Research Paper Reading

Backpropagation-Based Learning Techniques for Deep Spiking Neural Networks: A Survey

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Overview

1. Key Contribution
2. Training Deep SNNs
3. Optimizing Deep SNNs
4. Impact of encoding, training, architecture on accuracy-latency trade-off
5. Conclusion

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Key Contribution

- Survery on backpropagation-based learning method for SNN
  - List the trending methodology
  - List pros/cons, affection of each method

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ANN vs SNN

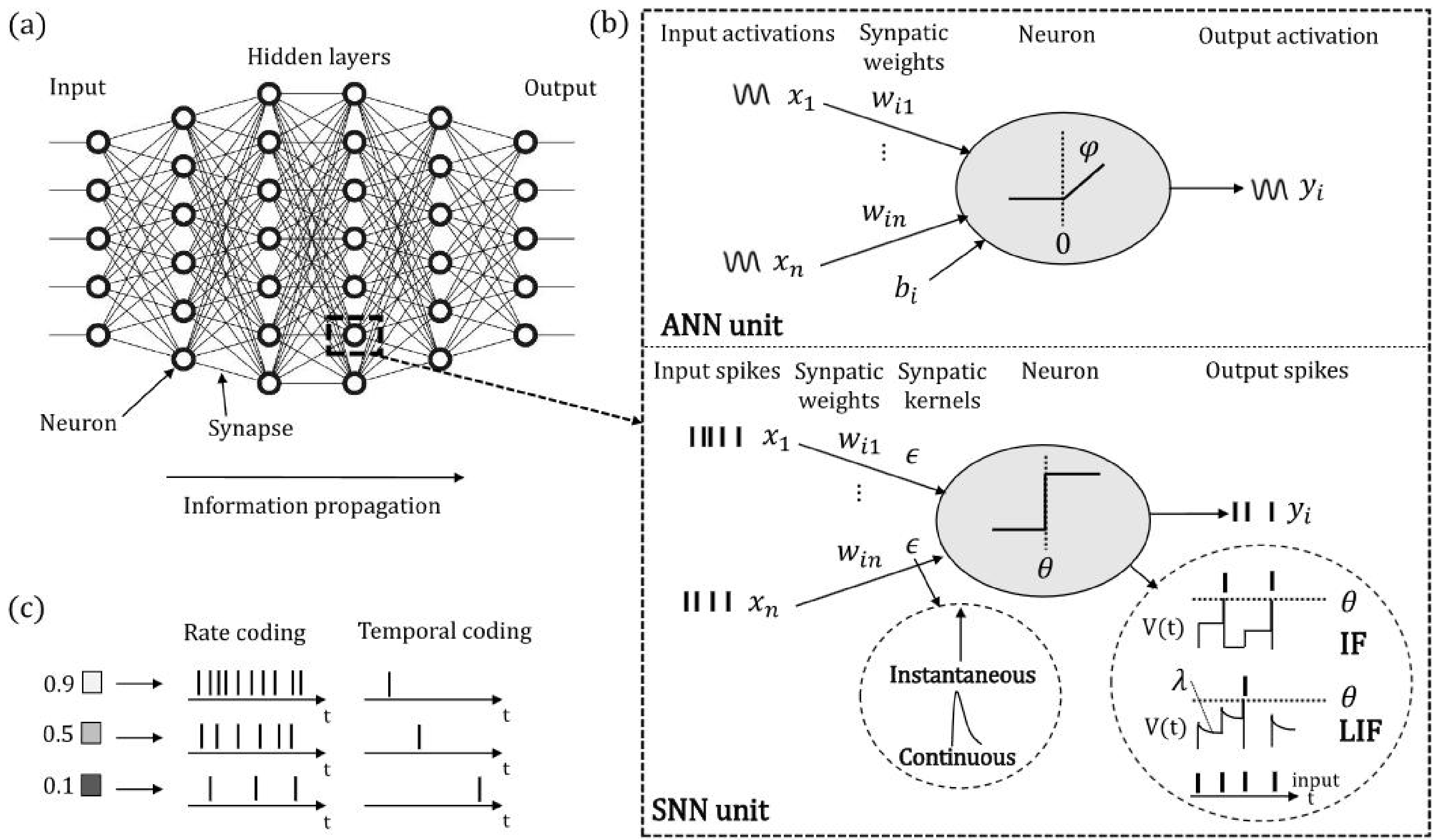


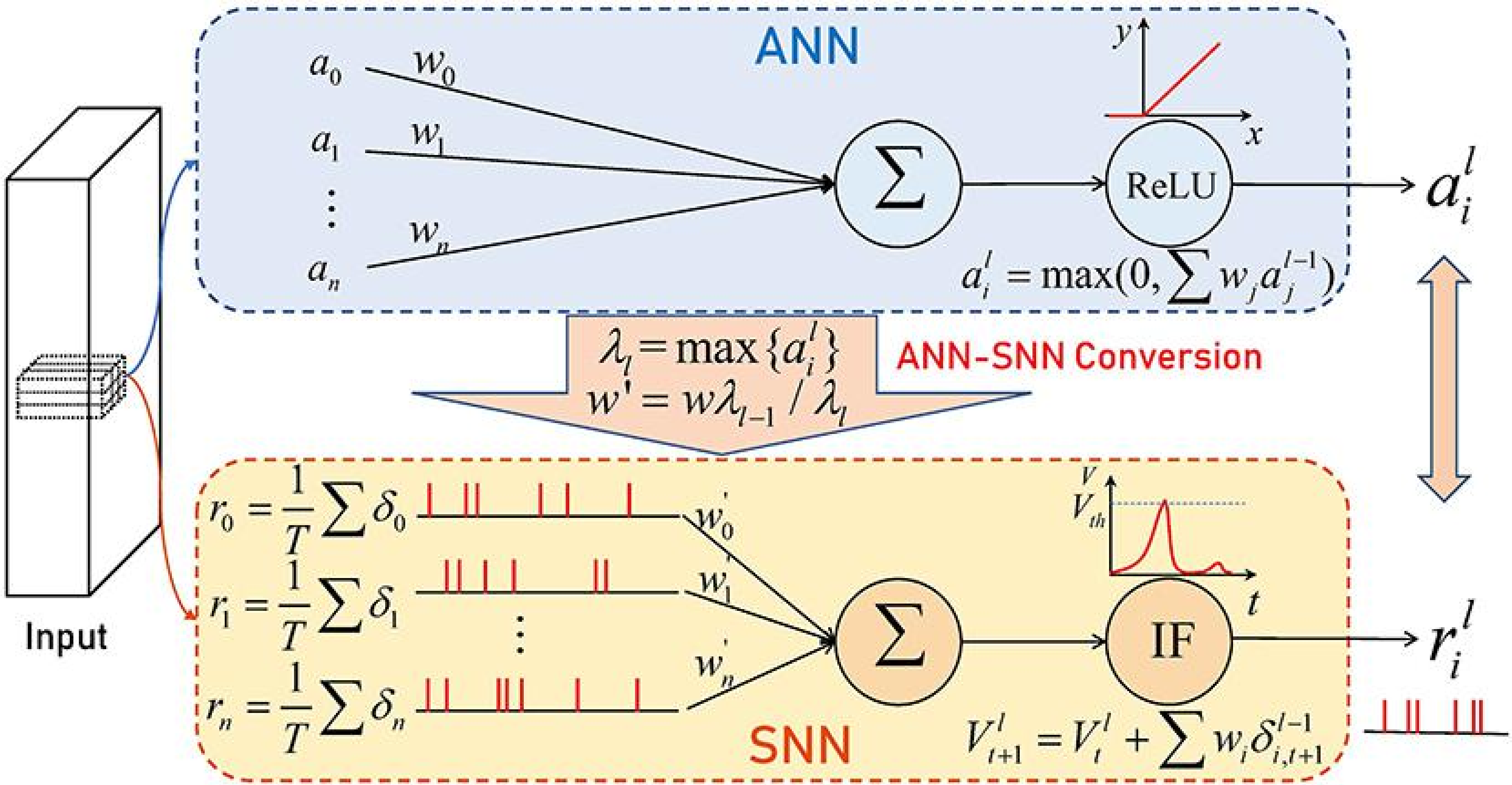
Fig. 1. (a) Feedforward fully connected neural network. (b) ANN and SNN neuron and synapse models. (c) Input encoding: example of pixel-to-spike conversion with a rate coding or temporal (latency) coding.

