Bringing a Blurry Frame Alive at High Frame-Rate with an Event Camera

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CVPR LONG BEACH CALIFORNIA
June 16-20, 2019

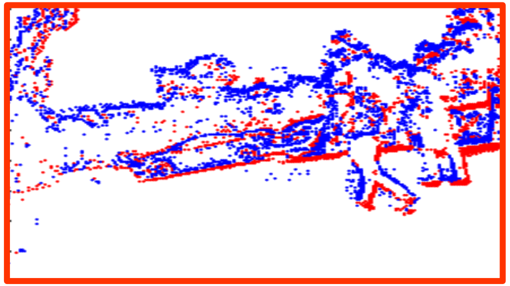
Problem Formulation

DAVIS

=

Intensity Image

+



events

Image	>10ms latency
Events	>0.02ms latency

Motivation

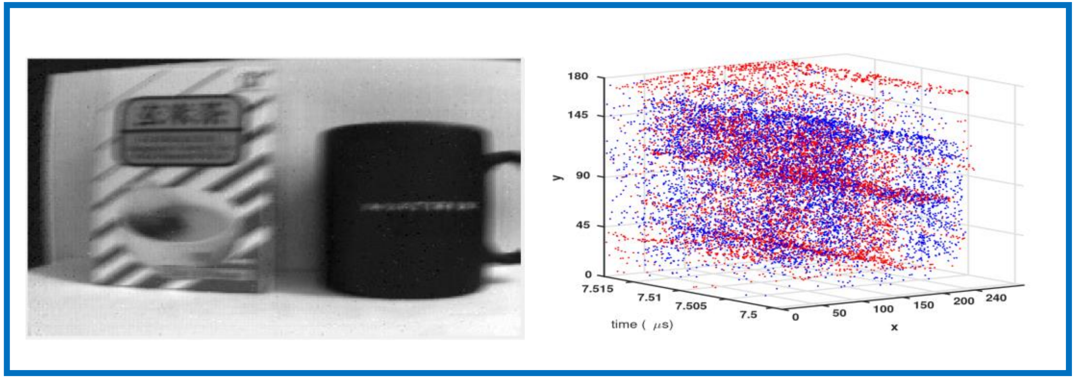
- **High temporal resolution for events;**
- **Inherent blurry effects for images;**

  Event cameras are more likely to capture a blur image as it is designed for high dynamic motion scenery.

  Possible Solution: reduce the exposure time – dark and noisy image.
- **Existing computer vision algorithms designed for standard cameras cannot be applied to event cameras directly.**

Our Goal

To reconstruct a **high frame-rate**, **sharp** video from a single blurry frame and its event data.

