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NEURAL INFORMATION PROCESSING SYSTEMS

Rethinking the Membrane Dynamics and Optimization Objectives of Spiking Neural Networks

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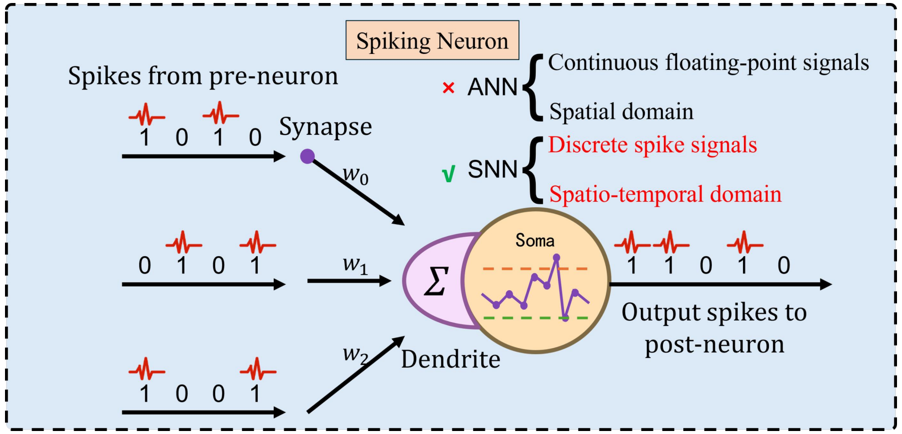
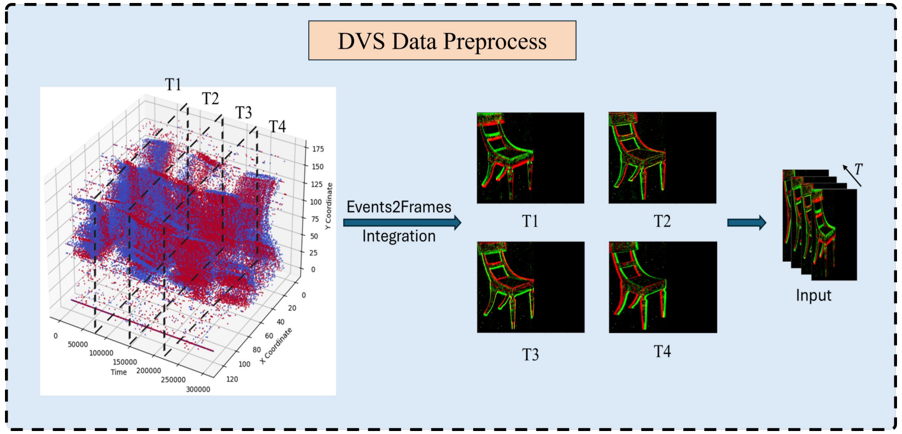
Background & Motivations

➢Neural Dynamics in Spiking Neural Networks





Are the neural dynamics of SNNs good enough?

➢ Challenges

- ◆ How to optimize the dynamics of SNNs?
- ◆ How to handle the output of SNNs?
- ◆ How to Design Optimization Objectives?

➢ Solutions

- ✓ Learnable **I**nitial **M**embrane **P**otential (IMP).
- ✓ **L**ast **T**ime **S**tep (LTS) Method for Static Task.
- ✓ **S**moothed **T**emporal **E**fficient **T**raining (TET-S).

