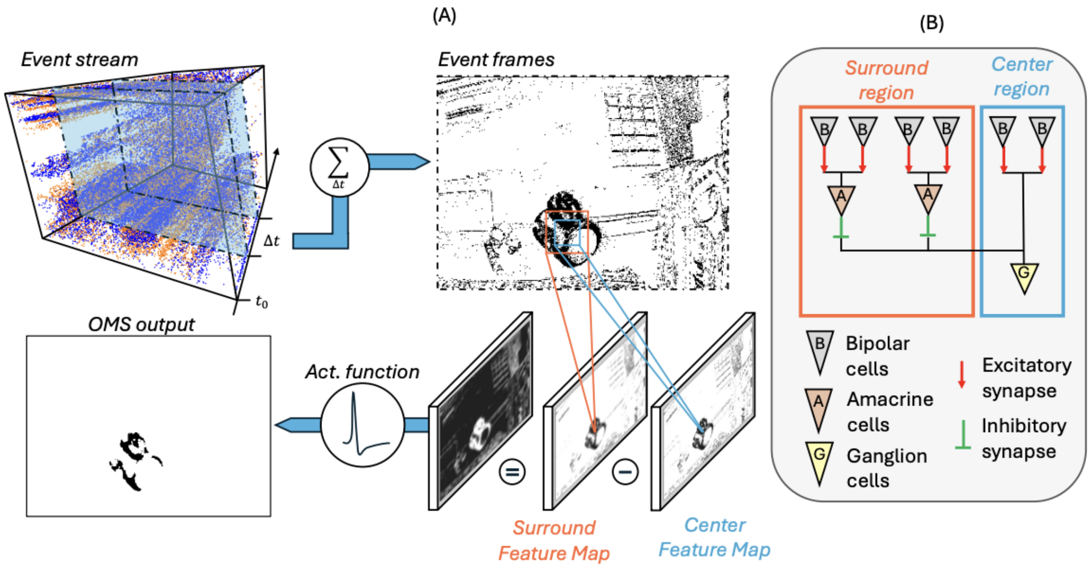
Retina-Inspired Object Motion Segmentation for Event-Cameras

Victoria Clerico, Shay Snyder, Arya Lohia, Md Abdullah-Al Kaiser, Gregory Schwartz, Akhilesh Jaiswal, Maryam Parsa



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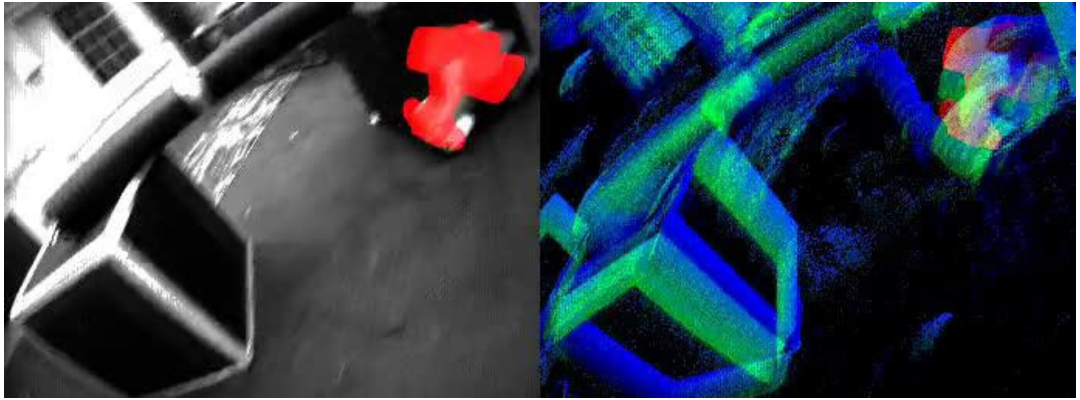
1. Ego-motion in Dynamic Vision Sensors (DVS)

Bio-inspired visual systems that capture per-pixel brightness changes asynchronously

