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Sparse Convolutional Recurrent Learning for Efficient Event-based Object Detection

Guangzhi Tang

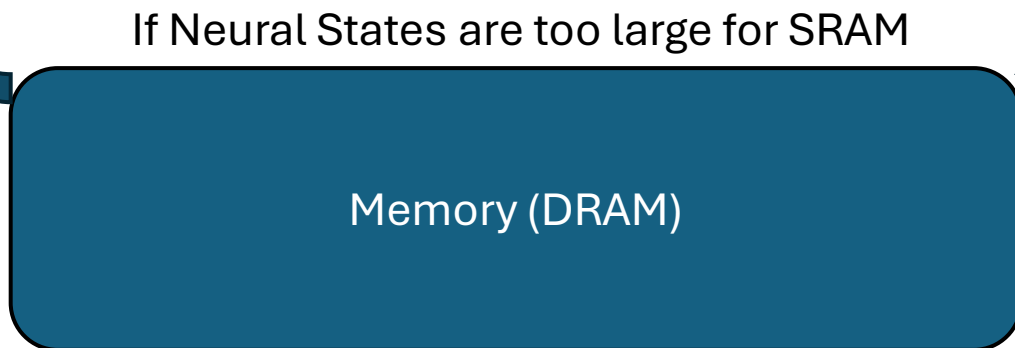
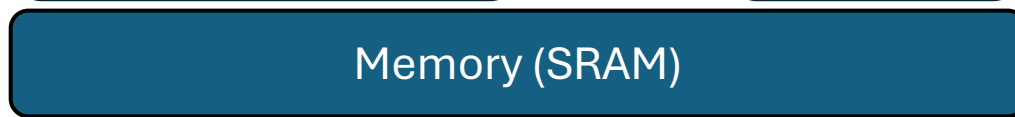
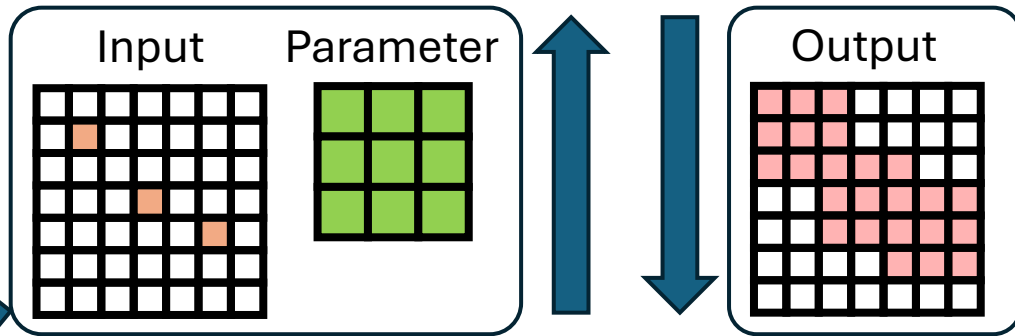
Assistant Professor

Department of Advanced Computing Sciences

Maastricht University

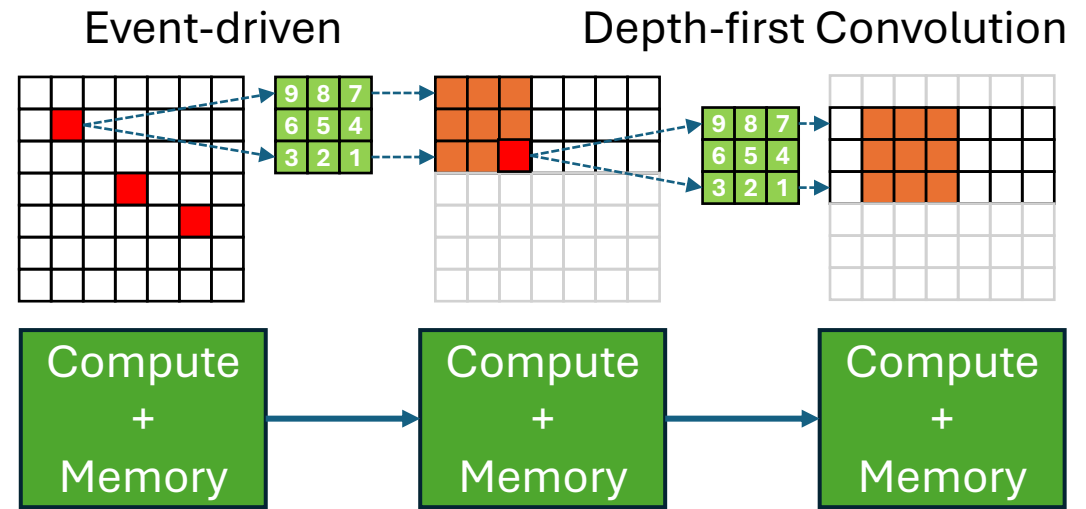
Making CNN more efficient on Digital Neuromorphic Processor