Analysis & Solutions

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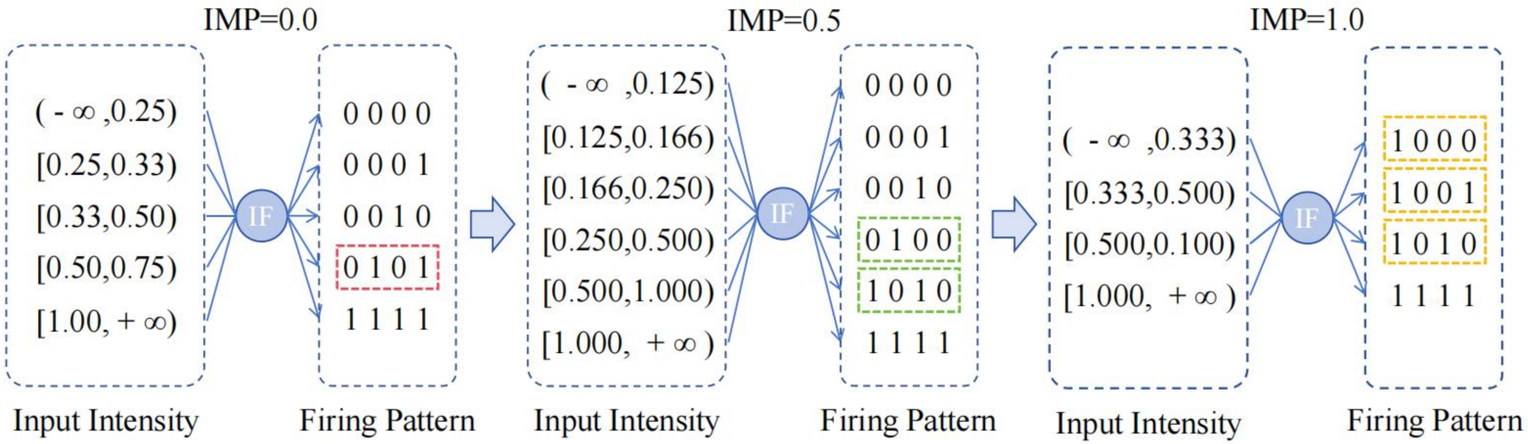
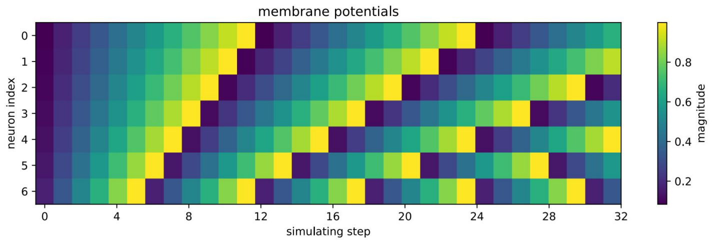
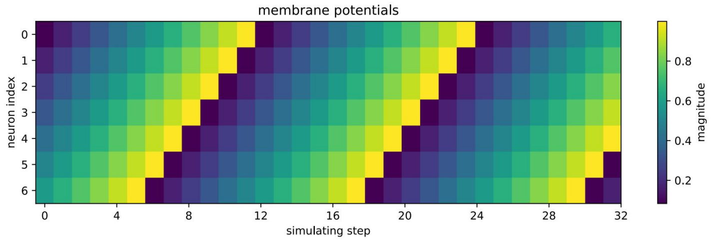
➢ Membrane Dynamics Related to Initial Membrane Potential