Object motion **with** ego-motion



Microsecond temporal resolution

Low-power consumption

High dynamic range > 120 dB

Reduced motion blur

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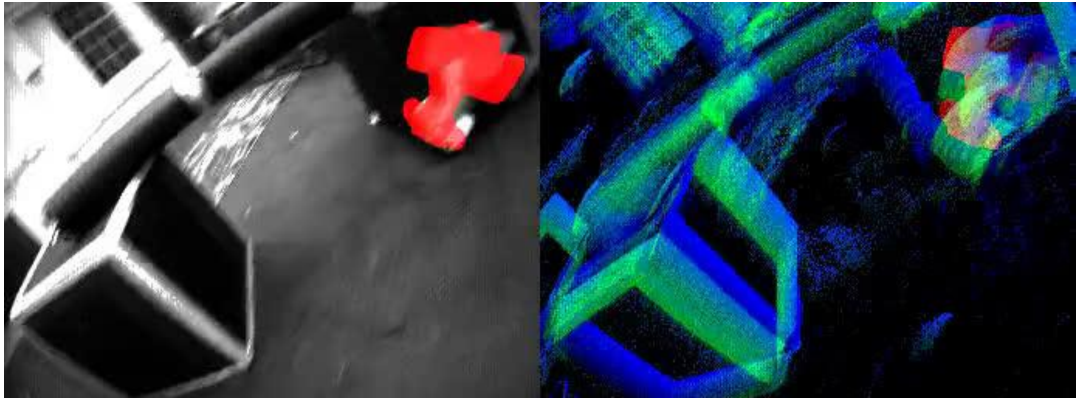
1. Ego-motion in Dynamic Vision Sensors (DVS)

How to suppress ego-motion to identify independent moving objects ?

→ Object Motion Sensitivity (OMS)



