



SpikeConverter: An Efficient Conversion Framework Zipping the Gap between Artificial Neural Networks and Spiking Neural Networks

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ANN-Converted SNN

- > **ANN:** High Precision, Dense Computation.
- > **SNN:** Low Computation cost.
- **Directly Trained SNN:** Low Precision, Moderate Delay. • **ANN-Converted SNN:** High Precision, Large Delay.
- > Highlight, this work:
- **High Precision:** As High Precision as ANN.
- **Small Delay:** Log Scale of that of ANN-Converted SNN.

Comparison of Current Methods								
	ANN	Directly Trained SNN	ANN-Converted SNN	This SpikeCo				
Network Type	ANN	SNN	SNN	S				
Training Method	BP	STBP	Not Needed	Not N				
Computation Cost	High	Low	Medium	Le				
Precision	High	Low	High	Hi				
Delay	Small	Medium	Large	Sn				

Challenges

> Low Precision of Directly Trained SNN Unlike ANN training that have mature and developing algorithm based on gradient descent, they can not be deployed on SNN. Other training alternative also leads to

inferior accuracy to ANN. Large Delay of ANN-Converted SNN Although ANN-converted SNN can match the precision

of ANN, their spike trains are very long to represent adaquate information comparable with ANN.

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SpikeConverter

- Work, Converter
- SNN
- Needed
- .OW
- High
- mall

- Soft Reset V_m(t) ♠ Reduce threshold from membrane voltage when fires, instead of resetting to zero in hard reset mechanism.
- Enables the accurate construction of ideal conversion identical relation:

$$\sum_{i} W_{i} \cdot \left(\sum_{t=1}^{T} X_{i}[t] \cdot k^{T-t} \right) = V_{th} \cdot \sum_{t=1}^{T} Y[t] \cdot k^{T-t}$$

Ideal Conversion Identical Relation

- > The identical relation between input and output spike trains.
- Holds under ideal condition: soft reset mechanism, **zero** membrane voltage after the last time step.

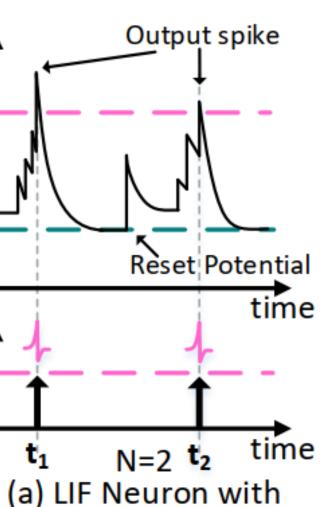
Temporal Seperation

- SNN can not respond to accumulated negative membrane voltage.
- > Lead to failing to follow the identical relation and influence the accuracy.
- Solution: temporal seperation, fire spikes after full accumulation.
- > Pipeline multiple inputs to make full ues of resource.

