Temporal-Coded Spiking Neural Networks with Dynamic Firing Threshold: Learning with Event-Driven Backpropagation

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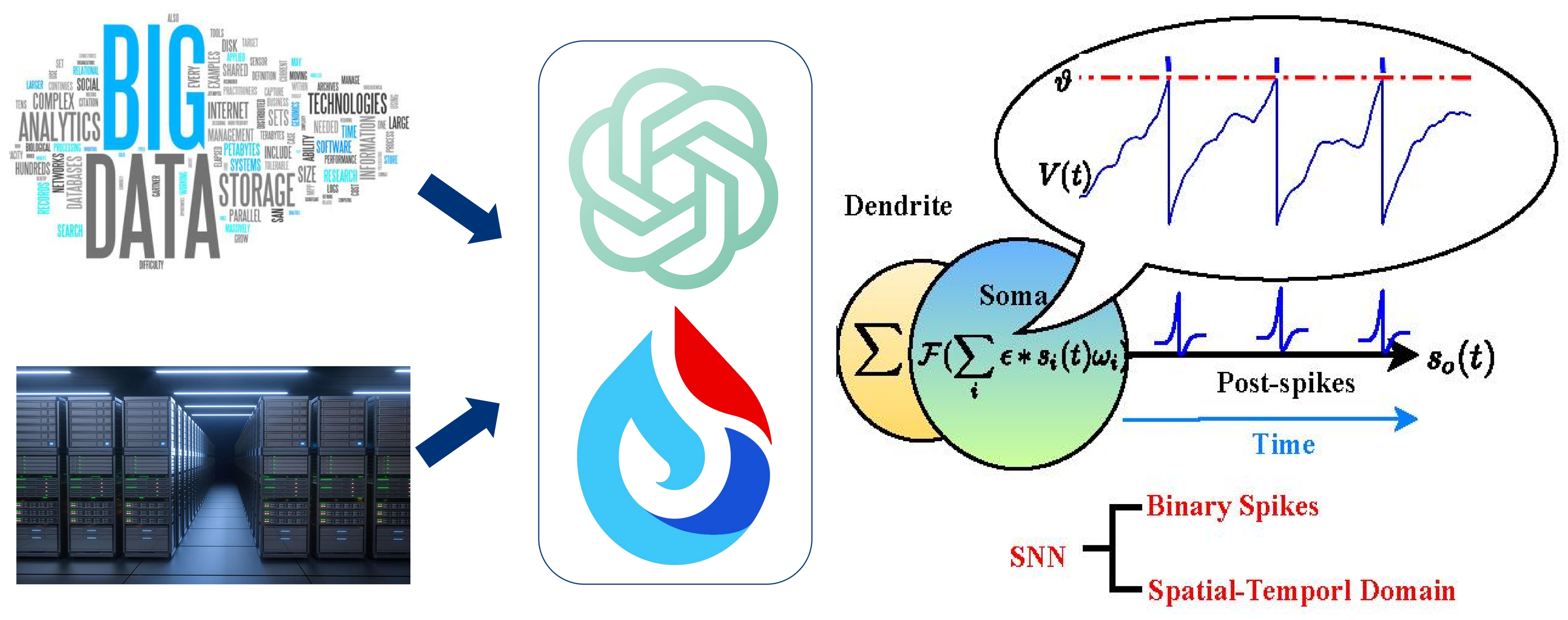
Motivation

