Computing Spatial Image Convolutions for Event Cameras

Cedric Scheerlinck

Prof. Rob Mahony
A/Prof. Nick Barnes

Image Convolutions

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.
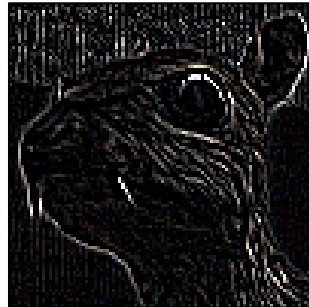
Image Convolutions

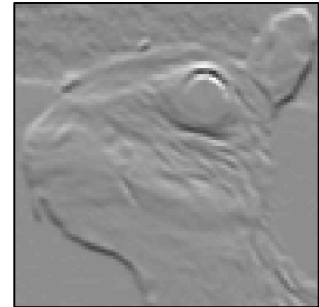$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

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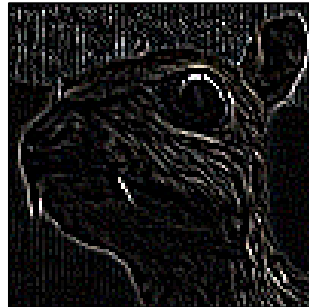
Image Convolutions

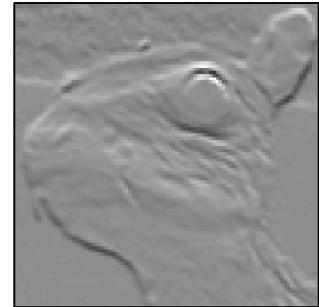$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

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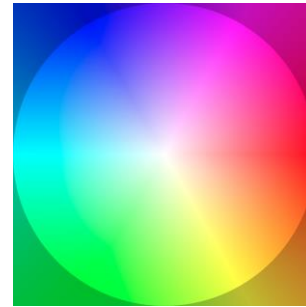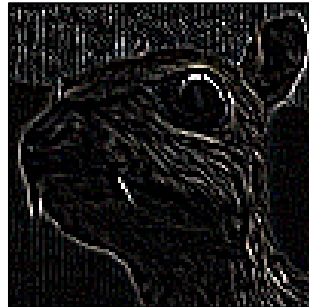$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

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Image Convolutions for Events

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \quad = $$

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Image Convolutions for Events

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \;\;\; = $$

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \quad ?$$

ON

OFF OFF OFF

t

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \quad = $$

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \quad ?$$

ON

OFF OFF OFF

t

Naïve approach: reconstruct image frames from events then apply convolution.

Can we do better?

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Consider one event ⊤↓ *OFF* [timestamp, x, y, ±1]

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Consider one event   ⊤ ↓ *OFF*   [timestamp, x, y, ±1]

Event image

0	0	0	0	0	0
0	0	0	0	0	0
0	0	-1	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Consider one event ⊤ [timestamp, x, y, ±1]

↓ *OFF*

Kernel

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

*

Event image

0	0	0	0	0	0
0	0	0	0	0	0
0	0	-1	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

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Image Convolutions for Events

Consider one event   [timestamp, x, y, ±1]

OFF

Kernel * Event image

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} *$$

0	0	0	0	0	0
0	0	0	0	0	0
0	0	-1	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

=

0	0	0	0	0	0
0	1	0	-1	0	0
0	2	0	-2	0	0
0	1	0	-1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Kernel * Event image

0	0	0	0	0	0
0	1	0	-1	0	0
0	2	0	-2	0	0
0	1	0	-1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

## Six virtual events, or a **convolved event**, can be generated

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Convolved events can be used as input to an event processing algorithm.

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

Convolved events can be used as input to an event processing algorithm.