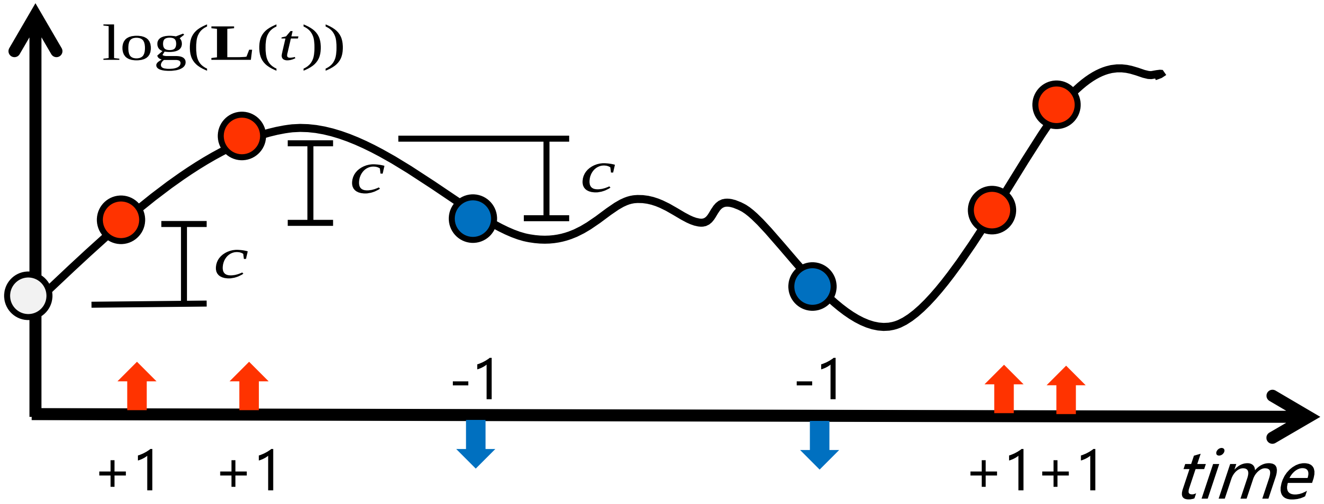


Input

Output

What is an Event?

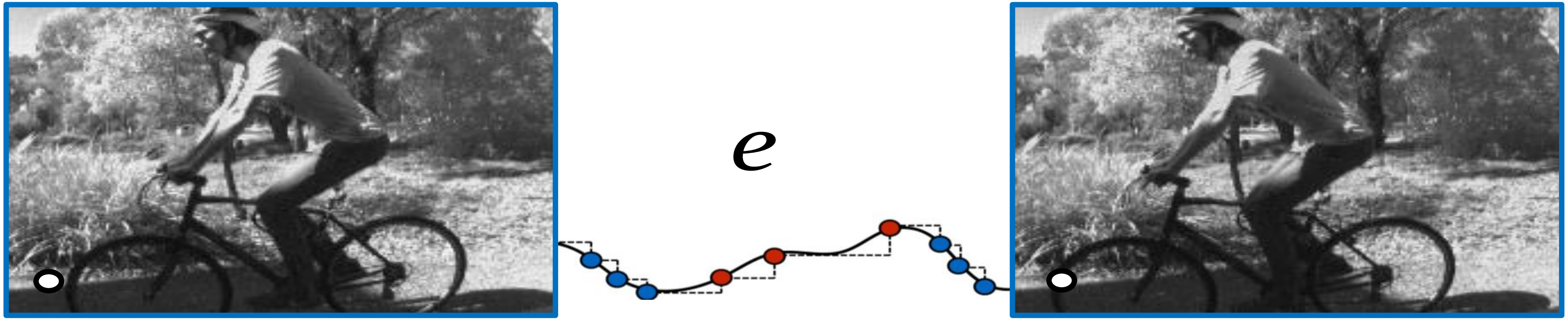
$\mathbf{L}(f)\ (x, y)$



$\mathbf{L}$ is the intensity image, f is the reference timestamp.

The event is triggered when a change in the **log intensity** exceeds a given **threshold** c .

What is an Event?



$\log(\mathrm{L}(f))$ **+** **Events** **=** $\log(\mathrm{L}(t))$

$$\mathbf{E}(t) = \int_f^t e(s)ds$$

$\mathbf{E}(t)$ denotes the **integral** of events between time $[f, t]$.

What is blur?