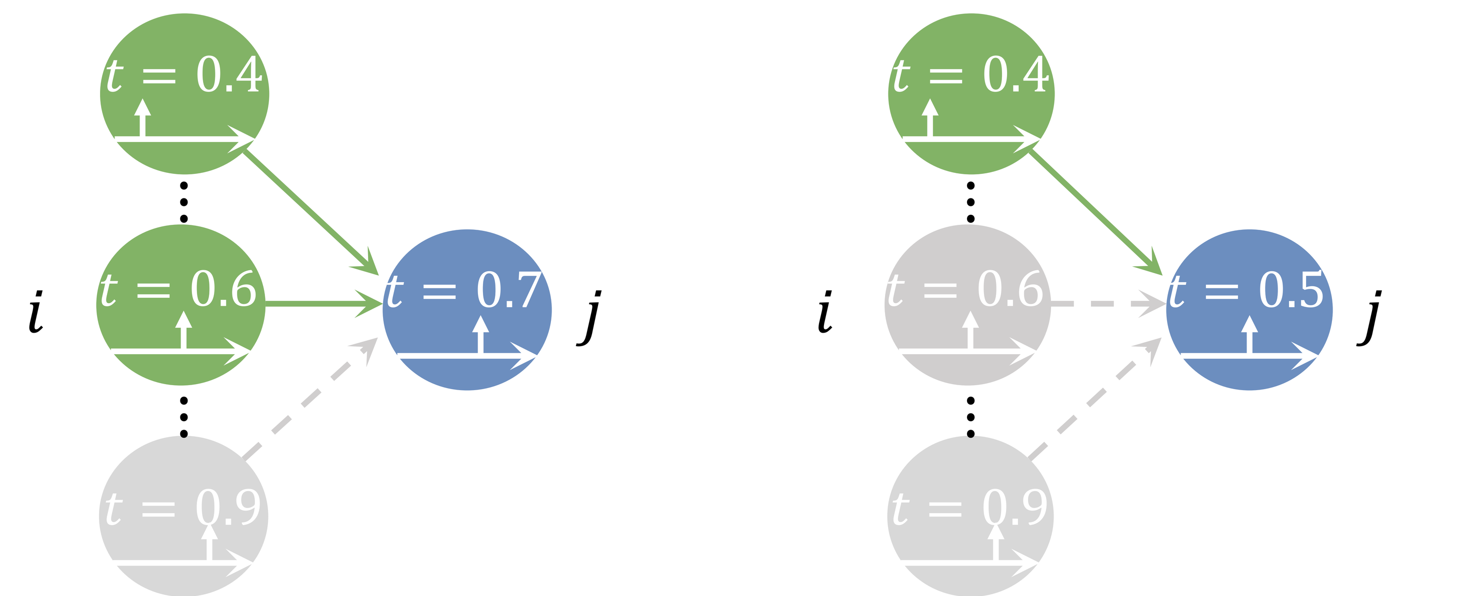


(a) High energy consumption (b) Energy-efficient alternative

Brain-inspired spiking neural networks (SNNs) provide an energy efficient alternative to deep learning. As the SNN coding scheme, Time-To-First-Spike (TTFS) encodes information via the time of a single spike, further reducing the power consumption of SNNs.

Problem Analysis

➢ Over-sparsity of spikes



(a) Asynchronous transmission (b) TTFS-based decision strategy

➢ The complexity of finding 'causal set'