2. Biological inspiration

1) Photoreceptors

Contain light sensitive pigments and produce electrical currents

2) Bipolar cells

Adapt rapidly to changes in luminance

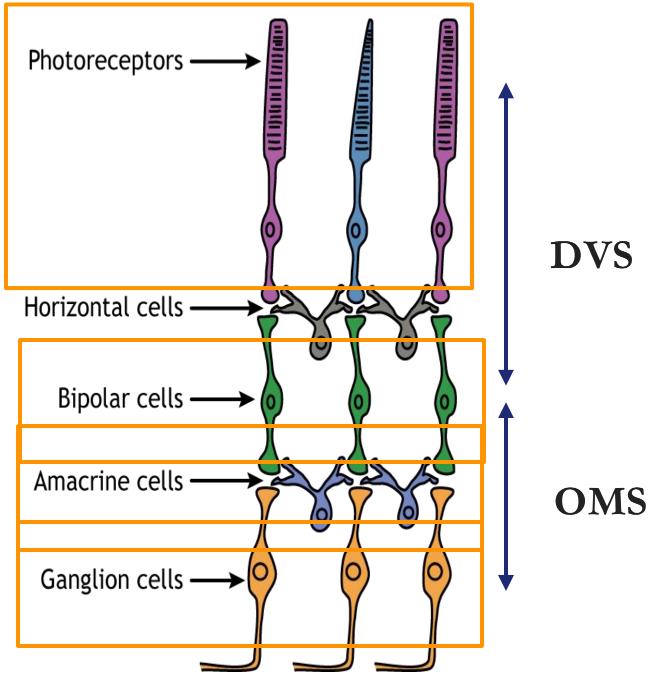
3) Amacrine cells

Perform lateral inhibition from adyactent RGCs

4) Ganglion Cells

Send information to the optical nerve

Retinal layers



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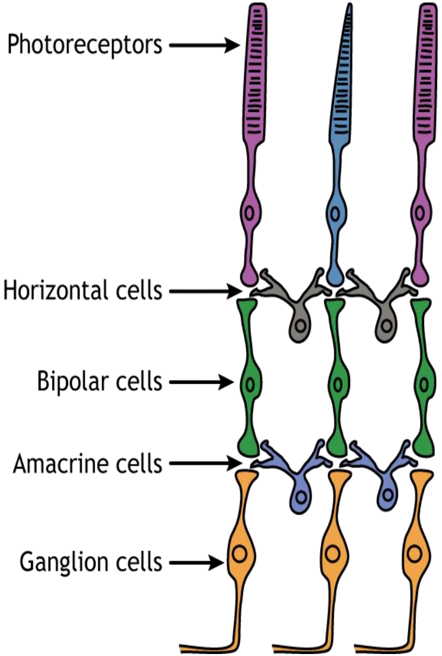
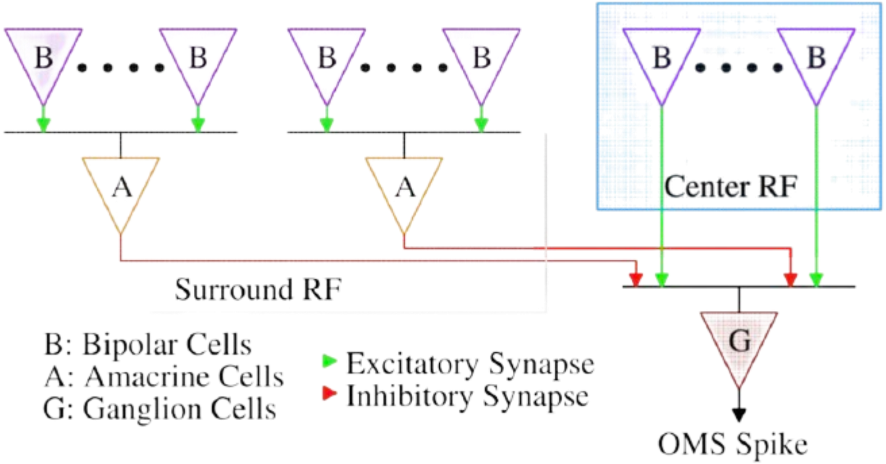
2. Biological inspiration

Neuroscience



Visual Receptive Fields (RFs)

Surround and Center Regions



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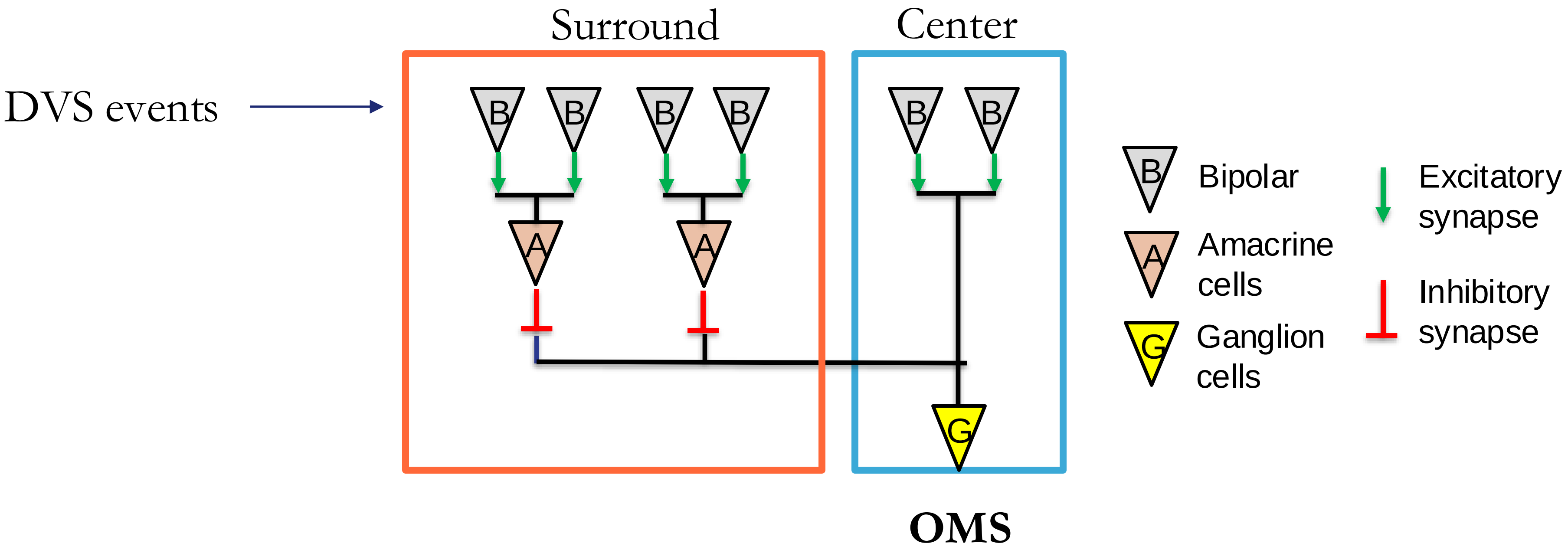
3. Methodology