$$\mathbf{B} = \frac{1}{T}\int_{f-T/2}^{f+T/2} \mathbf{L}(t)dt$$

blur ←

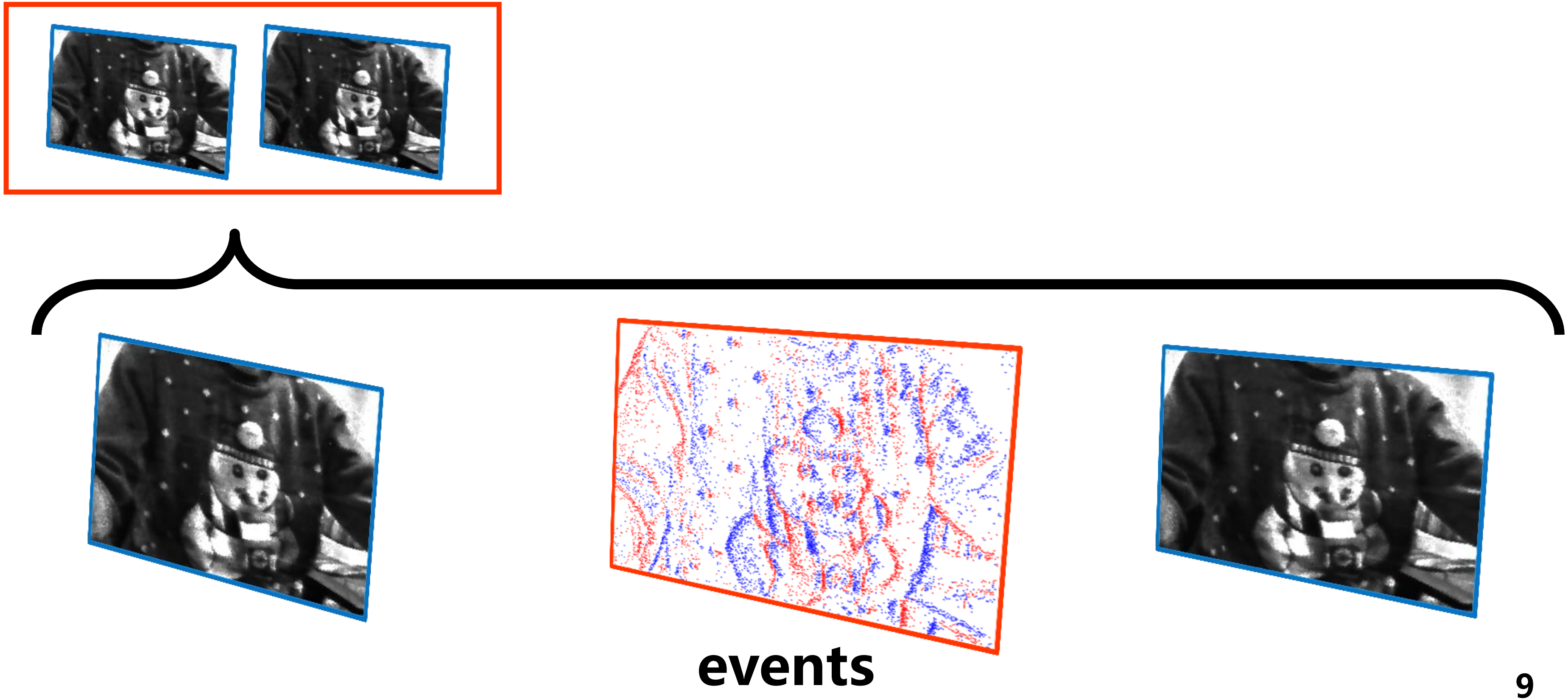
$\mathbf{B}$ is the blur image, equals to the **integral** of the latent images during the exposure time $[f-T/2, f-T/2]$.

Pipeline – Event-based Double Integral (EDI)

Blur Image

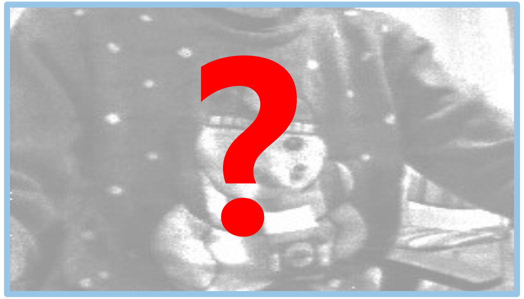
Latent Images

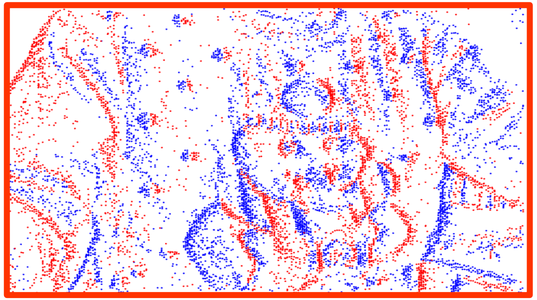
Pipeline – Event-based Double Integral (EDI)



Model – First Integral

$$\mathbf{L}(t) = \mathbf{L}(f)\exp(c\mathbf{E}(t))$$

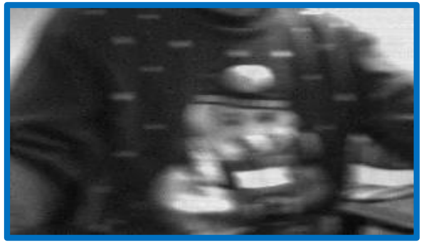




$$\mathbf{E}(t) = \int_f^t e(s)ds$$

Initial condition $\mathbf{L}(f)$ and threshold c are unknown.