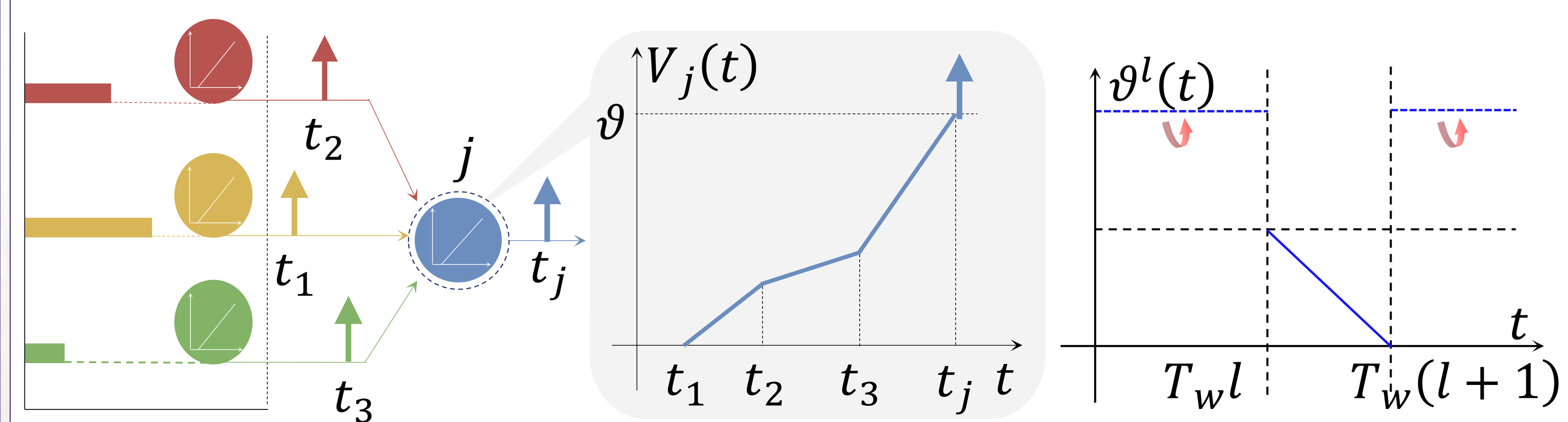
Algorithm get_causal_set

for i= 1 to N **do**
  if $i == N$ **then**
    $next\_input\_spike \leftarrow \infty$
  else
    $next\_input\_spike \leftarrow \mathbf{z}^{\text{sorted}}[i+1]$
  end if
  if $\sum_{k=1}^{i} \mathbf{w}^{\text{sorted}}[k] > 1 \quad \wedge \quad \frac{\sum_{k=1}^{i} \mathbf{w}^{\text{sorted}}[k]\mathbf{z}^{\text{sorted}}[k]}{\sum_{k=1}^{i} \mathbf{w}^{\text{sorted}}[k]-1} < next\_input\_spike$ **then**
    return $\{\text{sort\_indices}[1], .., \text{sort\_indices}[i]\}$
  end if
end for

Due to the above challenges, TTFS-based SNNs suffer from shallow layers and poor performance.

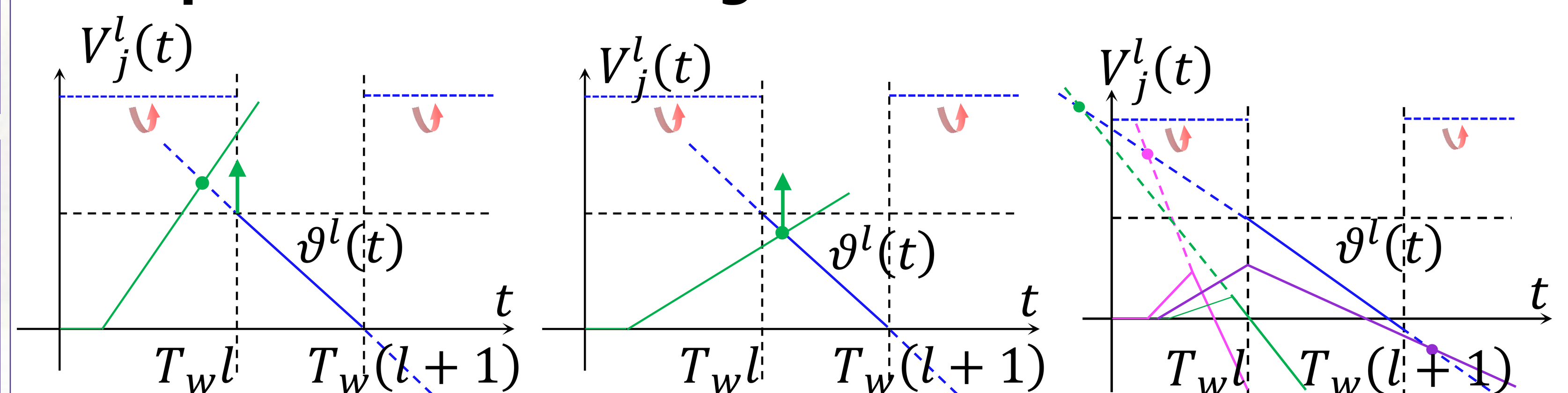
Method

➢ ReL-PSP neuron & Dynamic firing threshold (DFT)



We integrate the DFT mechanism into Rel-PSP neurons to solve the aforementioned issues, which regulates the spiking activity of each layer within the non-overlapping time window.

➢ Proposed DTA-TTFS algorithm



Based on the DFT, we further propose the DTA-TTFS algorithm, where the single spike time is viewed as the information carrier, and the learning is performed strictly in an event-driven manner.

Conclusion

- We comprehensively analyze the main shortcomings of existing methods to achieve high performance in TTFS-based deep SNNs.
- We propose a simple yet efficient dynamic firing threshold, namely the DFT, for spiking neurons that can effectively address the aforementioned issues.
- We introduce a direct training algorithm for TTFS-based deep SNNs, namely DTA-TTFS, where the timing of a single spike is considered the basic information carrier and the learning process is performed strictly in an event-driven manner.
- We conduct experiments on benchmark image classification tasks, and achieves state-of-the-art accuracy. Furthermore, **we** demonstrate the ultra-low power capability of the SNN with DTA-TTFS on a developed neuromorphic accelerator CanMore.