Adjusting synaptic weights



Adjusting Initial Membrane Potential

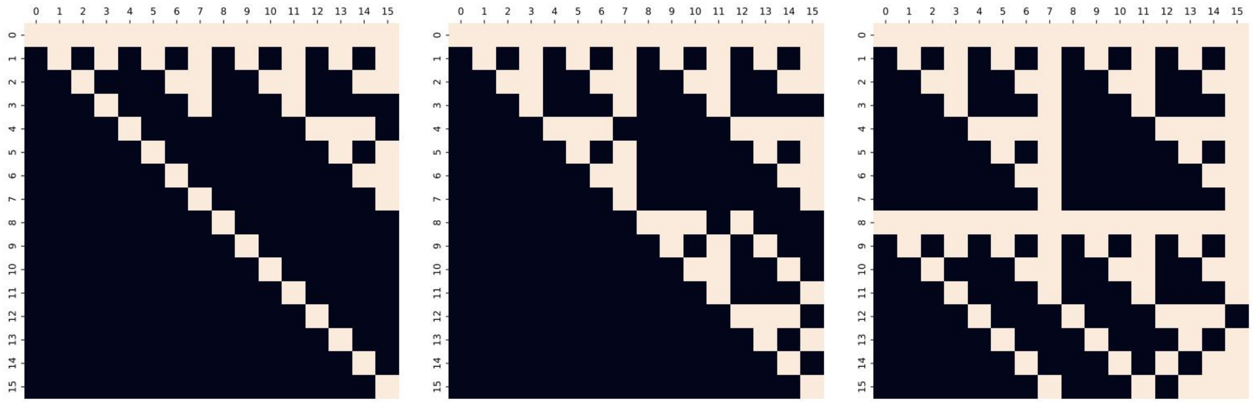
➢ Learnable Initial Membrane Potential

Constant IMP

$$h[t] = (1-\tau)s[t] + I[t], \quad h \in \mathbb{R}^{T\times N}, \quad I \in \mathbb{R}^{T\times N}$$
$$o[t] = h[t] > V_{th}, \quad o \in \{0,1\}^{T\times N}, \quad V_{th} \in \mathbb{R}$$
$$s[t+1] = h[t] - o[t], \quad s \in \mathbb{R}^{T\times N}, \quad s[0] \in \{0\}^N$$

Learnable IMP

$$h[t] = (1-\tau)s[t] + I[t], \quad h \in \mathbb{R}^{T\times N}, \quad I \in \mathbb{R}^{T\times N}$$
$$o[t] = h[t] > V_{th}, \quad o \in \{0,1\}^{T\times N}, \quad V_{th} \in \mathbb{R}$$
$$s[t+1] = h[t] - o[t], \quad s \in \mathbb{R}^{T\times N}, \quad s[0] = \mathbb{R}^N$$

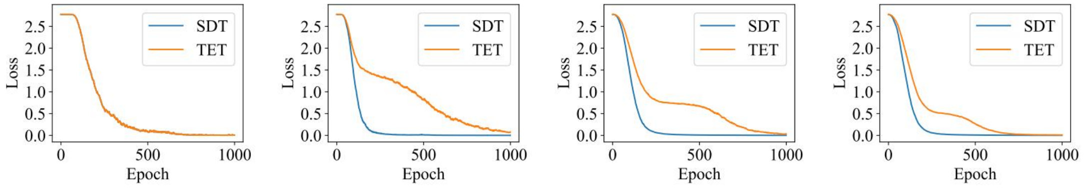


(a) IMP=0.0 (b) IMP=0.25 (c) Learnable IMP

Analysis & Solutions

➢ Performance of TET and SDT

Loss Function	Static Dataset(SEW-R18)			Neuromorphic Dataset(VGG11)		
	CIFAR10/100	ImageNet100	ImageNet1k	CIFAR10DVS	DVSG128	NCaltech101
SDT Loss	**94.56/76.58**	**78.42**	**63.21**	84.3	98.26	85.78
TET Loss	94.33/76.40	77.80	62.92	**85.6**	**98.61**	**86.32**



(a) T=1 (b) T=2 (c) T=4 (d) T=6

➢ Vanilla TET Method

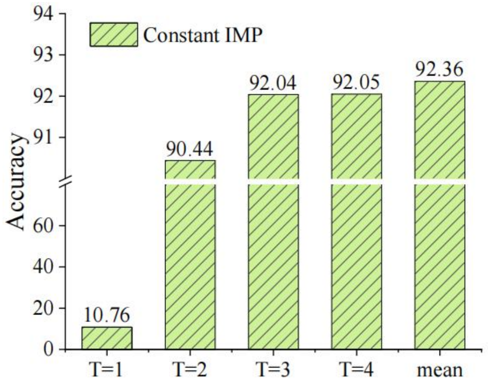
$$\mathcal{L}_{\text{TET}} = \frac{1}{T} \times \sum_{t}^{T} \mathcal{L}_{\text{CE}}(y[t], y_{gt}),\ where\ y[t] = f(s[t], x, \theta)$$

TET will supervise the output at each time step, which may lead to **slower convergence** compared to SDT.

$$\mathcal{L}_{\text{Total}} = (1-\lambda)\mathcal{L}_{\text{TET}} + \lambda\mathcal{L}_{\text{REG}}, \mathcal{L}_{\text{REG}} = \frac{1}{T}\sum_{t=1}^{T} \mathcal{L}_{\text{MSE}}(y[t], \phi)$$

$\mathcal{L}_{\text{REG}}$ and $\mathcal{L}_{\text{TET}}$ cannot converge to 0 simultaneously, which may weaken the model's final performance.