Layer-by-layer CNN processing on GPU

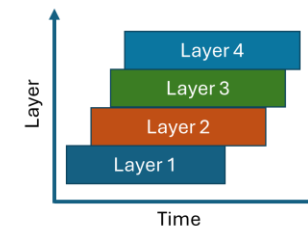


Can we exploit **sparse activation** inputs?

Can we avoid **intensive data movement and memory cost** of neural states and activations?

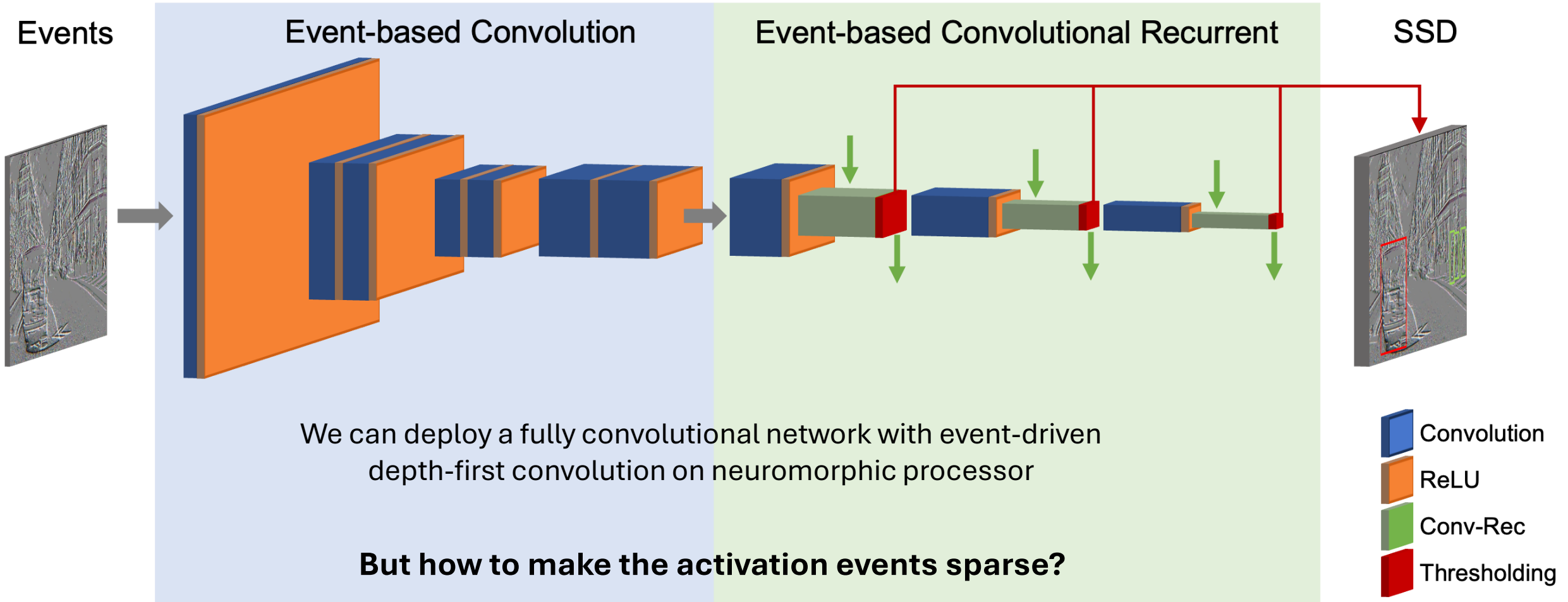


Reduce memory cost
Reuse 3 rows state memory

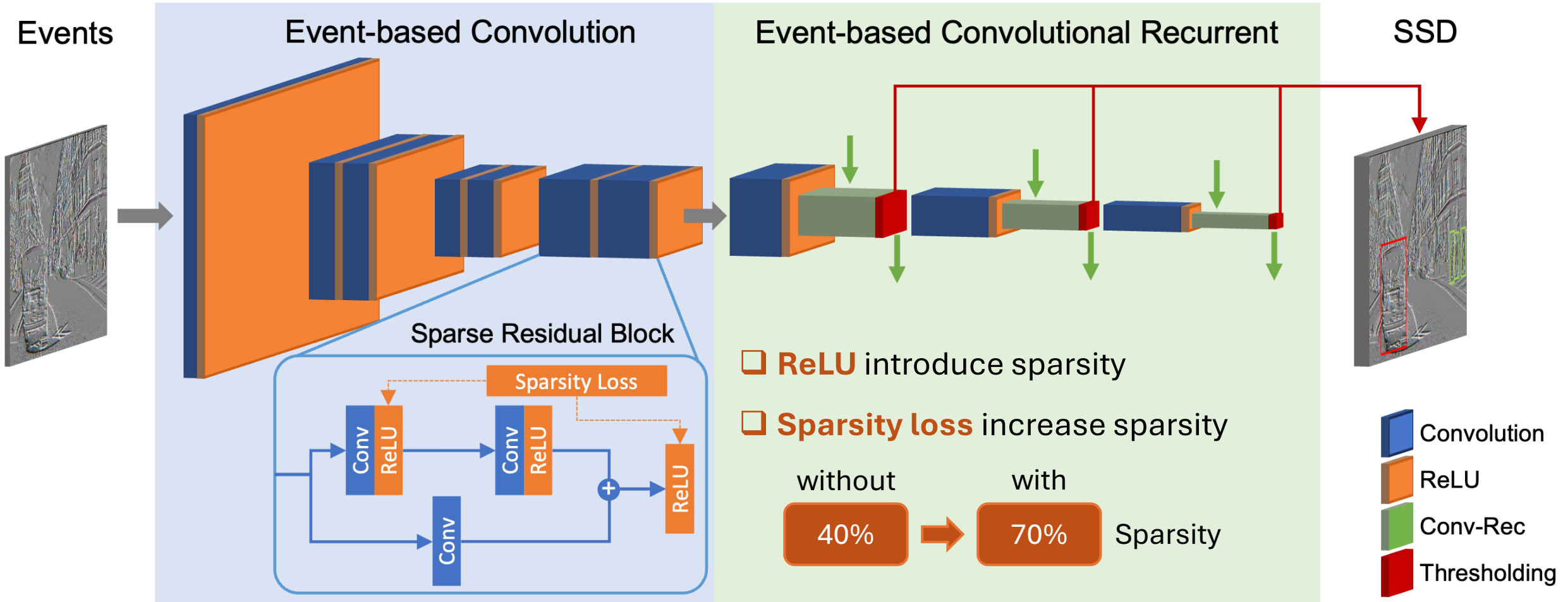


Reduce latency
Layer starts as soon as possible