For example image reconstruction [1]:
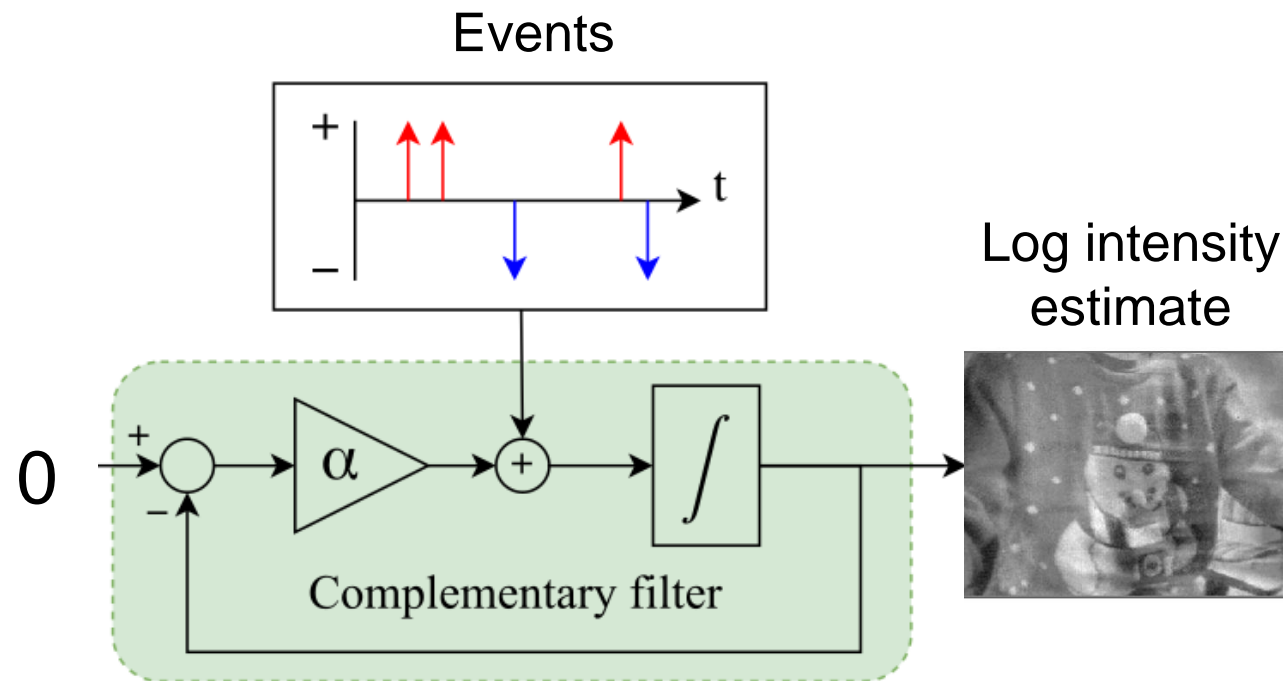
[1] (Scheerlinck et al., ACCV, 2018)

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Image Convolutions for Events

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Convolved events

Convolved estimate

0

Complementary filter

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.
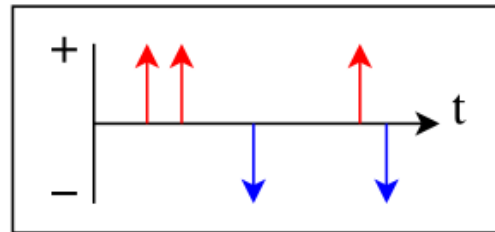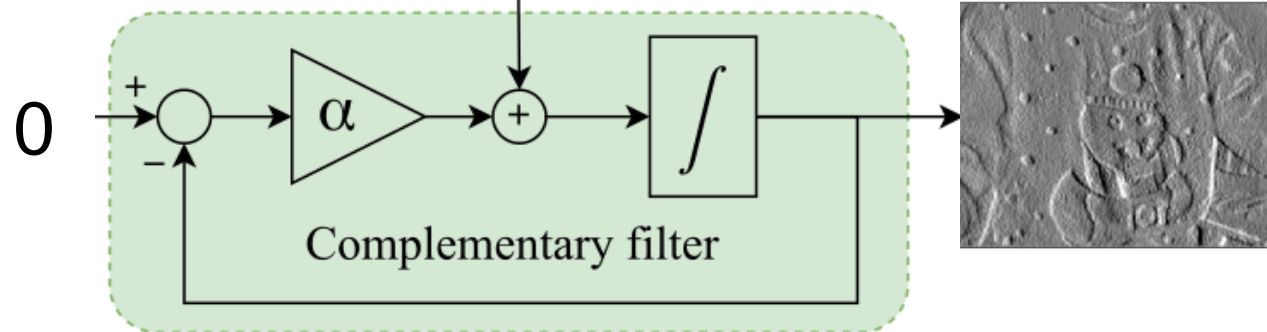
Results

