Spiking Discrepancy Transformer for Point Cloud Analysis

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ICLR

Introduction

Motivation:

While Spiking Self-Attention have shown promise in 2D vision, their direct application to 3D point clouds faces three critical limitations: (i) over-smoothing of salient edge/boundary features due to attention bias toward highly similar points; (ii) quadratic computational complexity prohibiting global modeling given the large token counts in point clouds; and (iii) incapacity to capture multi-scale features simultaneously given inherent data redundancy. These challenges necessitate a redesigned attention mechanism that preserves discriminative boundary information while enabling efficient local-to-global feature learning.

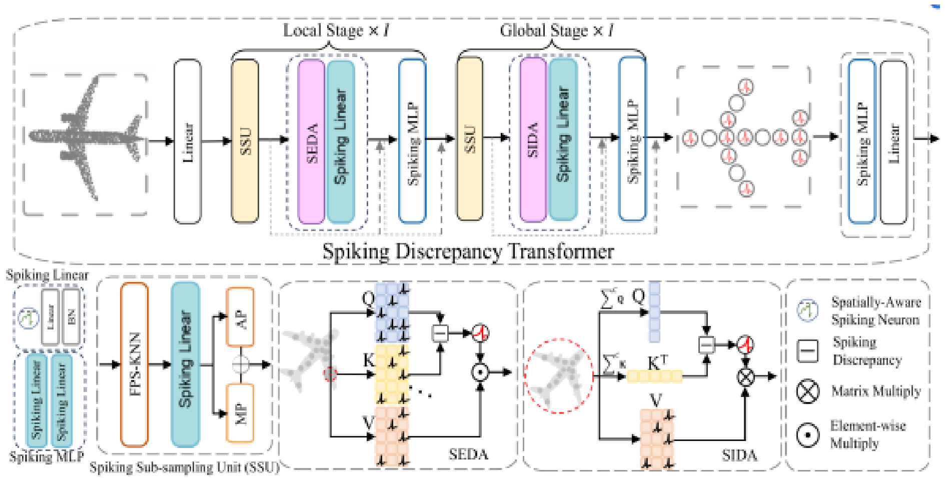
Contribution:

- We propose a Spiking Discrepancy Attention Mechanism (SDAM) tailored to the characteristics of point clouds. The mechanism includes Spiking Element Discrepancy Attention (SEDA) and Spiking Intensity Discrepancy Attention (SIDA), which effectively represent complex local-global spatial information.
- We design a Spatially-Aware Spiking Neuron that encodes spatial information in the initial membrane potential, thereby compensating for the loss of spatial information in spike representations.
- The Spiking Discrepancy Transformer achieves state-of-the-art performance among SNN-based approaches. Besides, our method's theoretical energy consumption is significantly lower compared to ANN-based approaches.

Robustnss Performance Comparison with Other Variants:

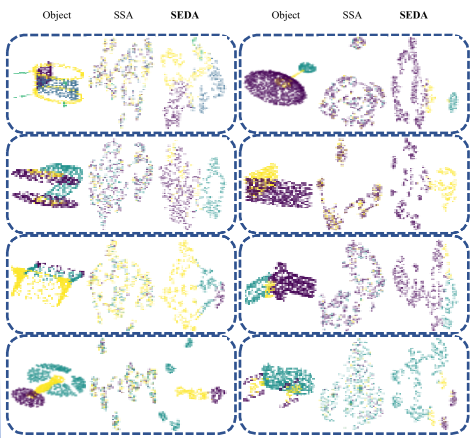
Models	Type	ACC_{clean}	ACC_{noise}	Uniform	Gaus.	Impulse	Upsamp.	Bg.
PointNet Qi et al. (2017a)	ANN	90.7	67.3	87.6	85.6	70.9	86.0	6.4
PointNet++ Qi et al. (2017b)	ANN	93.0	78.5	79.6	83.6	64.9	82.8	81.4
DGCNN Wang et al. (2019)	ANN	92.6	74.3	85.4	83.4	75.1	80.9	46.9
PointMLP Ma et al. (2022)	ANN	93.5	63.1	77.2	67.4	59.8	61.3	49.7
PCT Guo et al. (2021)	ANN	92.9	71.9	87.9	86.1	60.9	82.6	42.1
Point Transformer Zhao et al. (2021)	ANN	93.7	78.0	89.9	88.2	69.9	74.3	67.7
PTV3 Wu et al. (2024c)	ANN	94.5	86.0	91.3	90.0	77.4	86.8	84.4
SSA Zhou et al. (2023c)	SNN	89.8	86.9	88.8	89.0	86.4	84.8	85.7
SEDA	SNN	92.3	90.0	91.0	91.0	91.6	87.4	88.7
SIDA	SNN	92.1	87.8	90.4	90.0	89.3	84.2	85.3
SDT	SNN	92.5	90.4	91.2	91.5	91.8	88.2	89.2

