

High-Fidelity ANN-to-SNN Conversion via Closed-Loop CKA Distillation

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One-line claim

A source-preserving closed-loop refinement framework repairs conversion errors after ANN-to-SNN mapping, enabling low-latency SNNs with high fidelity.

Core mechanism

Freeze the source ANN, convert once, then fine-tune the SNN with global output distillation and adaptive local CKA feature alignment.

PROBLEM

Open-loop conversion creates a fidelity-latency trade-off

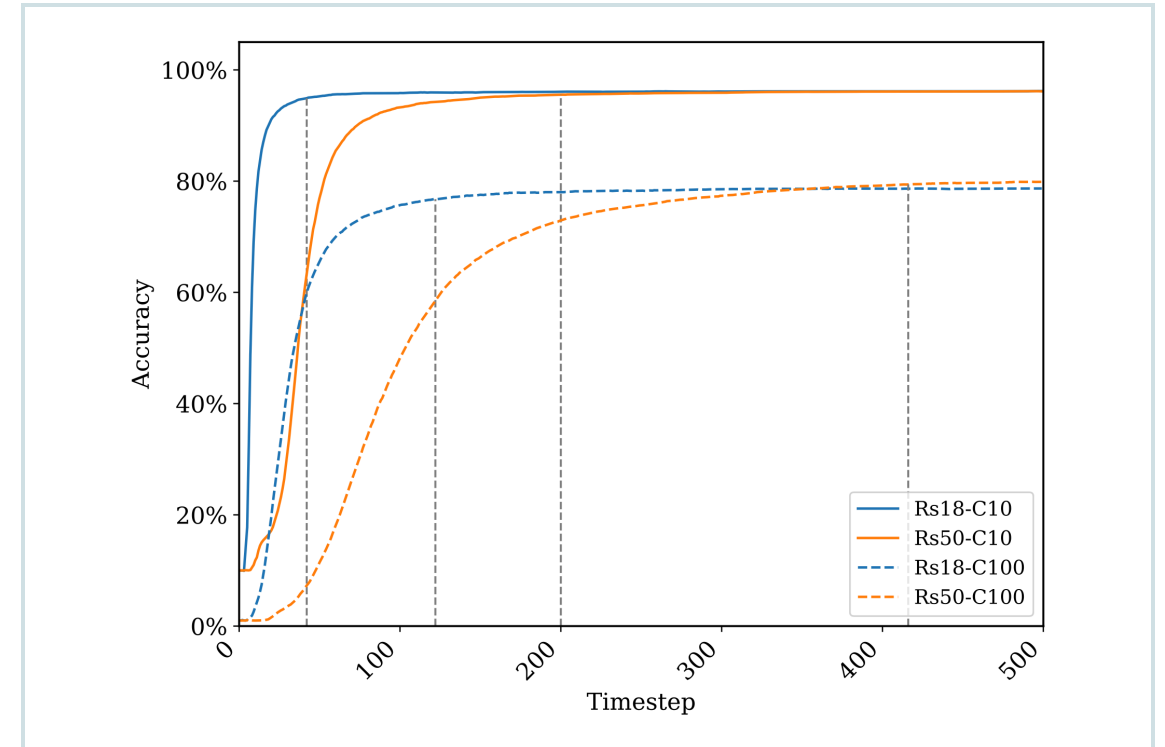
Conventional ANN-to-SNN conversion inherits strong ANN weights, but discrete spike quantization errors accumulate through depth. High fidelity often requires long inference windows.

416

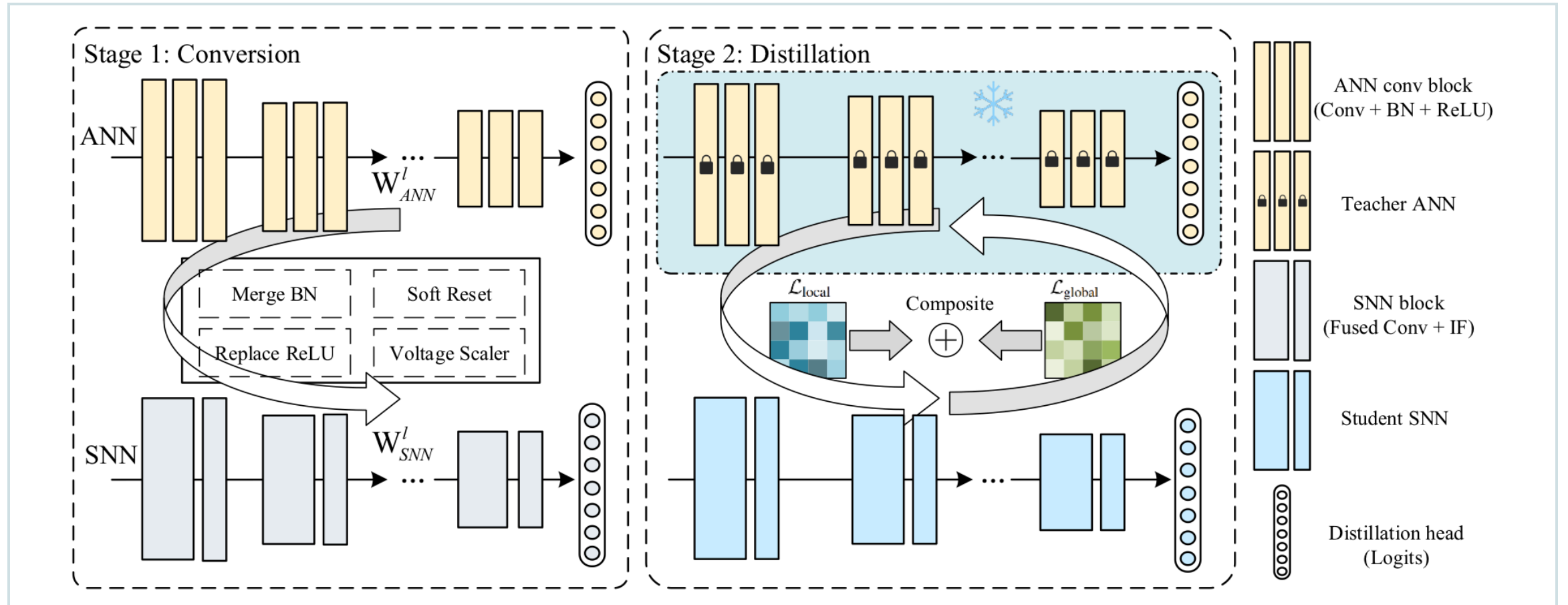
timesteps for ResNet-50 / CIFAR-100 to reach 95% final accuracy.