Identity

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Gaussian

$$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

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Results

Sobel

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.
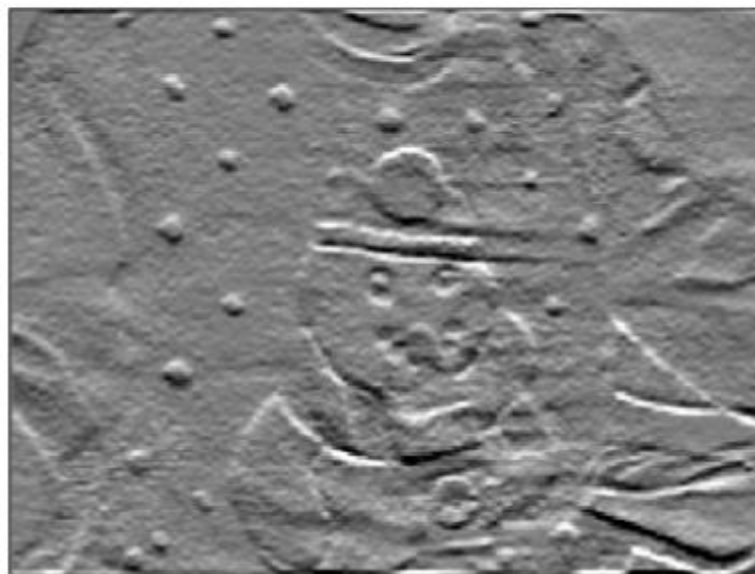
Results

Laplacian

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & -12 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$
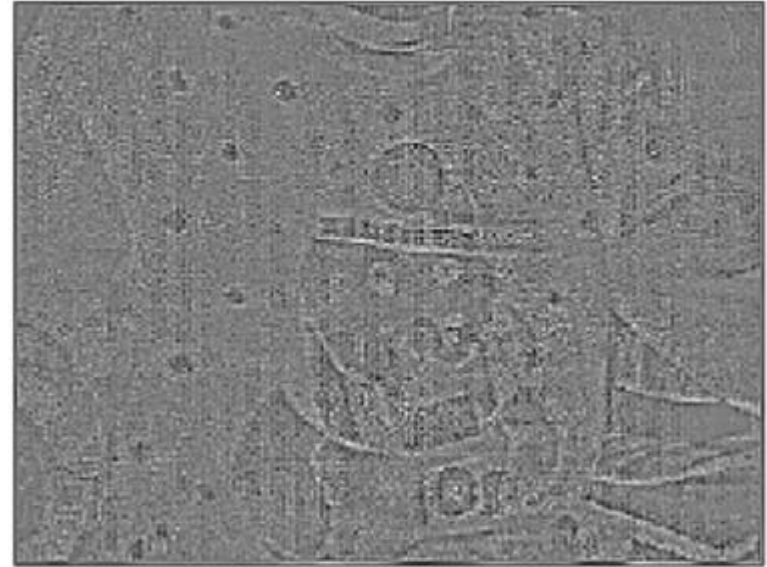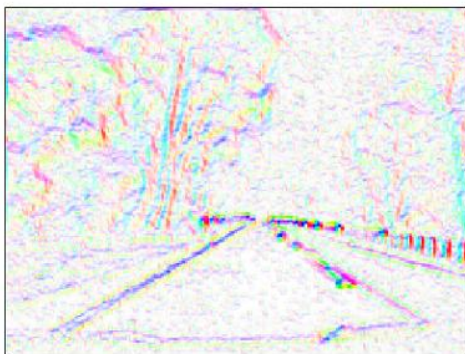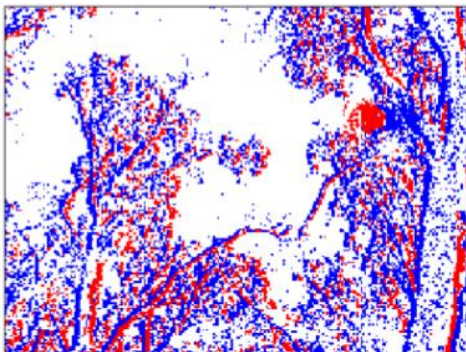