Difference between ANN & SNN

Training Deep SNNs

- ANN-to-SNN conversion
  - Conversion with Rate Coding
  - Conversion with Temporal Coding
- Backpropagation-Based Learning Algorithms
  - Spatial Approaches
  - Spatiotemporal Approaches
  - Single-Spike Approaches

ANN-to-SNN conversion



*Y. Li et al. "BSNN: Towards faster and better conversion of artificial neural networks to spiking neural networks with bistable neurons"

- **Activation transformation use rate-coding or temporal-coding**
- **Normalized weights**

ANN-to-SNN conversion with Rate Coding

- Problems:
  - The conversion process results in errors in some cases
    - the ANN activation is too high and cannot be accurately represented by the spike rate given a fixed simulation duration
- Methods:
  - (1) Weight Normalizaiton (rescaling weights in each layer)
  - (2) Balances threshold in each layer
  - (3) Uses ANN statistics to determine the normalization
  - (4) Soft reset (decrese a certain value not reset)

ANN-to-SNN conversion with Temporal Coding

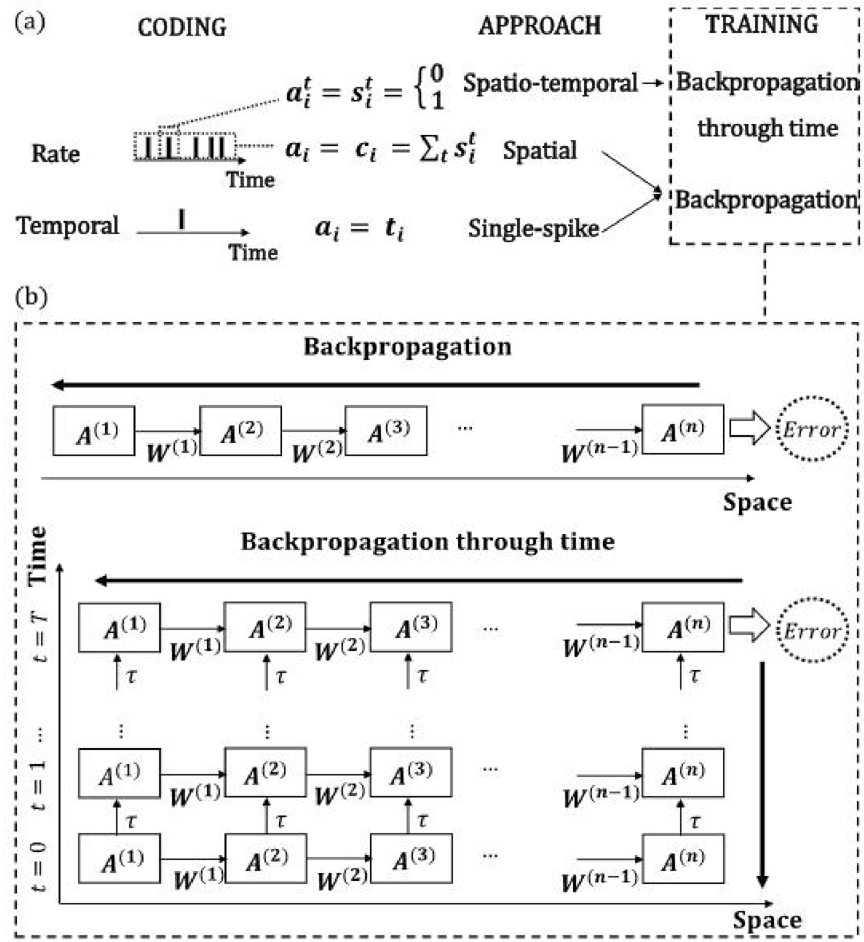
- Advantages:
  - Reduce the number of spikes compared to rate-coding
    - Reduce energy consumption
- Methods:
  - (1) Using equivalence for the ANN activations and the spike in SNN
    - Same accuracy with rate-coding
  - (2) Temoporal coding with two types of spike (positive and negative); (3) Threshold balancing; (4) Tranform to Log dimension
    - Increase the accuray with fewer timesteps
    - Increase the complexity of hardware
- Problems:
  - Less robust to noise in hardware implementation

