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论文

深度脉冲神经网络梯度替代学习算法研究综述

 $a^{1,2}, b^{2*}$

- 1. 作者单位, 城市 000000
- 2. 作者单位, 城市 000000
- 3. 作者单位, 城市 000000
- * 通信作者. E-mail: abc@xxxx.xxx

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摘要 摘要主要包括本文的研究目的、方法、结果和结论, 注意突出创新点. 应避免出现图、表、公式、参考文献引用等. 对应的英文摘要长度在 200 词左右.

关键词 关键词 1, 关键词 2, 关键词 3, 关键词 4, 关键词 5

- 1 引言
- 2 脉冲神经网络的常用概念和评测基准
- 3 脉冲神经网络的梯度替代训练算法
- 3.1 基础学习算法

 $\operatorname{SLAYER}:$ Spike Layer Error Reassignment in Time

Spatio-temporal backpropagation for training high-performance spiking neural networks

SuperSpike: Supervised learning in multi-layer spiking neural networks

Differentiable spike: Rethinking gradient-descent for training spiking neural networks

3.2 ANN 辅助训练

A Tandem Learning Rule for Effective Training and Rapid Inference of Deep Spiking Neural Networks

Distilling Spikes: Knowledge Distillation in Spiking Neural Networks

引用格式: 作者 1, 作者 2, 作者 3, 等. 引用的标题. 中国科学: 信息科学, 在审文章 Xing M, Xing M M, Xing M, et al. Title for citation (in Chinese). Sci Sin Inform, for review Constructing Deep Spiking Neural Networks from Artificial Neural Networks with Knowledge Distillation

Self-Architectural Knowledge Distillation for Spiking Neural Networks

3.3 神经元和突触改进

深度脉冲神经网络的主要组分是神经元和突触,两者均对网络性能有着重要影响,有大量研究对其进行改进,提出了多种新型神经元和突触模型。PLIF(Parametric Leaky Integrate-and-Fire) 神经元模型[1] 基于经典的 LIF 神经元模型,将膜时间常数 τ_m 参数化并设置为可学习,其神经元的阈下神经动态为:

$$H[t] = V[t-1] + k(a) \cdot \left(-(V[t-1] - V_{reset}) + X[t] \right), \tag{1}$$

其中膜时间常数的倒数,即 $\frac{1}{\tau_m}$ 被重参数化为 $\frac{1}{\tau_m} = k(a)$,而 a 是真正的可学习参数。 $k(a) \in (0,1)$ 是限幅函数,确保 $\tau_m > 1$ 以防止神经元出现自充电的情况,在实践中通常取 $k(a) = \frac{1}{\exp(-a)}$ 。PLIF 神经元通常设置每一层只有一个可学习参数 a,即该层神经元的膜时间常数是共享的,既大幅度减少了参数量,又与生理实验证据中相邻脑区神经元性质类似这一特性符合;而不同神经元层的参数 a 在训练后不尽相同,保持了神经元的异质性。

Incorporating learnable membrane time constant to enhance learning of spiking neural networks GLIF: A unified gated leaky integrate-and-fire neuron for spiking neural networks

Multi-level firing with spiking ds-resnet: Enabling better and deeper directly-trained spiking neural networks

Parallel Spiking Neurons with High Efficiency and Ability to Learn Long-term Dependencies Temporal backpropagation for spiking neural networks with one spike per neuron

CLIF: Complementary Leaky Integrate-and-Fire Neuron for Spiking Neural Networks

Learning Delays in Spiking Neural Networks using Dilated Convolutions with Learnable Spacings

Exploiting Neuron and Synapse Filter Dynamics in Spatial Temporal Learning of Deep Spiking Neural Network

3.4 网络结构改进

Spiking deep residual network

Deep residual learning in spiking neural networks

Advancing Spiking Neural Networks towards Deep Residual Learning

Temporal-wise Attention Spiking Neural Networks for Event Streams Classification

Attention Spiking Neural Networks

Inherent Redundancy in Spiking Neural Networks

Spike-based dynamic computing with asynchronous sensing-computing neuromorphic chip

Spikformer: When spiking neural network meets transformer

SpikingResformer: Bridging ResNet and Vision Transformer in Spiking Neural Networks

Spike-driven Transformer

Spike-driven Transformer V2: Meta Spiking Neural Network Architecture Inspiring the Design of Next-generation Neuromorphic Chips

QKFormer: Hierarchical Spiking Transformer using Q-K Attention

AutoSNN: Towards Energy-Efficient Spiking Neural Networks

Neural Architecture Search for Spiking Neural Networks

Differentiable hierarchical and surrogate gradient search for spiking neural networks

正则化方法 3.5

Direct training for spiking neural networks: Faster, larger, better

Going deeper with directly-trained larger spiking neural networks

Neuromorphic Data Augmentation for Training Spiking Neural Networks

Revisiting Batch Normalization for Training Low-Latency Deep Spiking Neural Networks From Scratch

Temporal Effective Batch Normalization in Spiking Neural Networks

Temporal efficient training of spiking neural network via gradient re-weighting

RMP-Loss: Regularizing Membrane Potential Distribution for Spiking Neural Networks

Membrane Potential Batch Normalization for Spiking Neural Networks

3.6 事件驱动学习算法

Hybrid macro/micro level backpropagation for training deep spiking neural networks Spike-train level backpropagation for training deep recurrent spiking neural networks Temporal spike sequence learning via backpropagation for deep spiking neural networks Training spiking neural networks with event-driven backpropagation

Exploring Loss Functions for Time-based Training Strategy in Spiking Neural Networks

在线学习算法 3.7

Synaptic plasticity dynamics for deep continuous local learning (decolle)

Online training through time for spiking neural networks

Towards memory-and time-efficient backpropagation for training spiking neural networks

Online stabilization of spiking neural networks

High-Performance Temporal Reversible Spiking Neural Networks with O(L) Training Memory and O(1) Inference Cost

NDOT: Neuronal Dynamics-based Online Training for Spiking Neural Networks

3.8 训练加速方法

Sparse spiking gradient descent

SpikingJelly: An open-source machine learning infrastructure platform for spike-based intelligence

Addressing the speed-accuracy simulation trade-off for adaptive spiking neurons

参考文献 -

1 Wei Fang, Zhaofei Yu, Yanqi Chen, Timothée Masquelier, Tiejun Huang, and Yonghong Tian. Incorporating learnable membrane time constant to enhance learning of spiking neural networks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2661–2671, 2021.

Title

Ming XING^{1,2}, Mingming XING^{2*}, Ming XING¹ & Ming XING³

- 1. Affiliation, City 000000, Country;
- 2. Affiliation, City 000000, Country;
- 3. Affiliation, City 000000, Country
- * Corresponding author. E-mail: abc@xxxx.xxx

Abstract An abstract (about 200 words) is a summary of the content of the manuscript. It should briefly describe the research purpose, method, result and conclusion. The extremely professional terms, special signals, figures, tables, chemical structural formula, and equations should be avoided here, and citation of references is not allowed.

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