Model – Second Integral



Blur Image

Latent Images – $\mathbf{L}(t)$ sequence

$$\mathbf{B} = \frac{1}{T}\int_{f-T/2}^{f+T/2} \mathbf{L}(t)dt$$

combine

$$\mathbf{L}(t) = \mathbf{L}(f)\exp(c\int_{f}^{t} e(s)ds)$$

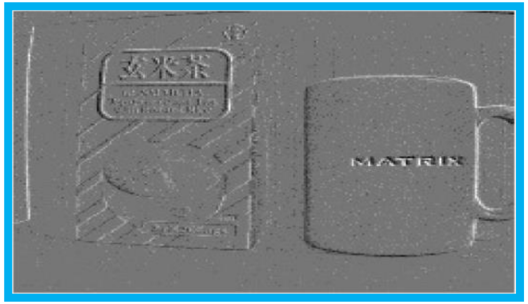
EDI

$$\mathbf{B} = \frac{\mathbf{L}(f)}{T}\int_{f-T/2}^{f+T/2} \exp\left(c\int_{f}^{t} e(s)ds\right)dt$$

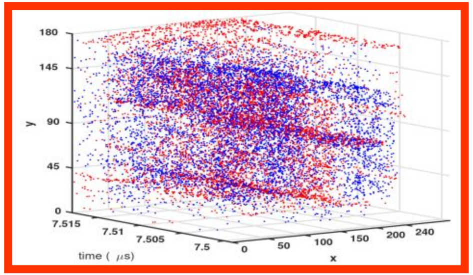
Model – Event-based Double Integral (EDI)

$$\mathbf{B} = \frac{\mathbf{L}(f)}{T}\int_{f-T/2}^{f+T/2}\exp\left(c\int_{f}^{t}e(s)ds\right)dt$$

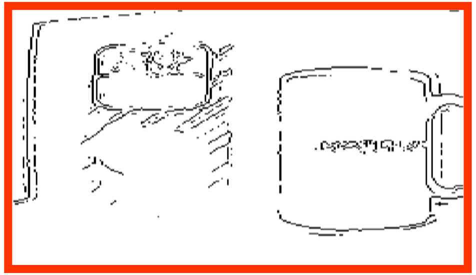
$$\log(\mathbf{L}(f)) = \log(\mathbf{B}) - \log\left(\frac{1}{T}\int_{f-T/2}^{f+T/2}\exp\left(c\int_{f}^{t}e(s)ds\right)dt\right)$$



Finding c



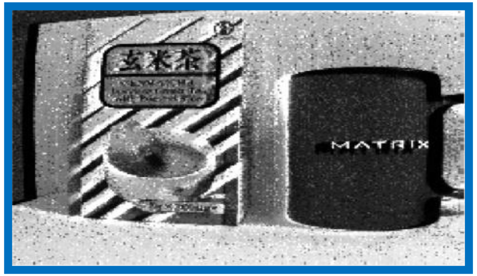
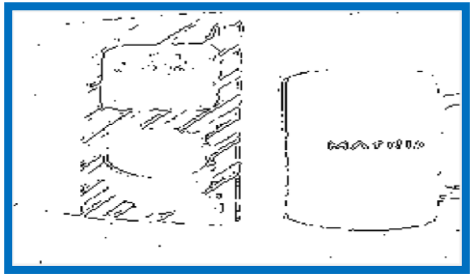
Events