Poisson Reconstruction
from Laplacian

Perez et al. (2003), Agrawal et al. (2006)
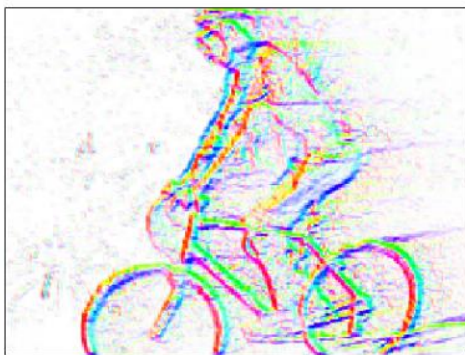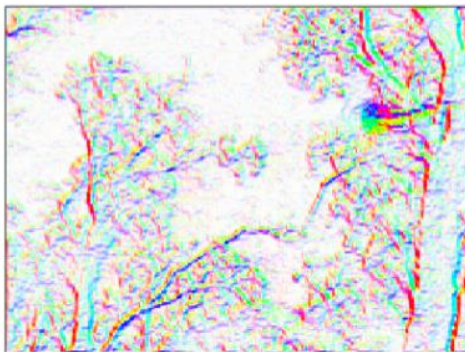
C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Results

Current events   **Gradient estimate**

Sobel

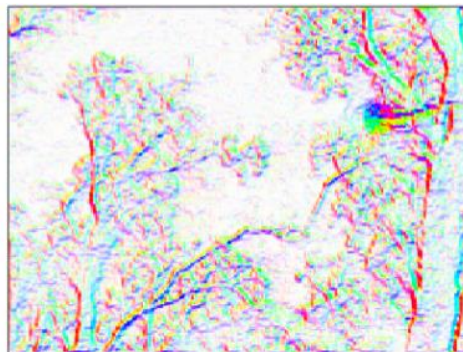$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

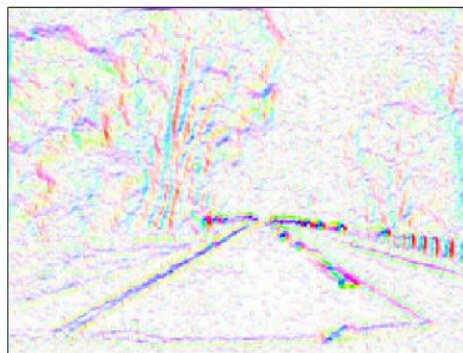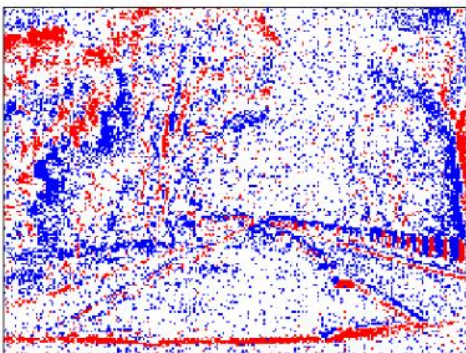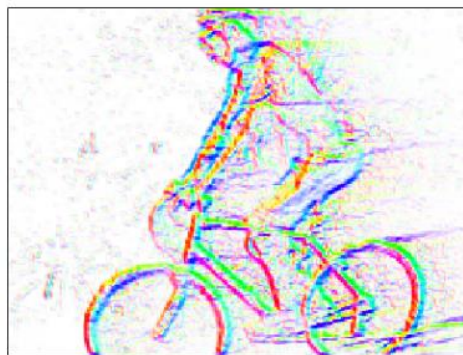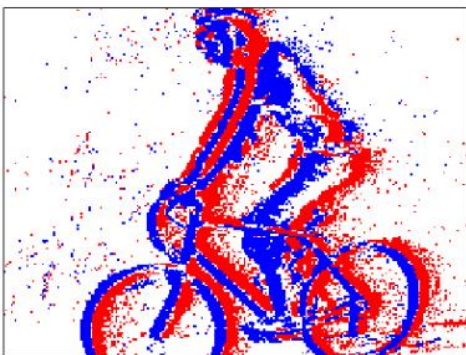$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Results