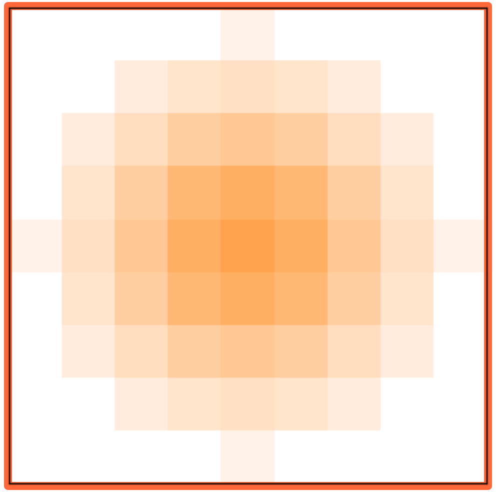
Modeled as convolutional kernels



3. Methodology

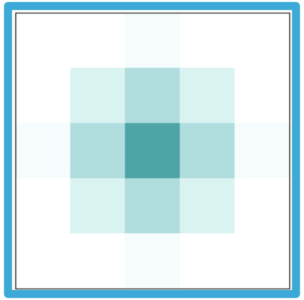
Modeled as convolutional kernels

Surround



8x8

Center



4x4

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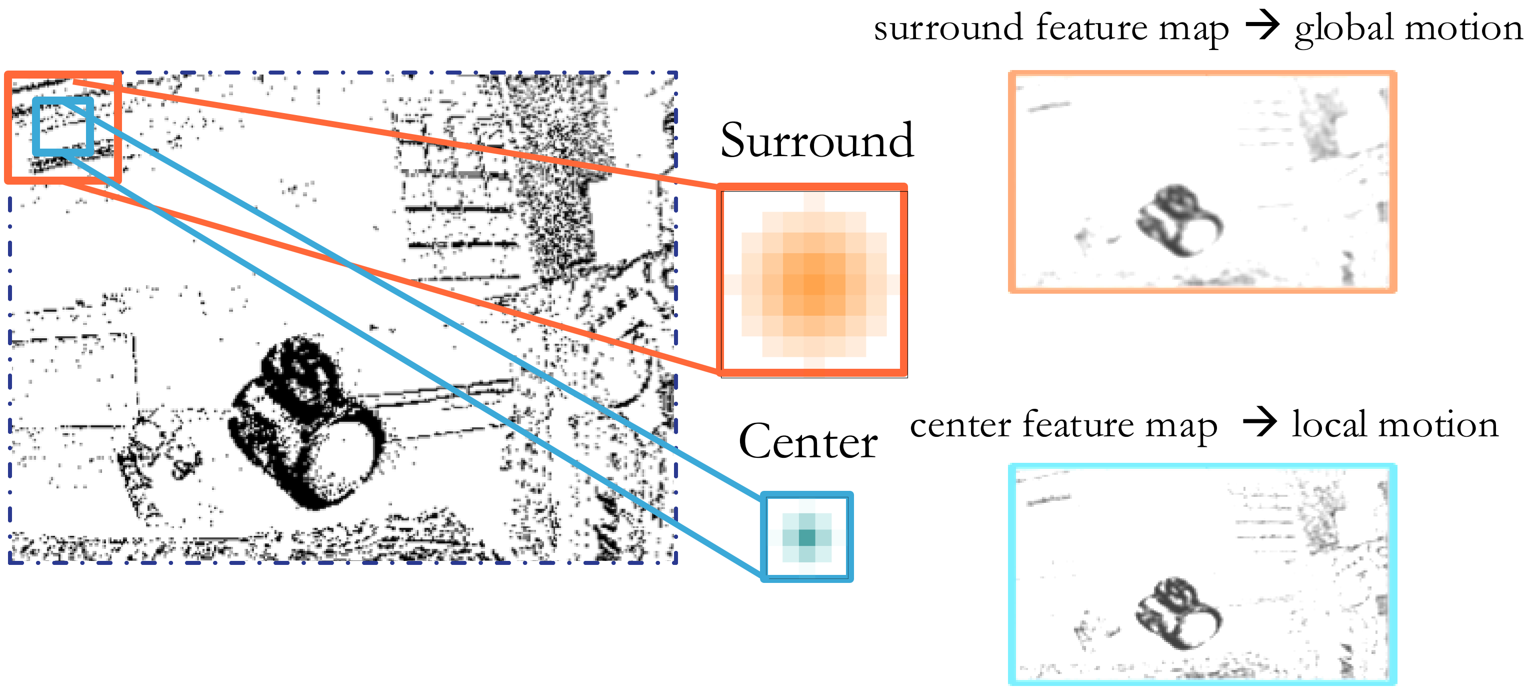
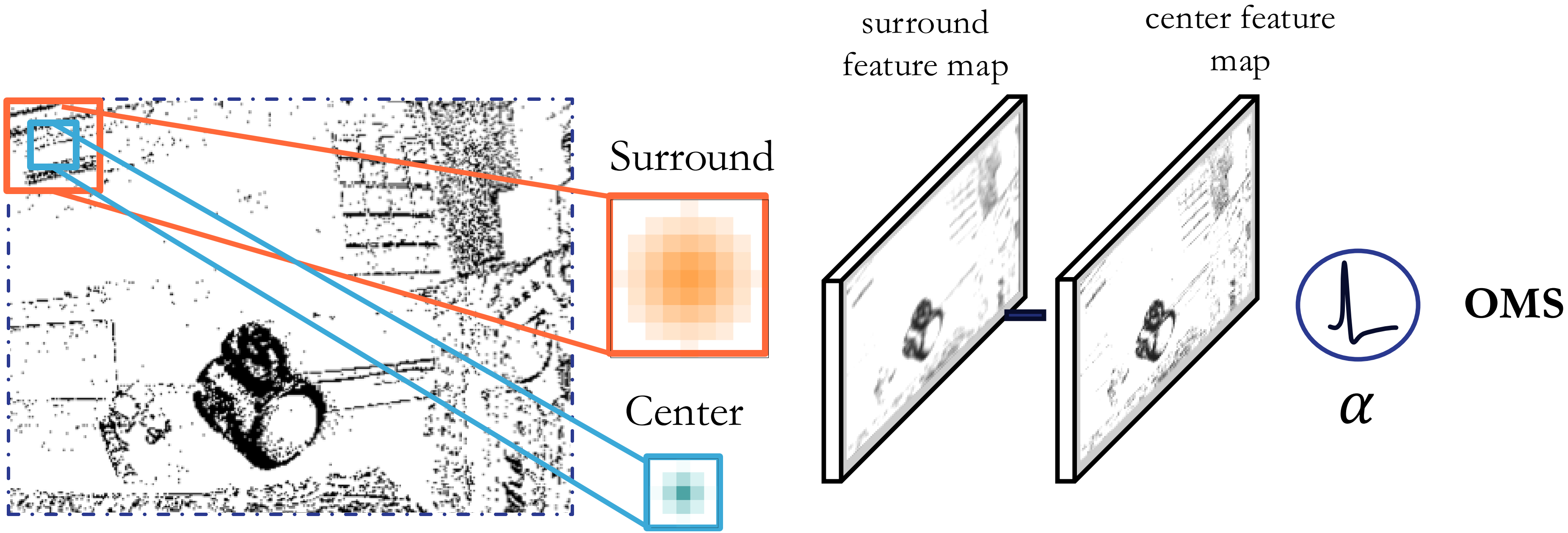
3. Methodology