9.90x

relative latency compared with ResNet-18 / CIFAR-10.



Closed-loop CKA distillation framework



Stage 1 maps a pretrained ANN into a student SNN. Stage 2 repairs conversion errors with teacher-guided dual alignment: global logits plus adaptive local CKA feature geometry.

OBJECTIVE

Dual alignment repairs semantic and representational drift

$$L_{\text{total}} = (1-a)L_{\text{task}} + a[bL_{\text{global}} + (1-b)L_{\text{local}}]$$

1 Global output feedback

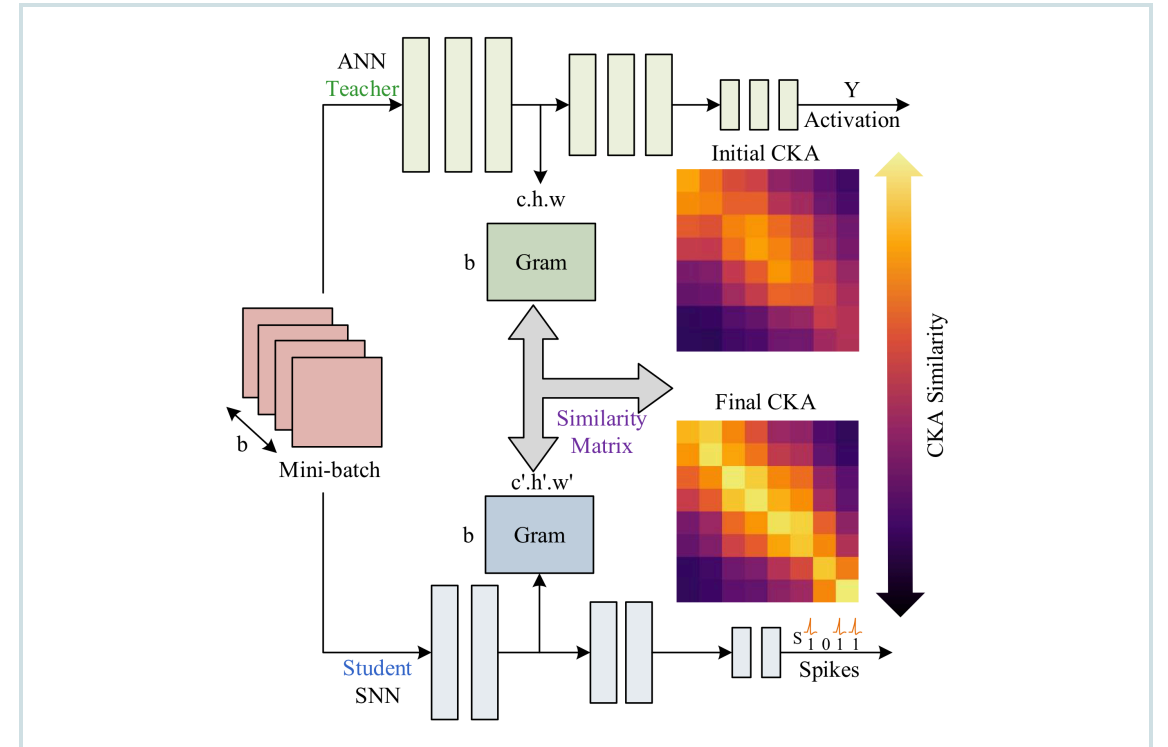
Align teacher ANN logits with SNN firing-rate logits via KL distillation.

2 Adaptive local CKA

Align intermediate representation geometry and prioritize layers with severe initial drift.

3 Time-dependent behavior

Local CKA stabilizes low-latency regimes; global alignment becomes stronger as firing rates converge.



RESULTS

Low-latency fidelity improves while robustness is preserved

90.05%

ResNet-18 / CIFAR-10 at T=2; baseline is 10.00%.

95.33%

ResNet-18 / CIFAR-10 at T=8, already close to source accuracy.

96.38%

T=32 versus 96.39% for the source ANN.