➢ Neural Dynamics Evolution in Static Tasks



Given that $(s[t+1], y[t]) \leftarrow f(s[t], x[t], \theta)$, assuming $x = x[t]$ for $t = 1, 2, ..., T$, the equation can be simplified to

$$\boldsymbol{y[t] = f(s[t], x, \theta)},$$

where $s[t]$ is the only time-varying term.

So, the accuracy of $y[t]$ depends only on $s[t]$.

➢ LTS Method & Smoothed TET

Since the accuracy of the last time step in static tasks is already close to the average accuracy, we propose using the last time step (LTS) for the SNN's output representation

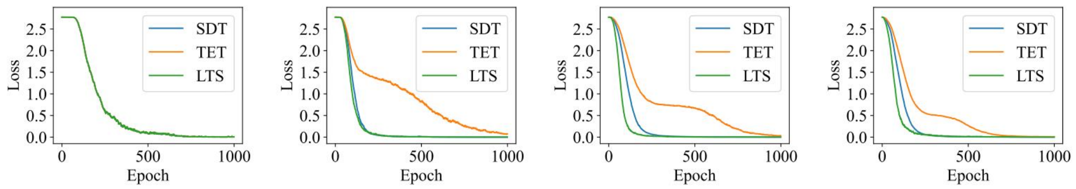
$$\mathcal{L}_{\text{LTS}} = \mathcal{L}_{\text{CE}}(y[T], y_{gt}), where\ y[T] = f(s[T], x, \theta).$$

and a smoothed version of TET for neuromorphic tasks.

$$\mathcal{L}_{\text{TET-S}} = \frac{1}{T} \times \sum_{t}^{T} \mathcal{L}_{\text{CE}}(y[t], \hat{y}_{gt}),\ where\ \hat{y}_{gt} = (1-\epsilon)y_{gt} + \frac{\epsilon}{K}$$

Experiments

➢ Convergence Speed



(a) T=1 (b) T=2 (c) T=4 (d) T=6

➢ Ablation Studies

Dataset	Method	Spiking Network	Time-steps	Accuracy(%)
CIFAR10-DVS	SDT($\epsilon = 0.0$)	VGG	10	83.70
	TET($\epsilon = 0.0$)	VGG	10	84.90
	TET-S($\epsilon = 0.1$)	VGG	10	85.60
	TET-S($\epsilon = 0.01$)	VGG	10	**86.10**
	TET-S($\epsilon = 0.001$)	VGG	10	85.40
	IMP+SDT($\lambda = 0.0$)	VGG	10	83.70
	IMP+TET($\lambda = 0.0$)	VGG	10	85.90
	IMP+TET-S($\lambda = 0.0$)	VGG	10	**86.20**
	IMP+TET-S($\lambda = 0.2$)	VGG	10	**87.10**
	IMP+TET-S($\lambda = 0.4$)	VGG	10	**86.40**
ImageNet100	TET	SEW-ResNet18	4	78.50
	SDT	SEW-ResNet18	4	79.10
	LTS	SEW-ResNet18	4	**80.20**
	IMP+TET	SEW-ResNet18	4	78.70
	IMP+SDT	SEW-ResNet18	4	79.90
	IMP+LTS	SEW-ResNet18	4	**80.80**