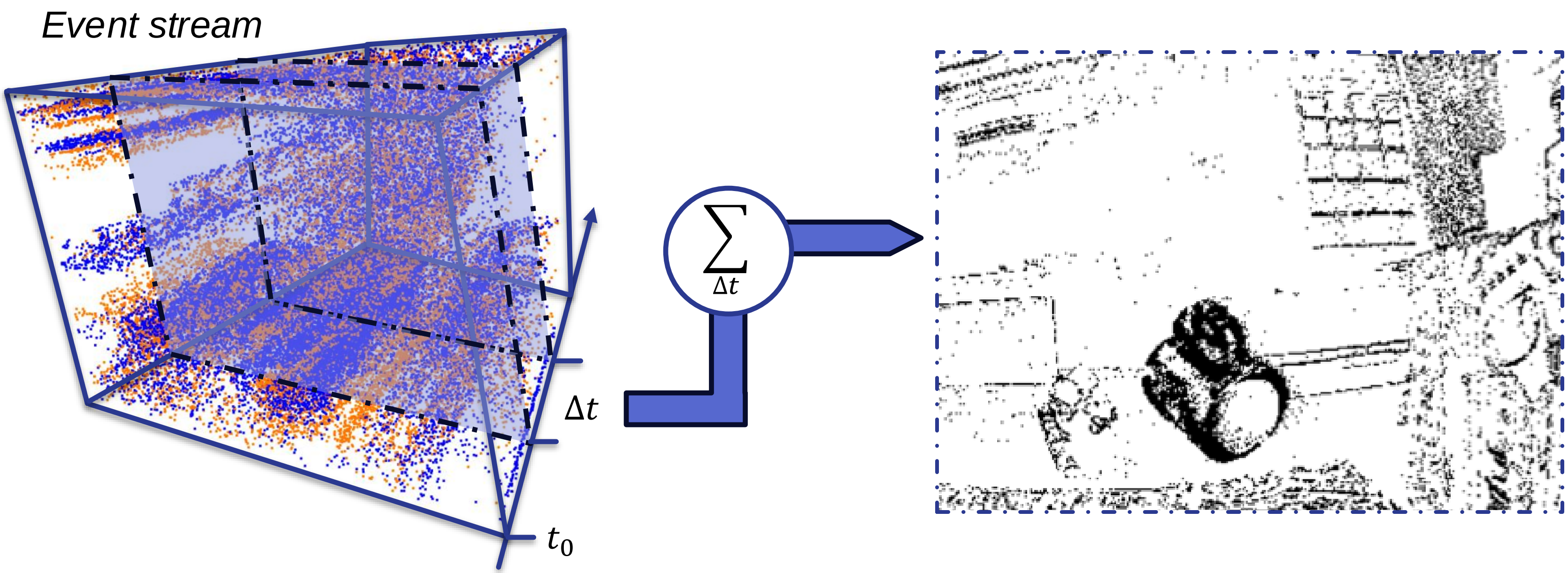


3. Methodology



3. Methodology

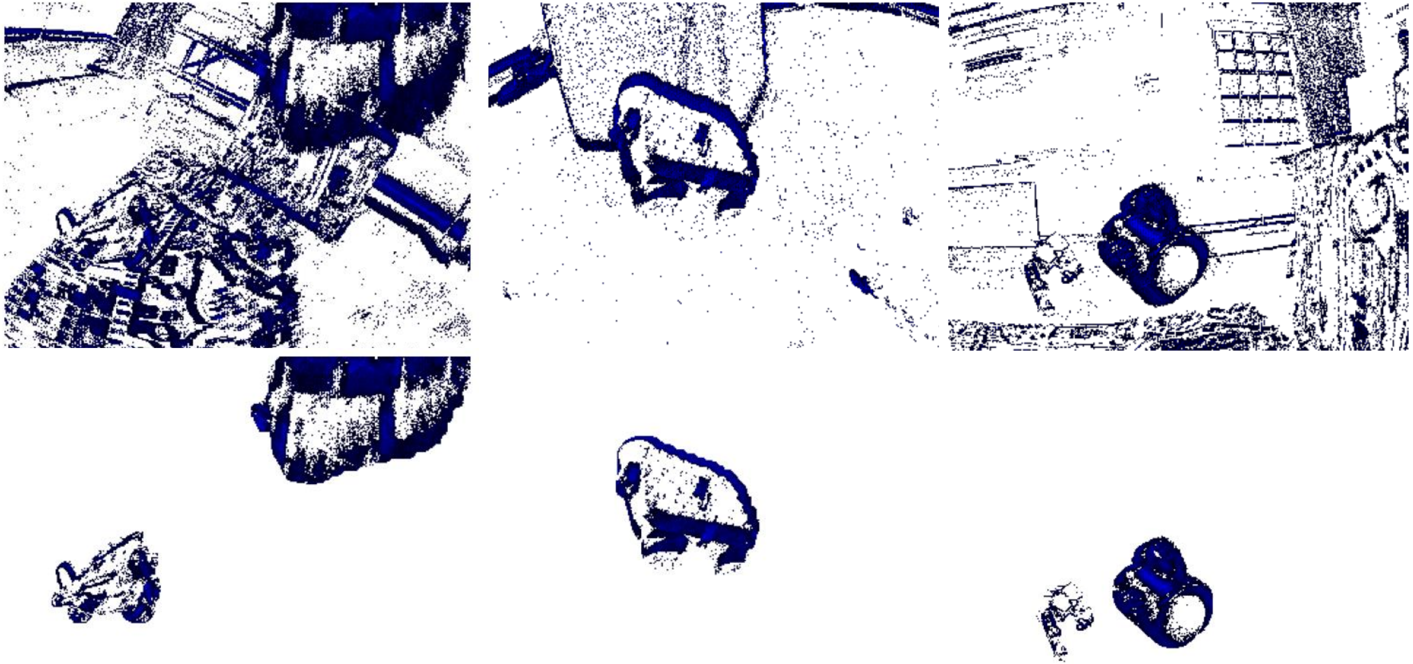
Time window accumulation



3. Methodology

Input

Groundtruth label

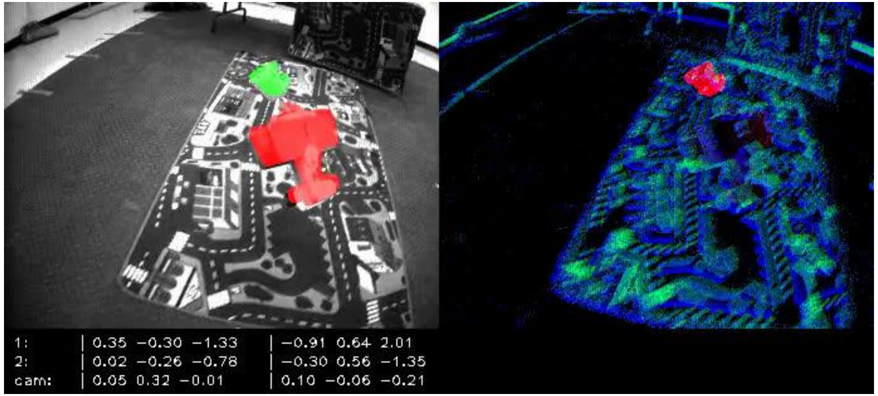


3. Methodology

Datasets: Event streams and motion masks (346x260 resolution)

EV-IMO [2]: real event dataset
- DAVIS 346C at 200 Hz
- Masks at 40 Hz

MOD [3]: synthetic dataset
- DVS simulator



Metrics
- Intersection over Union (%)
- Detection rate (%)

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4. Experiments: SOTA Comparisons

Comparable performance

Performance: mean IoU (%) over EV-IMO validation set

Method	box	floor	wall	table	fast
EV-IMO [1]	70 ± 5	59 ± 9	78 ± 5	79 ± 6	67 ± 3
PointNet++ [3]	80 ± 15	76 ± 10	74 ± 10	68 ± 23	20 ± 6
Gconv [4]	60 ± 18	55 ± 19	80 ± 7	51 ± 16	39 ± 19
SpikeMS [5]	65 ± 8	53 ± 16	63 ± 6	50 ± 8	38 ± 10
MSRNN [6]	80	85	82	85	75
Ours	$\mathbf{72 \pm 16}$	**94**	$\mathbf{82 \pm 6}$	$\mathbf{88 \pm 10}$	$\mathbf{69 \pm 3}$

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4. Experiments: SOTA Comparisons

mean IoU (%)

