties in backpropagation of temporal spike-driven learning methods for deep SNNs, loss functions in temporal spike-driven learning methods, temporal covariate shift problem in SNN online learning methods, and the combined application of spike-driven and online learning methods in spike stream classification tasks. The innovations of this thesis are summarized as follows:

**First, to address the the difficulty of training deep networks with spike-driven learning methods, we propose a pooling layer that preserves gradient magnitude and a backward propagation kernel function with consistent gradients, solving the vanishing gradient problem of spike-driven approaches.** We first demonstrate that the time-based spike-driven learning strategy can maintain the consistency of the total gradient sum across layers during backpropagation. Additionally, we analyze the pooling layers in the network, modifying the backpropagation method for average pooling layers to maintain gradient sum invariance. By introducing new backpropagation kernels, we successfully solve the reverse gradient problem in temporal gradient propagation of spikes. We achieve performance improvements of 0.45% and 1.04% on the Fashion-MNIST and CIFAR10 datasets, respectively, over previous state-of-the-art spike-driven learning methods and was successfully applied to the learning on the CIFAR100 dataset. Compared to BPTT methods, this approach saves approximately 75% to 90% of the gradient propagation steps across different datasets.

**Second, in response to the lack of temporal characteristics in the loss functions used in pulse-driven learning, we propose a loss function that incorporates temporal information and a method for adjusting scaling factors, enhancing the network's ability to encode temporal dynamics.** Through theoretical analysis, a potential connection between frequency encoding and time encoding within the network is identified. To address the inconsistency between the mean squared counting loss gradient and the number of spikes, we propose an enhanced counting loss. We also adjust the scaling factor used in weight normalization to the threshold. We achieve state-of-the-art performance among spike-driven methods on most datasets. Particularly, we achieve an accuracy improvement of 1.44% and 6.53% on the CIFAR10 and CIFAR100 datasets compared to previous methods.

**Third, to address the balance between stability and adaptability in online learning, we use online spiking renormalization and online threshold stabilizer to solve the issue of temporal covariate shift.** By introducing online spiking renormalization and online threshold stabilizer, we not only ensure the consistency of normalization parameters during training and inference, but also verify through theory and experiments the effectiveness of

the online threshold stabilization mechanism in stabilizing network training and controlling neuron firing rates. We achieve state-of-the-art performance among online learning algorithms of SNNs, with a 1.35% accuracy improvement on the Imagenet dataset compared to previous methods while reducing 33% time steps. Compared to BPTT methods, this approach saves approximately 40% and 86% of GPU memory usage at 4 and 30 time steps, respectively.

**Fourth, by integrating spike-driven and online learning methods, we address the inconsistency issue between network architecture and neuron models in network fusion, and construct a real-time spike stream recognition system based on SNNs.** We use a pretrained model obtained by spike-driven learning algorithm on the CIFAR100 dataset and finetunes it on the SpiReco dataset using online learning. The experimental results showed significantly superior performance to direct training, achieving improvements of 1.47% and 3.79% on the S-CIFAR and S-CALTECH sub-datasets, respectively. Furthermore, by constructing a spike stream recognition demonstration system, we visually demonstrates the actual capability of SNNs in handling spike stream tasks.

In summary, this thesis conducts in-depth research on efficient biologically plausible learning rules in SNNs including spike-driven and online learning methods, proposing improvement methods while analyzing the properties of learning methods and networks. Through these newly proposed methods and techniques, this thesis achieves significant performance improvements on multiple standard datasets, not only advancing the development of SNN learning algorithms but also offering new insights into understanding the brain's learning mechanisms.