Model Overview

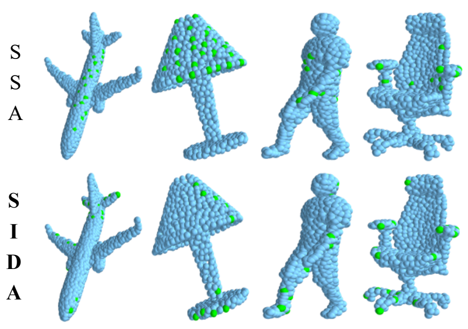


Visualization

SEDA



SIDA



Experimental Results

Classfication

Method	Type	Param(M)	ModelNet40 OA(%)↑	ModelNet40 mAcc(%)↑	ModelNet40 Energy(mJ)↓	ScanObjectNN OA(%)↑	ScanObjectNN mAcc(%)↑	ScanObjectNN Energy(mJ)↓
PointNet Qi et al. (2017a) [CVPR17]	ANN	3.47	89.20	86.00	2.07	68.20	63.40	2.07
PointNet++ Qi et al. (2017b) [NeurIPS17]	ANN	1.74	91.90	89.10	18.72	77.90	75.40	18.71
KPConv Thomas et al. (2019) [ICCV19]	ANN	15.20	92.10	90.70	94.53	85.30	83.69	94.50
PointTransformer Zhao et al. (2021) [ICCV21]	ANN	9.58	93.70	90.60	84.64	86.01	84.10	84.07
PointMLP Ma et al. (2022) [ICLR22]	ANN	12.60	**94.10**	**91.30**	72.38	85.40	83.90	72.36
Point-GPT Chen et al. (2024) [NeurIPS23]	ANN	19.46	94.00	91.03	20.48	**86.90**	85.17	20.47
PointGT Zhang et al. (2024c) [TMM24]	ANN	-	92.60	90.00	-	86.50	**84.90**	-
PointNet-SNN Lan et al. (2023b) [ICCV23]	ANN-to-SNN	3.50	88.17	84.02	0.26	66.56	60.33	0.27
KPConv-SNN Wu et al. (2024b) [AAAI24]	ANN-to-SNN	15.20	70.50	67.60	-	43.90	38.70	-
Spiking PointNet Ren et al. (2023) [NeurIPS23]	SNN	3.50	88.61	84.20	0.24*	65.40	61.30	0.28*
P2SResLNet Wu et al. (2024b) [AAAI24]	SNN	15.20	90.60	89.20	-	81.20	79.40	-
E-3DSNN Qiu et al. (2024a) [AAAI25]	SNN	3.27	91.70	88.40	1.76*	83.91*	81.92*	2.64*
SPT Wu et al. (2024a) [AAAI25]	SNN	9.64	91.43	89.39	13.3	82.23	80.12	13.5*
SDT (T=1)	SNN	**2.25**	**92.18**	88.92	**0.45**	**85.25**	**83.20**	**0.61**
SDT (T=4)	SNN	**2.25**	**92.46**	**89.48**	**1.33**	**86.19**	**84.37**	**2.11**

ShapeNetPart Segmentation

Method	Type	cat. mIoU(%)	ins. mIoU	Param(M)	Energy(mJ)
PointNet Qi et al. (2017a)	ANN	80.4	83.7	8.3	26.5
PCCN Wang et al. (2018)	ANN	81.8	85.1	-	-
PointNet++ Qi et al. (2017b)	ANN	81.9	85.1	1.7	22.5
DGCNN Wang et al. (2019)	ANN	82.3	85.1	1.5	23.1
SpiderCNN Xu et al. (2018)	ANN	81.7	85.3	2.2	41.4
PointConv Wu et al. (2019)	ANN	82.8	85.7	1.7	15.4
PointCNN Li et al. (2018)	ANN	84.6	86.1	46.4	328.7
KPConv Thomas et al. (2019)	ANN	**85.1**	86.4	20.7	144.5
PointTransformer Zhao et al. (2021)	ANN	83.7	**86.6**	7.8	127.0
PointMLP Ma et al. (2022)	ANN	84.6	86.1	5.2	54.2
PointGPT Chen et al. (2024)	ANN	84.1	86.2	6.8	102.3
E-3DSNN Qiu et al. (2024a)	SNN	81.7	83.8	4.9	8.8
SDT	SNN	**83.7**	**85.1**	4.6	**4.7**

S3DIS Results