Method	EV-IMO	MOD
EV-IMO [1]	77	–
EVDodgeNet [2]	65.76	75
0-MMS [7]	80.37	–
SpikeMS [5]	–	68
Ours	**80.17**	**70**

Method	# of Parameters
EVDodgeNet [2]	30k – 3M
EV-IMO [1]	40k
SpikeMS [5]	46k
Gconv [4]	117k
PointNet++ [3]	1.4M
MSRNN [6]	4.1M
Ours	**80**

x $10^3 – 10^6$ parameter reduction

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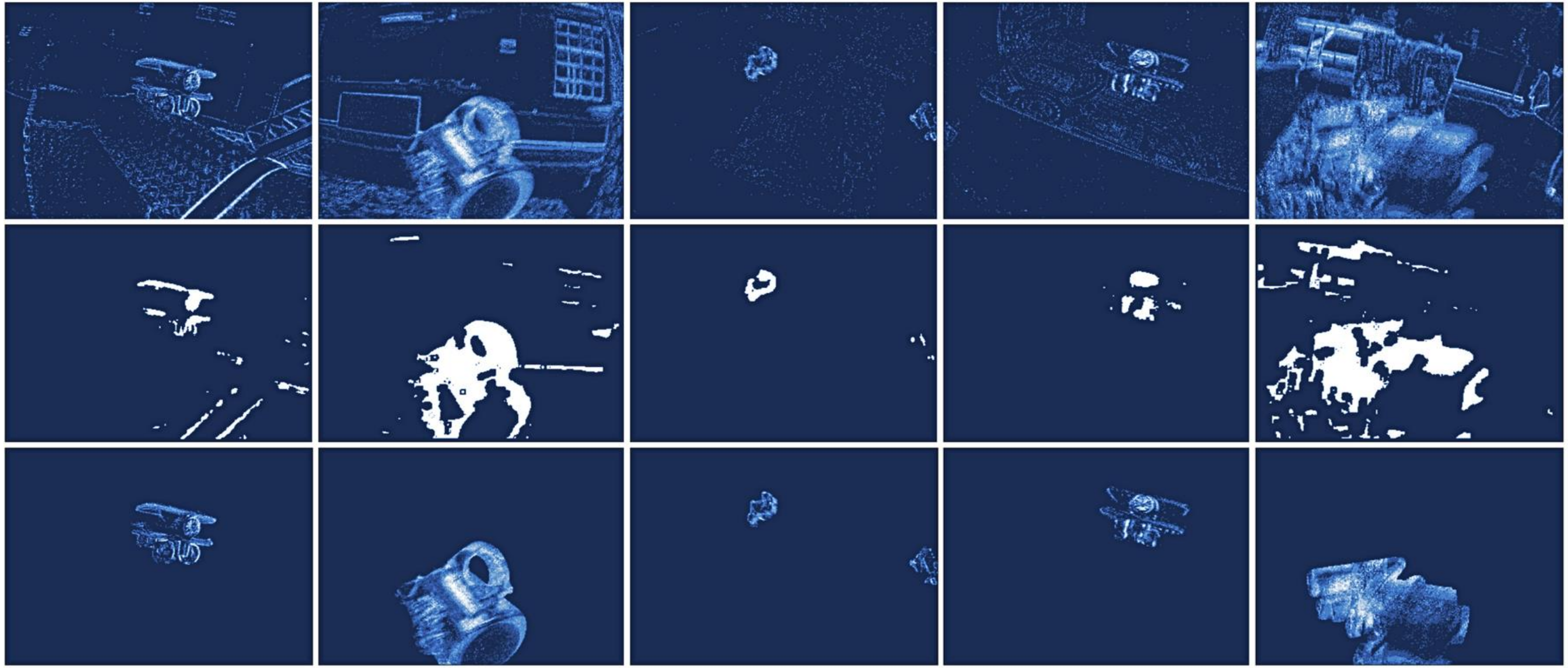
4. Experiments

DVS

OMS

Mask



Conclusions

- Our method achieves top performance with **10^3–10^6× fewer parameters** than existing methods (SOTA)
- **Learning-free bio-inspired** method, enabling robust motion segmentation across domains.
- Expanding to **additional visual features** can enhance intelligent visual systems.

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