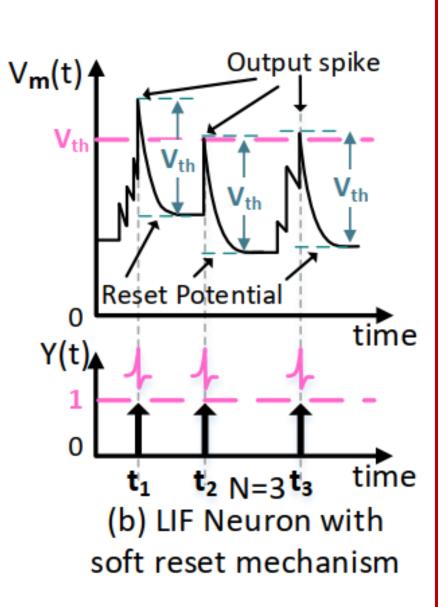
Inverse-LIF Neuron

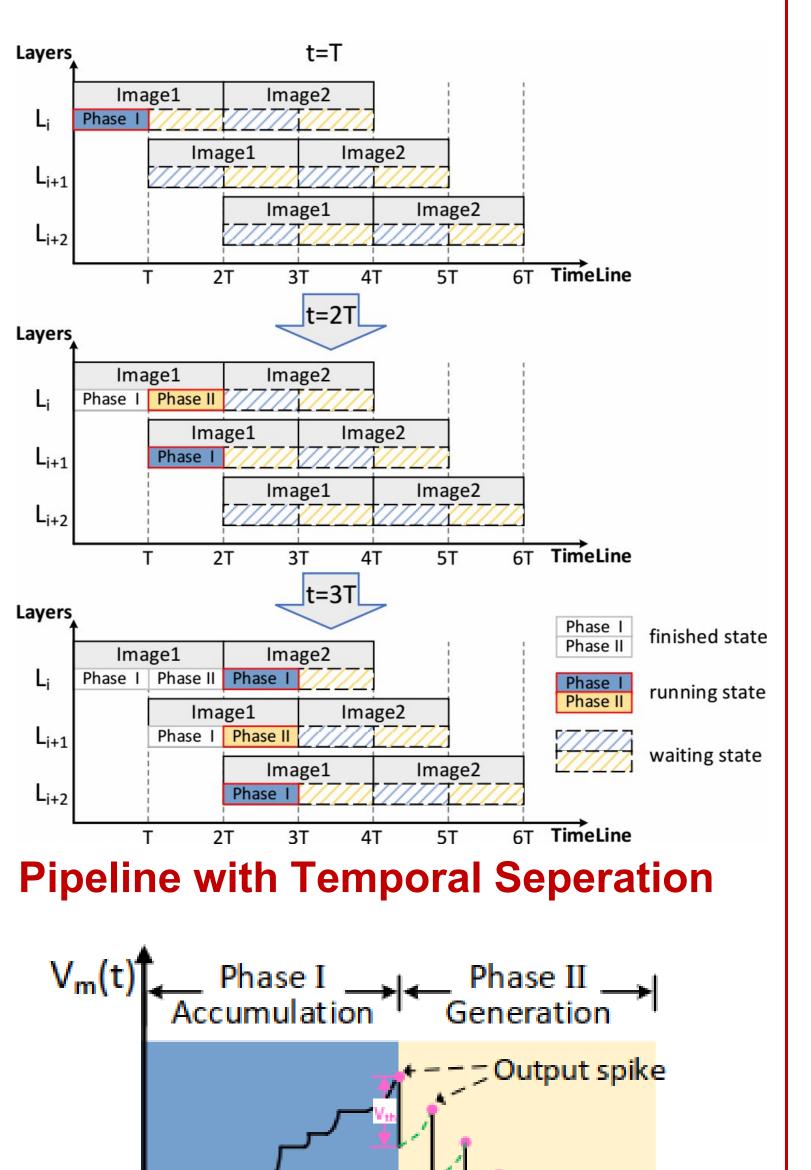
- > Membrane voltage inflates each time step.
- > Necessary for the implementation of temporal seperation.
- > Optional additional time step to increase precision.