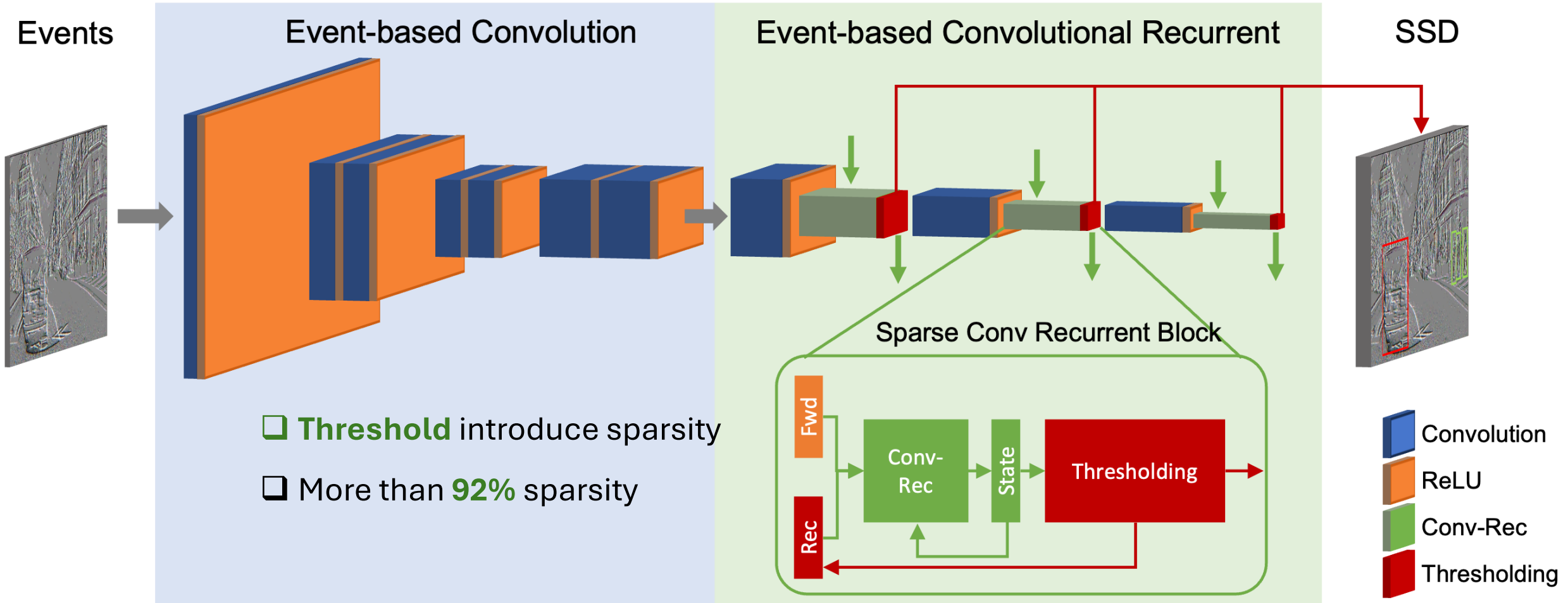
Using Fully Convolutional Network for Event-based Object Detection



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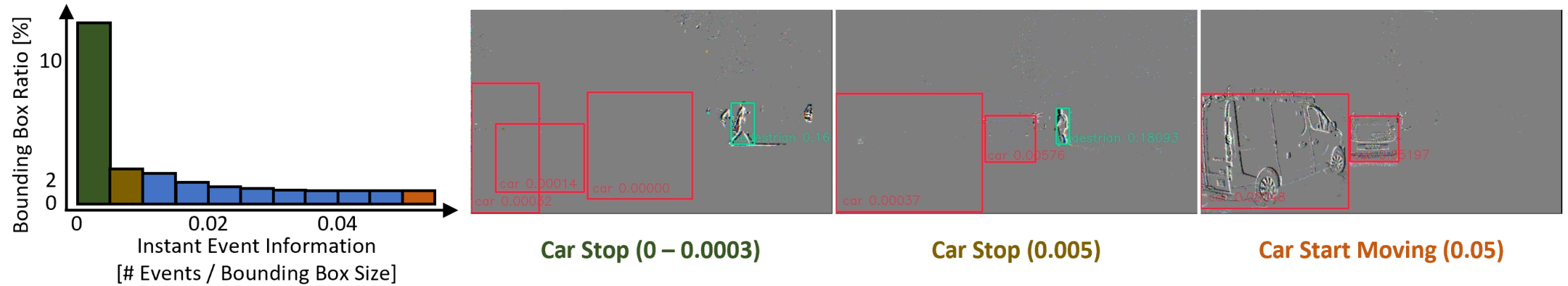