Pros & Cons of conversion

- Rate-coding:
  - Pros:
    - Simple, straight-forward to implement
    - Noise-resilience
  - Cons:
    - The conversion process results in errors in some cases
    - Large numer of spike; Hundreds to thousands of inference timesteps
- Temporal-coding:
  - Pros:
    - Reduce the timesteps compared rate-coding => reduce power consumption
  - Cons:
    - Less robust to noise in hardware implementation, lower accuracy compared to rate-coding
    - Hundreds to thousands of inference timesteps

Backpropagation-Based Learning

- The spatial approach
- The spatiotemporal approach
- The single-spike approach



Backpropagation-based learning methods

The spatial approach

- Approximating the SNN forward pass during the training
  - A lighter backpropagation, only in the spatial domain, as in ANN training
- The SNN is directly trained, but viewed as an ANN
- Problems:
  - surplus membrane potential of spiking neurons is not considered
  - spike discretization error can be reduced to zero
    - Affect training
  - not benefit from the spatiotemporal dynamics of SNNs

The spatiotemporal approach

- Propagate the gradient both in spatial and temporal dimensions using the BPTT (backpropagation through time)
- approximate the nondifferentiable spiking activity with a surrogate gradient
  - smoothing the spiking activity
  - degrades the accuracy
- The derivative of the error is decomposed into two factors
  - the interneuron dependencies
  - the intraneuron dependencies
- Problems:
  - Backpropagation when no spike

The single-spike approach

- Avoid the nondifferentiability problem from spatiotemporal approach (at least 1 fire per neuron)
  - Directly differentiating the spike times (temporal coding)
    - Not use BPTT, direct backpropagation on spike times
    - Cannot use BP in non-fire neuron => Use weight regularization => force fire spike at least once
    - Negative spike times to encourage neurons to fire => analyzie input-output relationship
  - Use IF neurons with linear synapses
    - Reduce the exploding gradient and dead neurons compared to alpha neurons
    - Derivation of the linear synapse =/= 0 and no leak model
      => More likely to fire
    - Approximate with instantaneous synapse => Gradient not exact
- Problems:
  - Only backpropagation on presynaptic neuron that had spikes
    - Fewer spike => Slow backpropagation => Slow convergence in loss minimization

Pros & Cons of Backpropagation-based

- Pros:
  - Better accuracy & latency with spatial and single-spike approaches
  - Spatiotemporal approaches are compatible with dynamic input data
  - BPTT reduce number of timestep => reduce latency & energy
- Cons:
  - Cost of BPTT is huge
    - Require storing all actiavtions & computing gradients all timesteps
  - Use approximate derivative for spiking activities
    - Not accurate => accumulate through layers => low accuracy
  - Vanishing & exploding gradients

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Optimizing Deep SNNs

- Improvement for backpropagration approaches
  - Improve accuracy, latency, spike sparsity
- Use similar techniques for backpropagation in ANNs
  - Transferring ANN techniques (Batch Norm., Drop Out, Regularization, ...)
  - Improve encoding & decoding
  - Use wider network architecture
  - Hybridization in training (mix ANN & SNN)
  - Tuning parameters specificially to SNNs

ANN techniques for SNN

- Regularization: (Decrease overfitting in training => improve the generalization of model)
  - Neuron Normalization Method
    - using auxiliary neruons at each convolutional layer
    - weight summation of spike count (from pre-neuron to post-neuron) => balance input current => increase accuracy
    - Require additional multiplications => increase complexity
- Dropout: (regularization - avoid training focus on one neuron)
  - Use in BPTT - keep random subset dropped in each timestep
    - Better convergence
- Batch Normalization: (reduce the training timesteps, increase scalability)
  - 9x efficiency compared non-BN model
  - Threshold-dependent spatiotemporal BN => Norm. the variance of the inputs => high accuracy, fewer timesteps
- Optimize network architectures
  - ResNet, VGG => increase accuracy