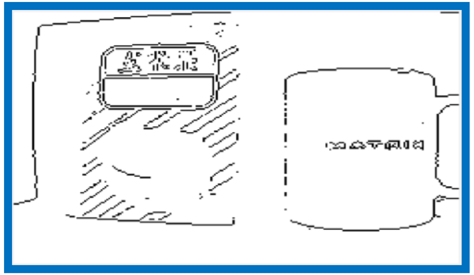
Edge

small c


large c

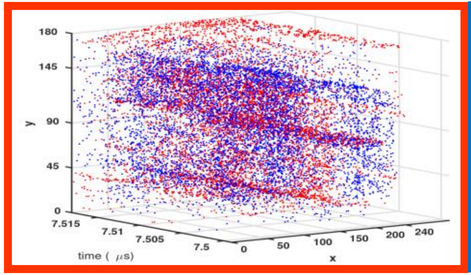
proper c

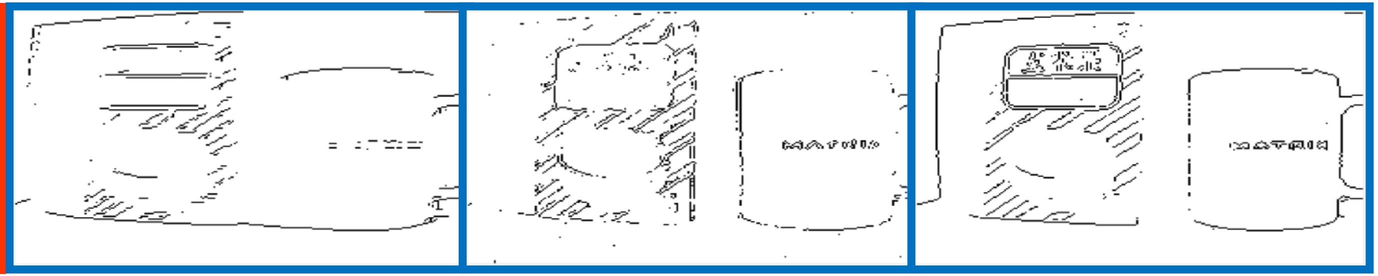



Reconstructed

Edge

Finding c

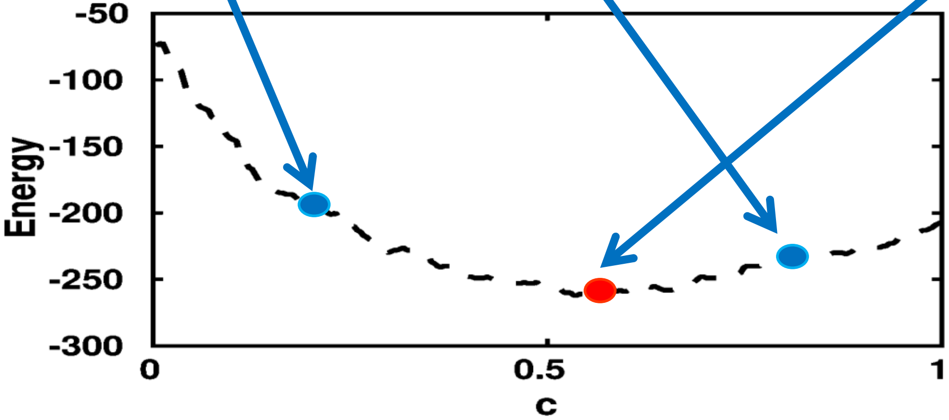




cross-correlation

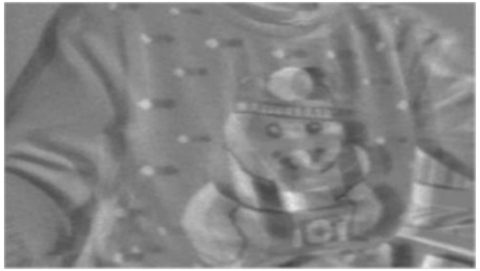
small c **large** c **proper** c