➢ Neuromorphic Task

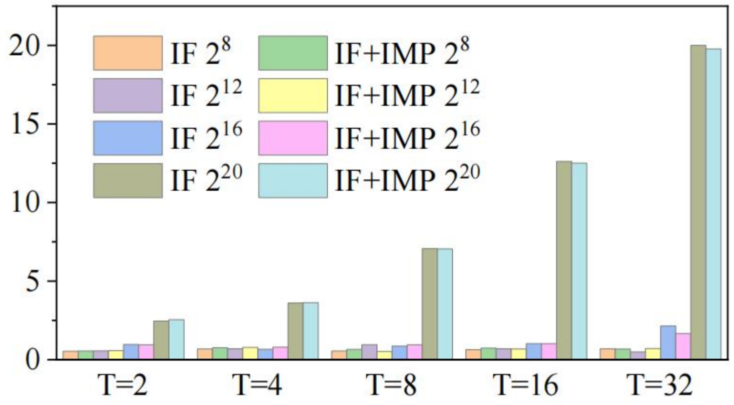
Dataset	Method	SNN Architecture	Size	Time Steps	Accuracy(%)
CIFAR10-DVS	GLIF[2]	Wide 7B Net	48	16	78.10
	NDA[3]	VGG	48	10	79.60
	TET[1]	VGG	48	10	83.17
	TEBN[4]	VGG	48	10	84.90
	PSN[5]	VGG	48	10	85.90
	IMP(ours)	VGG	48	10	**85.90**
	IMP+TET-S(ours)	VGG	48	10	**87.10**
	IMP+TET-S(ours)	VGG	48	8	**87.80**
	PLIF[6]	PLIF Net	128	20	74.80
	TDBN[7]	ResNet-19	128	10	67.80
	Dspike[8]	ResNet-18	128	10	75.40
	KLIF[9]	PLIF Net	128	15	70.90
	SEW ResNet[10]	Wide 7B Net	128	16	74.40
	Spikformer[11]	Spikformer	128	10	78.90
	Spikformer[11]	Spikformer	128	16	80.90
	NDA[3]	VGG	128	10	81.70
	IMP(ours)	VGG	128	16	**86.30**
	IMP+TET-S(ours)	VGG	128	16	**87.00**
N-Caltech101	NDA[3]	VGG	48	10	78.20
	EventMix[12]	ResNet18	48	10	79.47
	ESP[13]	SNN7-LIFB	48	10	81.74
	TCJA[14]	TCJA-SNN	48	10	82.50
	TKS[15]	VGG-TKS	48	10	84.10
	IMP(ours)	VGG	48	10	**84.68**
	IMP+TET-S(ours)	VGG	48	10	**85.01**
	EventDrop[16]	VGG	128	10	74.04
	NDA[3]	VGG	128	16	83.70
	EventRPG[17]	VGG	128	10	85.62
	STR[18]	VGG	128	10	85.91
	IMP(ours)	VGG	128	16	**86.12**
	IMP+TET-S(ours)	VGG	128	16	**87.86**

Experiments & Conclusion

➢ Static Task (ImageNet-1k)

Method	Network Architecture	Reset	Params	Time Steps	Accuracy(%)
PSN[5]	SEW ResNet-18	✗	11.69	4	67.63
	SEW ResNet-34	✗	21.79	4	70.54
Dspike[8]	ResNet-34	✓	21.79	6	68.19
	VGG-16	✓	138.42	5	71.24
TET[1]	SEW ResNet-34	✓	21.79	4	68.00
TDBN[7]	ResNet-34	✓	21.79	6	67.05
TEBN[4]	SEW ResNet-34	✓	21.79	4	68.28
GLIF[2]	ResNet-34	✓	21.79	4	67.52
Spikformer[11]	Spikformer-6-512	✓	23.37	4	72.64
	Spikformer-8-512	✓	29.68	4	73.38
SEW ResNet[10]	SEW ResNet-18	✓	11.69	4	63.18
	SEW ResNet-34	✓	21.79	4	67.04
	SEW ResNet-50	✓	25.56	4	67.78
	SEW ResNet-101	✓	44.55	4	68.76
	SEW ResNet-152	✓	60.19	4	69.26
LTS	SEW ResNet-18	✓	11.69	4	64.33(+1.15)
	SEW ResNet-34	✓	21.79	4	68.10(+1.06)
	SEW ResNet-50	✓	25.56	4	71.24(+3.46)
IMP+LTS	SEW ResNet-18	✓	14.17	4	**65.38**(+2.20)
	SEW ResNet-34	✓	25.54	4	**68.90**(+1.86)
	SEW ResNet-50	✓	36.67	4	**71.83**(+4.05)

➢ Execution Speed



➢ Contributions

- ✓ First implementation of learnable IMP with almost no extra computational consumption.
- ✓ Propose two learning method, LTS and TET, for static and neuromorphic task, respectively.
- ✓ Achieve SOTA on neuromorphic tasks and significantly improved on static tasks.

Thank You for Listening

References

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