Current events	Gradient estimate	Poisson integration

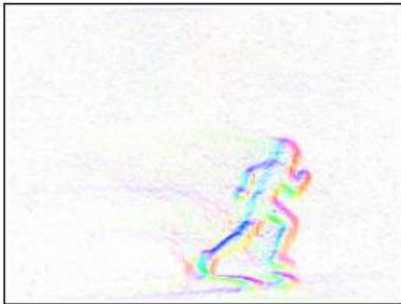C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

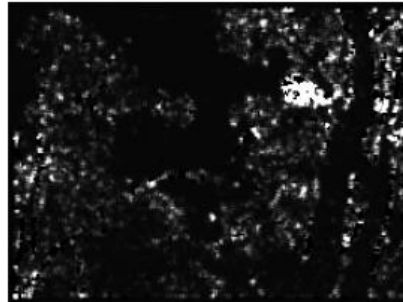# Results

Gradient can be used as input to asynchronous Harris corner detector.

When an event arrives, the Harris response is only updated in a local neighbourhood.

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Results

Gradient can be used as input to asynchronous Harris corner detector.
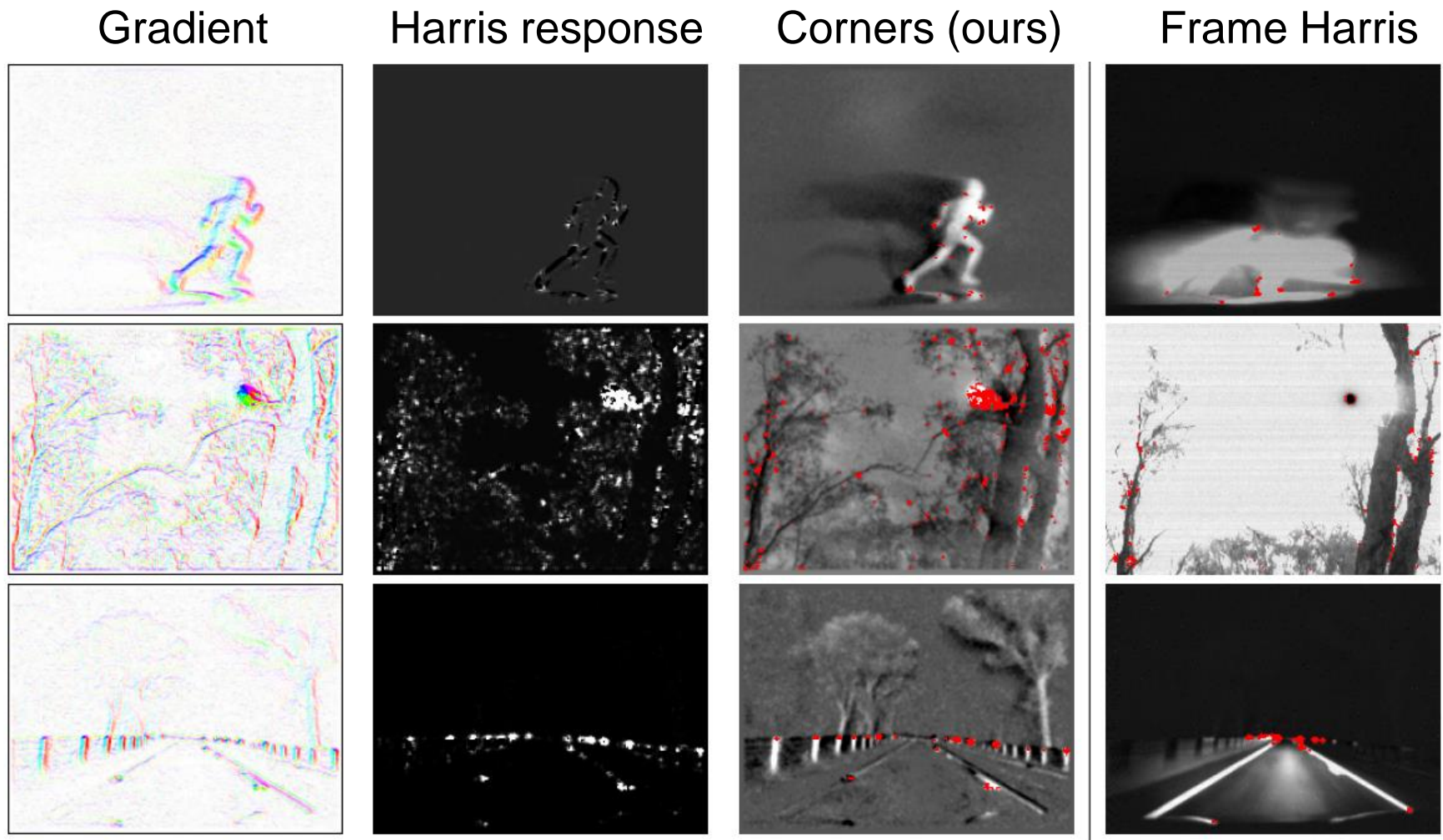
Gradient	Harris response	Corners (ours)	Frame Harris