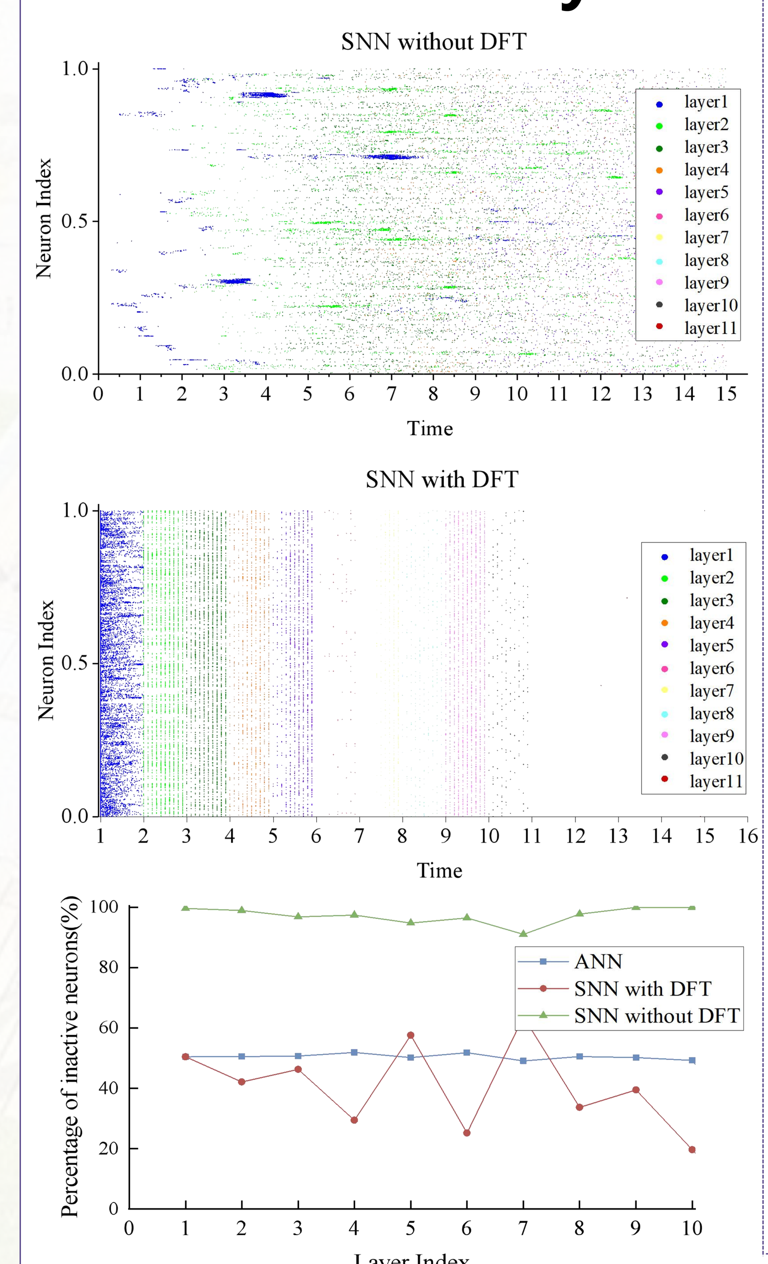
Experimental Results

➢ Performance Comparison

Datasets	Models	Network Architecture	Neural Coding	Method	Accuracy	Sparsity
MNIST	Mostafa 2017 [33]	MLP[1]	TTFS	DT	97.55%	0.51
	Zhang *et al.* 2020 [58]	CNN[1]	TTFS	DT	99.4%	0.6614
	Zhou *et al.* 2021 [60]	CNN[2]	TTFS	DT	99.33%	0.94
	DTA-TTFS	CNN[1]	**TTFS**	**DT**	**99.4%**	**0.3913**
CIFAR-10	Wu *et al.* 2022 [46]	VGG11	Rate	conv	91.24%	no
	Park *et al.* 2020 [37]	VGG16	TTFS	conv	91.43%	0.2459
	Zhou *et al.* 2021 [60]	VGG16	TTFS	DT	92.68%	0.62
	Park *et al.* 2021 [38]	VGG16	TTFS	DT	91.90%	0.1746
	DTA-TTFS	**VGG11**	**TTFS**	**DT**	**91.17%**	**0.4387**
	DTA-TTFS	**VGG16**	**TTFS**	**DT**	**93.05%**	**0.2561**
CIFAR-100	Park *et al.* 2020 [37]	VGG16	TTFS	conv	68.79%	0.2994
	Park *et al.* 2021 [38]	VGG16	TTFS	DT	65.98%	0.2780
	DTA-TTFS	**VGG16**	**TTFS**	**DT**	**69.66%**	**0.2845**

The DTA-TTFS algorithm obtains SOTA performance, achieving a harmonious balance between accuracy and sparsity.