Using Fully Convolutional Network for Event-based Object Detection

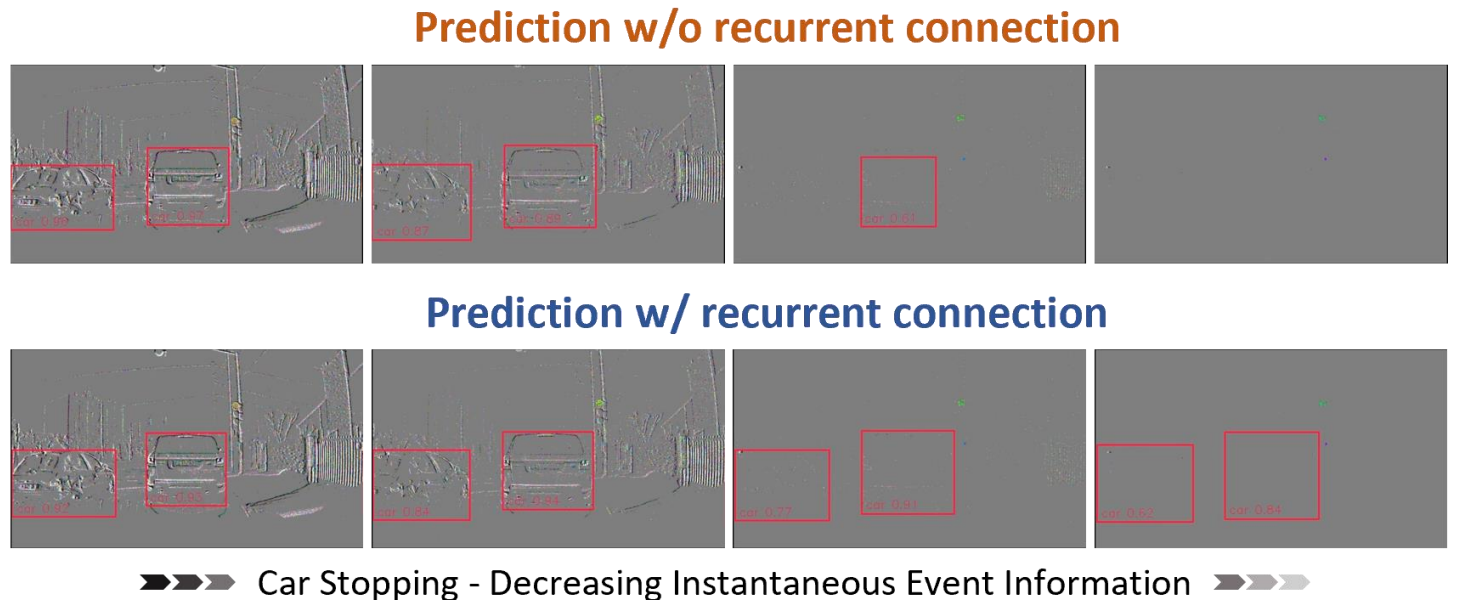
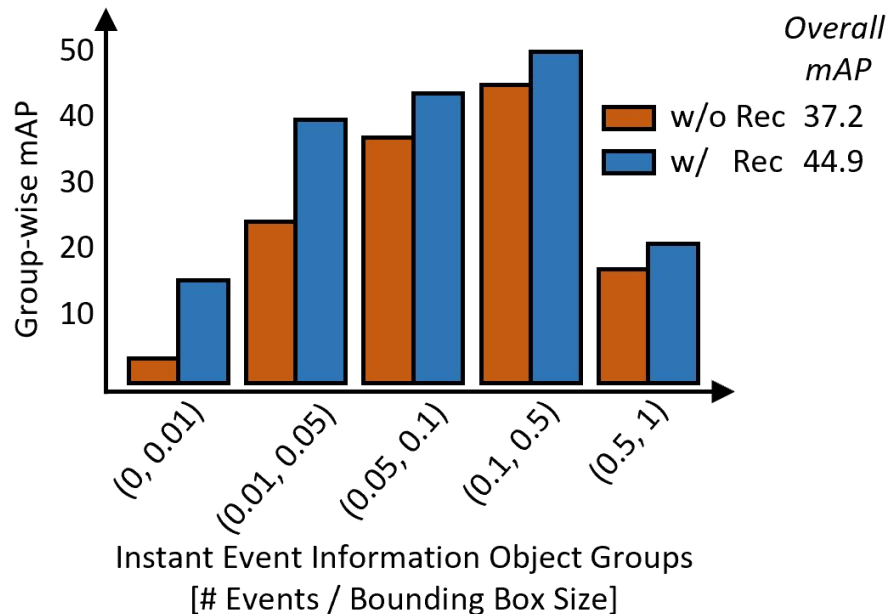


Is there still temporal learning with less than 10% of activation pass to next step?