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Results

Comparison to state-of-the-art event-based corner detection.

Eharris (Vasco'16)	FAST (Mueggler'17)	ARC (Ignacio'18)	**Ours**	Frame Harris
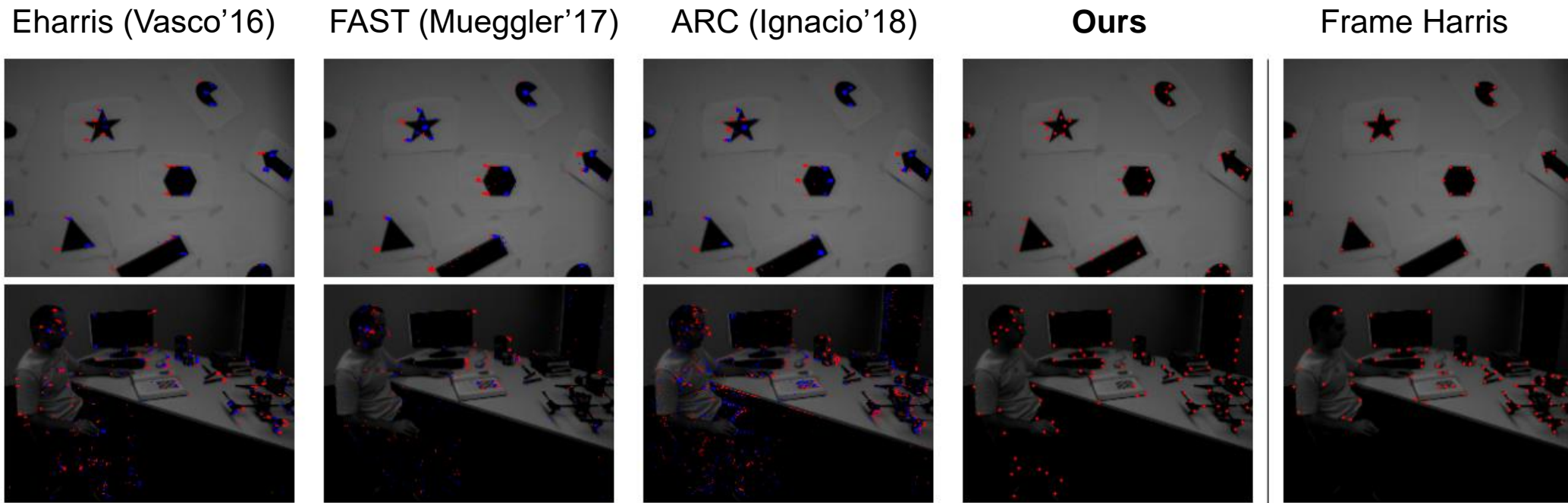
Since we output a continuous-time Harris response state, at any point in time we can apply non-maximum suppression to get clean corners.

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.

Conclusion

- We have introduced a methodology for event-based convolutions.

- Each event is individually convolved, producing a cluster of convolved events.

- Convolved events are fed into an asynchronous image reconstruction algorithm to produce a continuous-time state estimate of the convolved image.

- We introduce an asynchronous Harris corner detector based on gradients produced by our method.

C. Scheerlinck, N. Barnes, R. Mahony, "Computing Spatial Image Convolutions for Event Cameras," arXiv, 2018.