Improving encoding & decoding

- Encoding:
  - Poisson spike generation
    - Famous in spatial & spatiotemporal approaches
  - Discrete cosine transformation (make use of temporal dimension)
    - Decomposing the input into a basis of spectral component
    - Fine grain spike vectors => increase accuracy, reduce latency
    - But 2 matrix multiplications => increase complexity
  - Add encoding layer (real-value not binary) - hybrid layers
    - As first layer
    - 1 spike layer, 1 encoding layer

    => reduce timesteps, increase complexity
- Decoding:
  - Apply loss function, high-precision activations on output neurons
    - Increase accuracy
    - Increase parameters, more neurons => increase complexity

Wide Network Architecture

- Increase number of neurons per layer
  - Improve accuracy, low latency
  - ResNet, VGG
  - Increase in width more benefit in depth
    - Width - Increase quality for backpropagation
    - Depth - Difficult to backpropagation

Training Hybridization

- ANN-SNN Network Hybridization
  - Improve encoding accuracy
  - Good benefit from small dataset (CIFAR-10)
  - Low benefit from big dataset (ImageNet)
- Tandem Learning
  - Training process is reduced
  - Temporal information cannot used
- Conversion and direct training Hybridization
  - Good accuracy
  - High number of inference timestep

Leveraging the specificity of SNN

- Neuron's leak and threshold
  - Control input-output => good for backpropagation
  - Reduce timesteps
- Synapse Dynamics
  - Add filter to increase the accuracy but increase complexity
- Surrogate gradient
  - Approximate the drivative of spike
    - Training is fast, but not good in big scale

Results (1)

COMPARISON OF BACKPROPAGATION-BASED ALGORITHMS ON STATIC VISION DATASETS

Learning strategy	Paper	Coding	Neurons + synapses	Architecture	Regularization method	Additional training strategy	Timesteps	Acc. (%)
CIFAR-10								
Spatial	[45]	rate	IF + instantaneous	VGG-8	/	/	/	89.99
Spatio-temporal	[51]	rate	LIF + instantaneous	VGG-8	neuron normalization, dropout	encoding layer, voting layer	12	90.53
	[53]	rate	LIF + instantaneous	ResNet-11	dropout	/	100	90.95
	[54]	rate	LIF + exponential	VGG-8	/	encoding layer	5	91.41
	[58]	rate	IF + instantaneous	ResNet-11	batch normalization, dropout	surrogate gradient tuning	20	90.20
	[56]	rate	LIF + instantaneous	VGG-8	batch normalization, dropout	encoding layer, voting layer	8	93.50
	[67]	rate	LIF + instantaneous	VGG-9	batch normalization	/	25	90.50
	[57]	rate	LIF + instantaneous	ResNet-19	batch normalization	encoding layer, voting layer	6	93.16
Single-spike	[64]	time	IF + exponential	VGG-16	weight regularization	/	/	92.68
CIFAR-100								
Spatio-temporal	[58]	rate	IF + instantaneous	ResNet-50	batch normalization, dropout	surrogate gradient tuning	40	58.5
	[67]	rate	LIF + instantaneous	VGG-11	batch normalization	/	30	65.8
ImageNet								
Spatio-temporal	[57]	rate	LIF + instantaneous	ResNet-34	batch normalization	encoding layer, voting layer	6	67.05
	[68]	rate	LIF + instantaneous	ResNet-152	batch normalization	encoding layer	4	69.26
Single-spike	[64]	time	IF + exponential	GoogLeNet	weight regularization	/	/	68.8

Increase accuracy, reduce latency with optimization techniques

Results (2)

COMPARISON OF BACKPROPAGATION-BASED ALGORITHMS ON NEUROMORPHIC VISION DATASETS

Learning strategy	Paper	Coding	Neurons + synapses	Architecture	Regularization method	Additional training strategy	Timesteps	Acc. (%)
CIFAR-10-DVS								
Spatio-temporal	[51]	rate	LIF + instantaneous	VGG-5	neuron normalization, dropout	encoding layer, voting layer	20	60.5
	[56]	rate	LIF + instantaneous	VGG-6	batch normalization, dropout	encoding layer, voting layer	20	74.8
	[67]	rate	LIF + instantaneous	VGG-7	batch normalization	/	20	63.2
	[57]	rate	LIF + instantaneous	ResNet-19	batch normalization	encoding layer, voting layer	10	67.8
DVSGesture								
Spatio-temporal	[55]	rate	LIF + continuous	5-layer CNN	/	synapse kernel optimization	/	96.09
	[56]	rate	LIF + instantaneous	VGG-7	batch normalization, dropout	encoding layer, voting layer	20	97.57
	[57]	rate	LIF + instantaneous	ResNet-17	batch normalization	encoding layer, voting layer	40	96.87