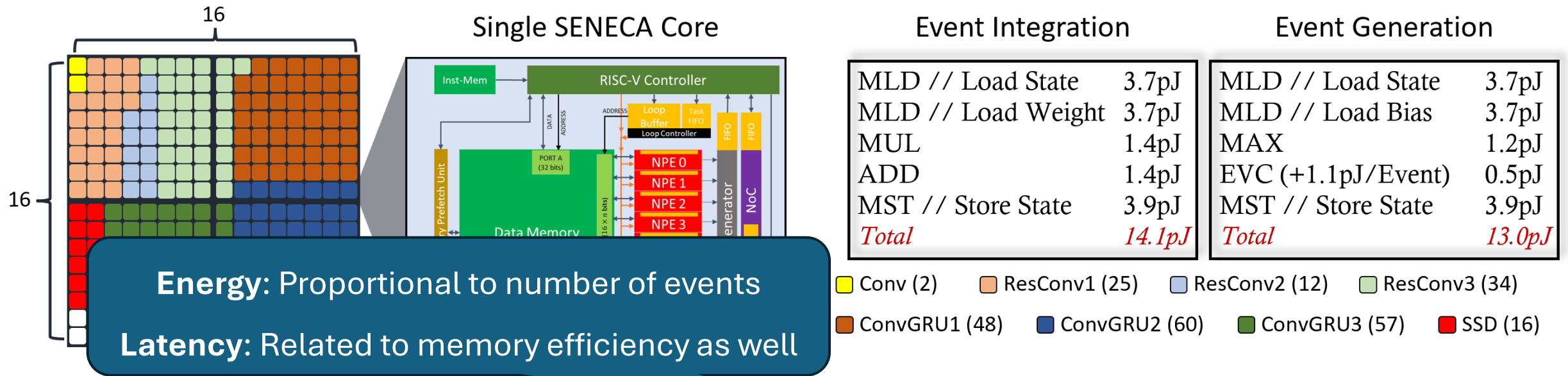
Effectiveness of Sparse Convolutional Recurrent Learning



Less or no events when the relative speed of camera and objects reduces



Hardware Simulation Study on the SENECA Neuromorphic Processor



Method	Recurrent Dimension	Sparse Recurrent	Sparsity Loss	Recurrent Unit	Energy (mJ)	Latency (ms)	Memory (Mb)	Cores	GSOp
SEED	128	Yes	Yes	3 × GRU	39.3	21.6	90.8	236	2.75
	256	Yes	Yes	3 × GRU	54.7	44.9	245.1	254	3.83
SEED (w/ ablations)	128	Yes	No	3 × GRU	68.1	44.0	90.8	256	4.79
	256	Yes	No	3 × GRU	80.9	81.43	245.1	254	5.69
	256	No	No	3 × GRU	284.3	240.1	226.1	234	20.1
RED (w/o SE)	256	No	No	5 × LSTM	368.6	1077.3	404.1	343	26.1
	256	No	No	5 × LSTM	368.6	40.7	404.1	1446	26.1



Shenqi Wang



Yingfu Xu



Amirreza Yousefzadeh



Sherif Eissa



Henk Corporaal



Federico Corradi

Sparse Convolutional Recurrent Learning for Efficient Event-based Neuromorphic Object Detection

Shenqi Wang^{1,2}, Yingfu Xu¹, Amirreza Yousefzadeh^{1,3}, Sherif Eissa⁴, Henk Corporaal⁴, Federico Corradi⁴, **Guangzhi Tang¹**

¹imec the Netherlands, ²Delft University of Technology, ³University of Twente, ⁴Eindhoven University of Technology, ⁵Maastricht University

Neuromorphic Computing and Event-based Neural Networks

Self-Driving Cars Cost 1000 W, Robots Cost 50W

Human Brain 10¹¹ neurons 10s of W, Rat Brain 10⁸ neurons 10s of mW

Neuromorphic Computing develops Energy Efficient AI systems inspired by the key computing paradigms of the brain