➢ Validation Study

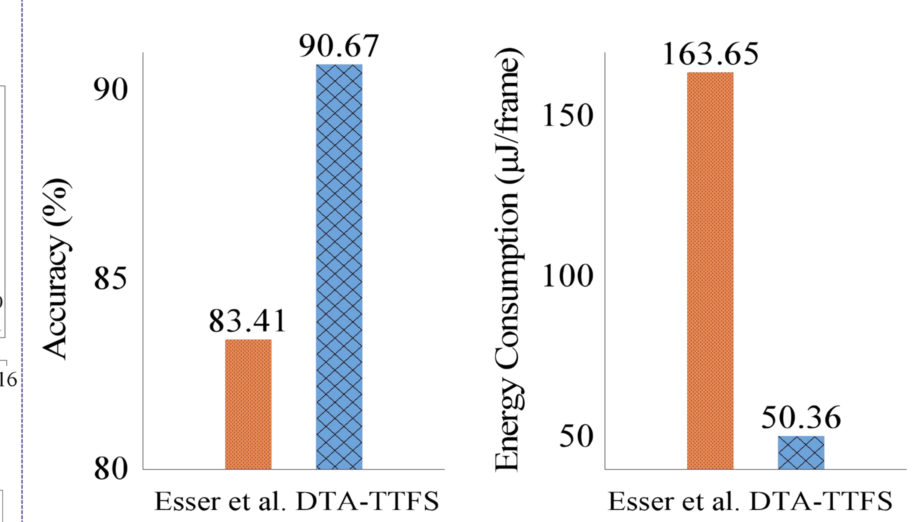


Validation studies demontrate that :

- **The SNN with DFT successfully regulate the spike activity in each layer within a permitted time window.**
- **The SNN with DFT exhibits a comparable amount of inactive neurons to that of ANN.**

➢ Energy Consumption

Neural Coding	Time Step	Spike (10^6)	Acc. (%)	Normalized Energy	
				TrueNorth	SpiNNaker
Rate [19]	512	2.612	93.39	1	1
Phase [26]	1500	35.196	91.21	7.1476	9.6785
Burst [36]	1125	6.92	91.41	2.3781	2.4865
TTFS [37]	680	0.069	91.43	0.8074	0.4950
TTFS [38]	544	0.067	91.9	0.6478	0.3989
DTA-TTFS	**160**	**0.073**	**93.05**	**0.1987**	**0.1304**



Both theoretical analysis and hardware validation prove the energy efficiency of our method.

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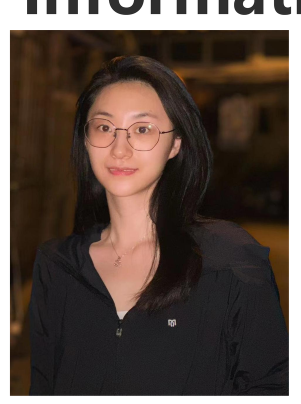
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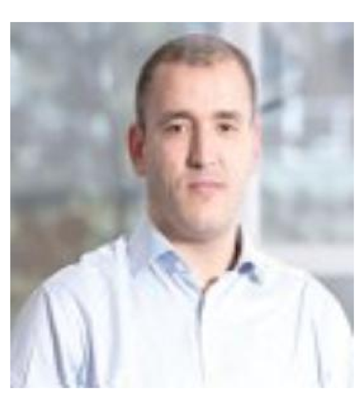
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