hard reset mechanism





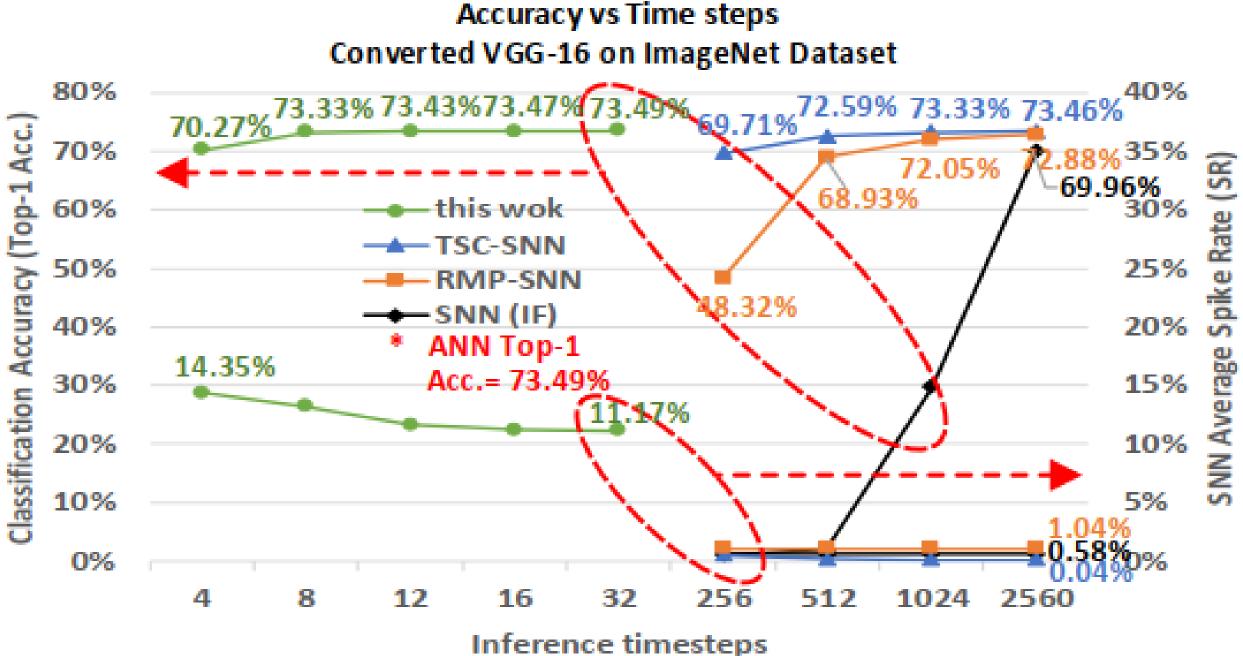
Less than V_t

2T time

Results on ImageNet

Network Architecture	Spiking Neuron Model	ANN (Top-1)	Time Steps	SNN (Top-1)	Accuracy Loss
ResNet-34 (Sengupta et al. 2019)	IF (hard-reset)	70.69%	4096	65.47%	5.22%
ResNet-34 (Han, Srinivasan, and Roy 2020)	RMP (soft-reset)	70.64%	4096	69.89%	0.75%
ResNet-34 (Han and Roy 2020)	TSC (soft-reset)	70.64%	4096	69.93%	0.71%
ResNet-34 [This work]	SpikeConverter (soft-reset)	70.64%	16	70.57%	0.07%
VGG-16 (Rueckauer et al. 2017)	Converted-SNN (hard-reset)	63.89%	400	49.61%	14.28%
VGG-16 (Sengupta et al. 2019)	IF (hard-reset)	70.52%	2560	69.96%	0.56%
VGG-16 (Han, Srinivasan, and Roy 2020)	RMP (soft-reset)	73.49%	2560	73.09%	0.4%
VGG-16 (Han and Roy 2020)	TSC (soft-reset)	73.49%	2560	73.46%	0.03%
VGG-16 (Deng and Gu 2021)	ReLU+threshold (soft-reset)	73.47%	128	71.06%	2.41%
VGG-16 [This work]	SpikeConverter (soft-reset)	73.49%	16	73.47%	0.02%
MobileNet-v2 [This work]	SpikeConverter (soft-reset)	71.88%	16	71.71%	0.17%

Inference Performance



Inference Computation Cost

		Co
er	6.0E+08	
mber of Additions p Inference	5.0E+08	
	4.0E+08	
	3.0E+08	
	2.0E+08	
	1.0E+08	
Num	0.0E+00	
		л

Results

Addition Operations vs Time steps Converted VGG-16 on the ImageNet Dataset