Input, Output, Core 1, Core 2

P1: Event-based Computing

- High activation sparsity
- Compute non-zero event

 P2: Data-flow Computing

- Instant data consumption
- Near-memory computation

SENECA Neuromorphic Architecture [1]

Scalable and flexible architecture design, Event-driven depth first convolution with P1 & P2

The Need of Temporal Learning for Event-based Object Detection

Group-wise mAP, Instant Event Information (# Events / Bounding Box Size)

Many objects in the Prophesee's 1 Mpx dataset has little instant event information

SEED - Sparse Event-driven Efficient Detector [2]

Events, Event-based Convolution, Event-based Convolutional Recurrent, SSD, Sparse Residual Block, Sparse Conv-Rec Block

Suitable for Recurrent Units with Gating

Method	mAP	GSOp	Param(M)
SEED+GRU	44.9	3.83	13.9
SEED+MinimalRNN	43.7	3.93	7.9
SEED+MGU	44.7	3.45	10.7
SEED+LSTM	40.1	4.16	15.9

Sparse convolutional recurrent for general gated recurrent units (GRU, MGU, LSTM ...), Extremely high activation sparsity for recurrent processing (>92% for all layers), Two-stage sparsity-aware training with activation sparsity loss for fine-tuning

Event-based Object Detection with Minimal Computes

Method	Network	1 Mpx		Gen1		Param(M)
		mAP	GSOp	mAP	GSOp	
ASTMNet [10]	TACN+Conv+Rec+SSD	48.3	-	46.7	-	>39.6
SNS [11]	Spiking DenseNet+SSD	-	-	18.9	2.33	8.2
SpikingYOLO [12]	Spiking+YOLOv8	-	-	40.4	14.3	23.1
RED [7]	SENet+ConvLSTM+SSD	43.0	26.1	40.0	8.26	24.1
RVT-B [13]	MaxVT+LSTM+YOLOX	47.4	15.6	47.2	5.05	18.5
RVT-S [13]	MaxVT+LSTM+YOLOX	44.1	8.69	46.5	2.78	9.9
RVT-T [13]	MaxVT+LSTM+YOLOX	41.5	3.87	44.1	1.29	4.4
SEED-56 (Ours)	ECNN+E-ConvGRU+SSD	44.3	3.83	44.3	1.32	13.9
SEED-128 (Ours)	ECNN+E-ConvGRU+SSD	44.1	2.75	44.5	0.99	4.8

Benchmarked on two event-based object detection datasets (1 Mpx, Gen1), Achieve state-of-the-art object detection performance in mAP, Reduce number of synaptic operation >50% compared to efficient network architecture design with vision transformer

[1] Xu, Yingfu, et al. "Optimizing event-based neural networks on digital neuromorphic architecture: a comprehensive design space exploration." *Frontiers in Neuroscience*, 2024.
 [2] Wang, Shenqi, et al. "Sparse convolutional recurrent learning for efficient event-based neuromorphic object detection." *In Review*, 2025.
 [3] Wang, Shenqi, and Tang, Guangzhi. "Context-aware sparse spatiotemporal learning for event-based vision." *In Review*, 2025.

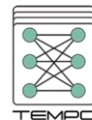
Extend to Event-based Optical Flow [3]

Motion, Intensity Change, Events, Predict, Emulate, Optical Flow

Network	Index A01		Index B01		Index B02		Index B03		Average
	AP	Sparsity	AP	Sparsity	AP	Sparsity	AP	Sparsity	
SENet+ConvLSTM+SSD	43.0	26.1	40.0	8.26	40.0	8.26	40.0	8.26	40.0
SEED-56 (Ours)	44.3	3.83	44.3	1.32	44.3	1.32	44.3	1.32	44.3
SEED-128 (Ours)	44.1	2.75	44.5	0.99	44.5	0.99	44.5	0.99	44.5

Extend our sparse recurrent learning with conditional computing, Event-based optical flow prediction with sparse EV-FlowNet, Improve accuracy and sparsity on drone-based dataset

Contact: Guangzhi Tang, Assistant Professor, DACS, Maastricht University



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Thank You