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Impact (1) - CIFAR 10

Paper	Architecture	Encoding layer	Training	Timesteps	Acc. (%)
CIFAR-10					
[38]	ResNet-20	×	conversion (rate)	2048	91.36
[38]	ResNet-20	×	conversion (rate)	256	89.37
[39]	ResNet-20	×	conversion (time)	2048	91.42
[39]	ResNet-20	×	conversion (time)	256	90.10
[40]	ResNet-20	✓	conversion (rate)	16	91.62
[66]	ResNet-20 (L)	×	conversion (rate)	250	91.12
[66]	ResNet-20 (L)	×	conversion (rate) + backpropagation	250	92.22
[70]	ResNet-20 (L)	✓	conversion (rate) + backpropagation	5	90.29
[70]	ResNet-20 (L)	✓	conversion (rate) + backpropagation (+ leak & threshold tuning)	5	91.78
[57]	ResNet-19 (L)	✓	backpropagation	6	93.16
[53]	ResNet-11 (L)	×	backpropagation	100	90.95
[58]	ResNet-11 (L)	×	backpropagation (+ batch normalization + surrogate gradient tuning)	20	90.20
[72]	ResNet-20	/	ANN (+ batch normalization)	/	91.25
[70]	ResNet-20 (L)	/	ANN	/	92.79

Number of parameters of the architectures (estimated according to the details given in the associated papers): ResNet-20: 0.27M. ResNet-20 (L): 11M. ResNet-19 (L): 13M. ResNet-11 (L): 18M. ResNet-34: 21M. ResNet-34 (M): 22M. ResNet-34 (L): 85M. VGG-16: 138M.

Impact (2) - ImageNet

ImageNet					
[38]	ResNet-34	×	conversion (rate)	4096	69.89
[38]	ResNet-34	×	conversion (rate)	256	≈20
[39]	ResNet-34	×	conversion (time)	4096	69.93
[39]	ResNet-34	×	conversion (time)	256	55.65
[40]	ResNet-34	✓	conversion (rate)	64	72.35
[66]	ResNet-34 (M)	×	conversion (rate)	250	56.87
[66]	ResNet-34 (M)	×	conversion (rate) + backpropagation	250	61.48
[57]	ResNet-34	✓	backpropagation (+ batch normalization)	6	63.72
[57]	ResNet-34 (L)	✓	backpropagation (+ batch normalization)	6	67.05
[68]	ResNet-34	✓	backpropagation (+ batch normalization)	4	67.04
[73]	ResNet-34	/	ANN (+ batch normalization)	/	73.31
[38]	VGG-16	×	conversion (rate)	4096	73.09
[38]	VGG-16	×	conversion (rate)	256	48.32
[39]	VGG-16	×	conversion (time)	2560	73.46
[39]	VGG-16	×	conversion (time)	256	69.71
[40]	VGG-16	✓	conversion (rate)	64	72.85
[66]	VGG-16	×	conversion (rate)	250	62.73
[66]	VGG-16	×	conversion (rate) + backpropagation	250	65.19
[70]	VGG-16	✓	conversion (rate) + backpropagation	5	64.32
[70]	VGG-16	✓	conversion (rate) + backpropagation (+ leak & threshold tuning)	5	69.00
[73]	VGG-16	/	ANN (+ batch normalization)	/	73.36

Number of parameters of the architectures (estimated according to the details given in the associated papers): ResNet-20: 0.27M. ResNet-20 (L): 11M. ResNet-19 (L): 13M. ResNet-11 (L): 18M. ResNet-34: 21M. ResNet-34 (M): 22M. ResNet-34 (L): 85M. VGG-16: 138M.

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Conclusion

- Based the expectation to choose the suitable techniques
  - High Accuracy, low latency
  - Low complexity, low-power, low area cost

Thank you

for your attention.