Fibonacci search



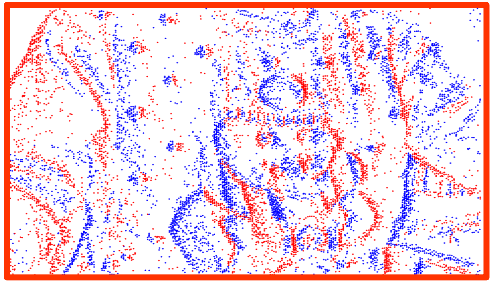
Results

Blur Image

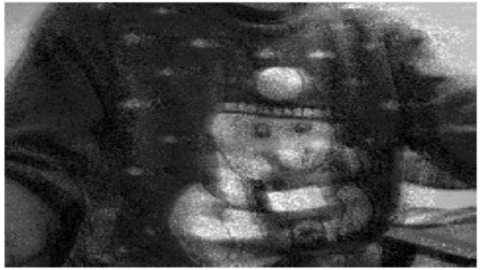


[1] Only use event

[3] Only use image



Events

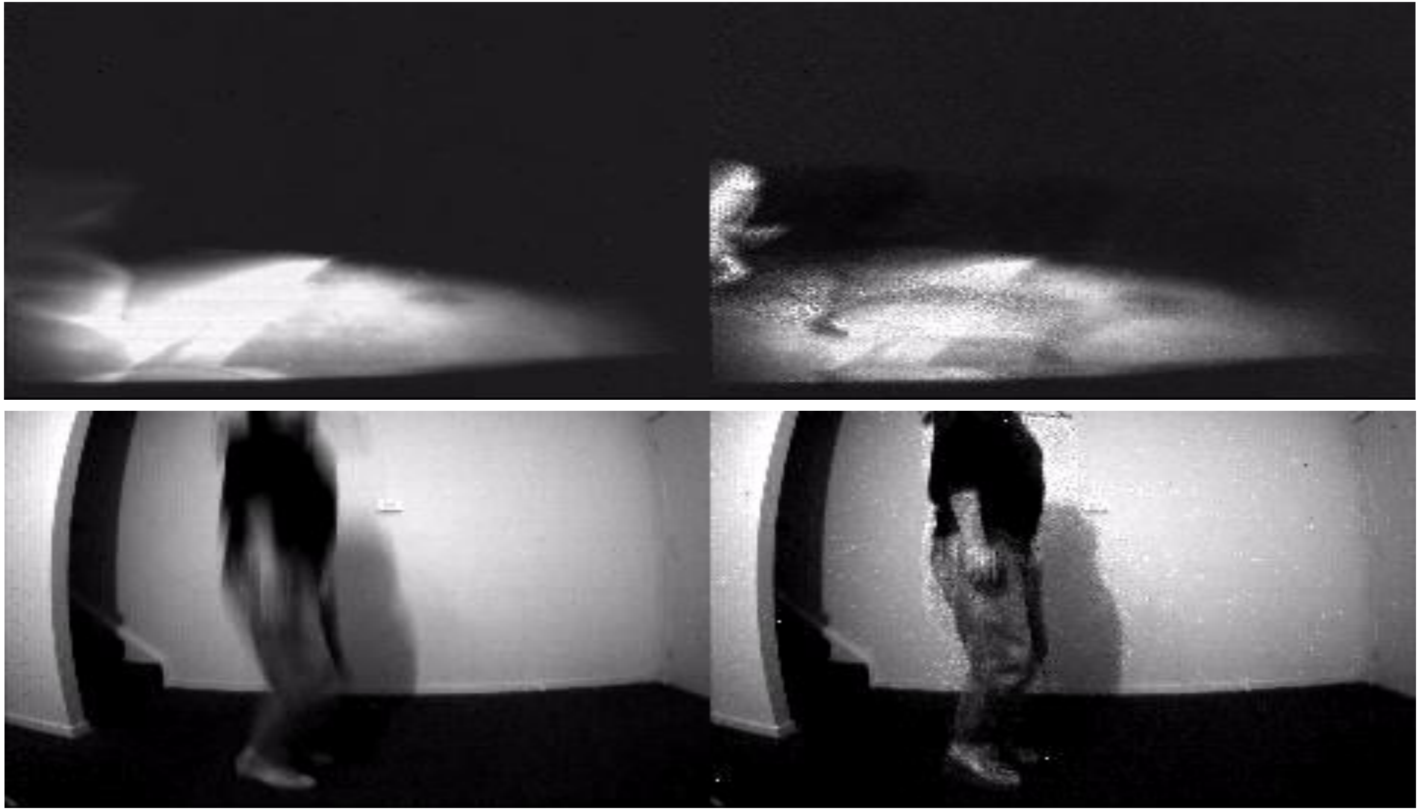


[2] Event & Image

Ours Event & Image

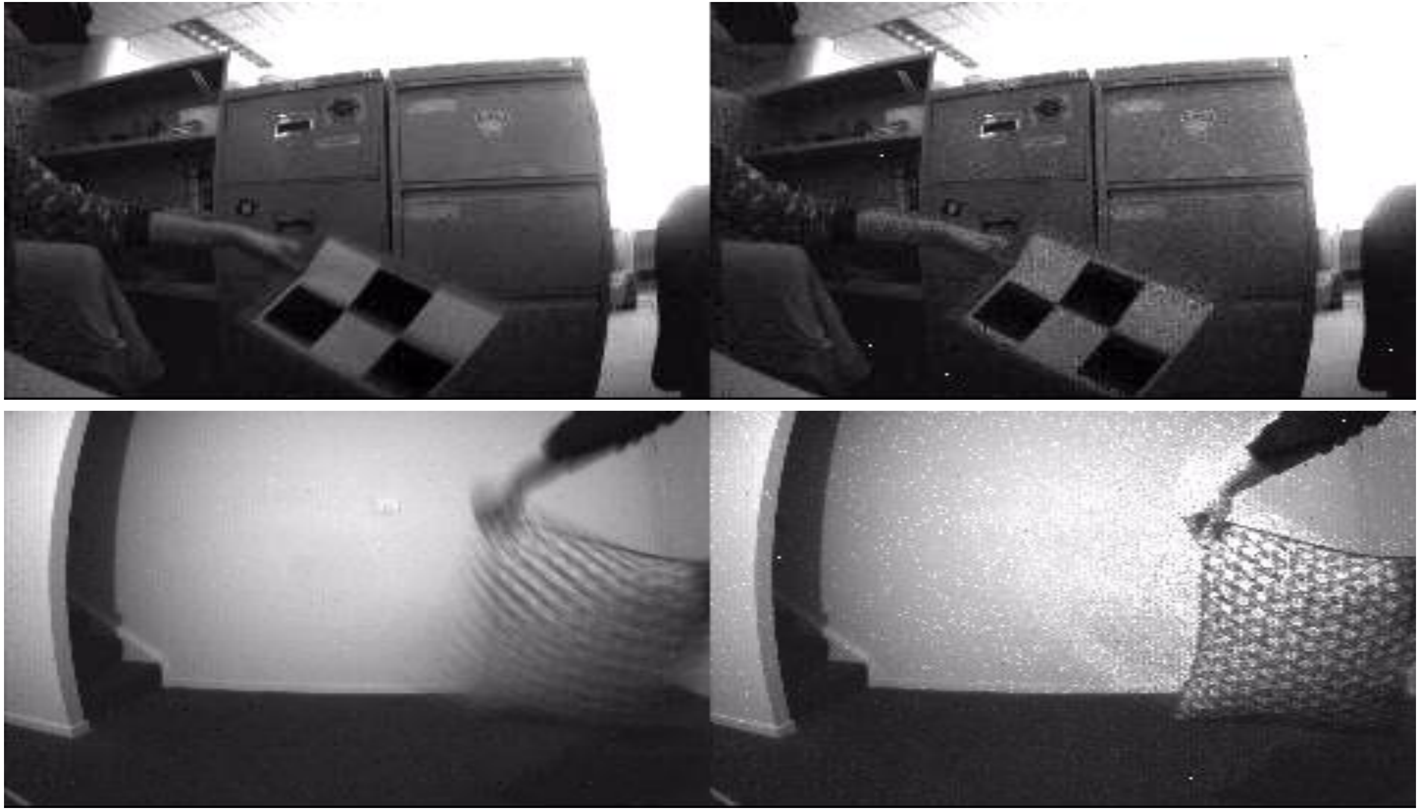
[1] C. Reinbacher, et al. Real-time intensity-image reconstruction for event cameras using manifold regularisation. BMVC, 2016
[2] C. Scheerlinck , et al. Continuous-time intensity estimation using event cameras. ACCV, 2018
[3] M. Jin , et al. Learning to extract a video sequence from a single motion-blurred image. CVPR 2018

Results



Input blur image Output sharp video

Results

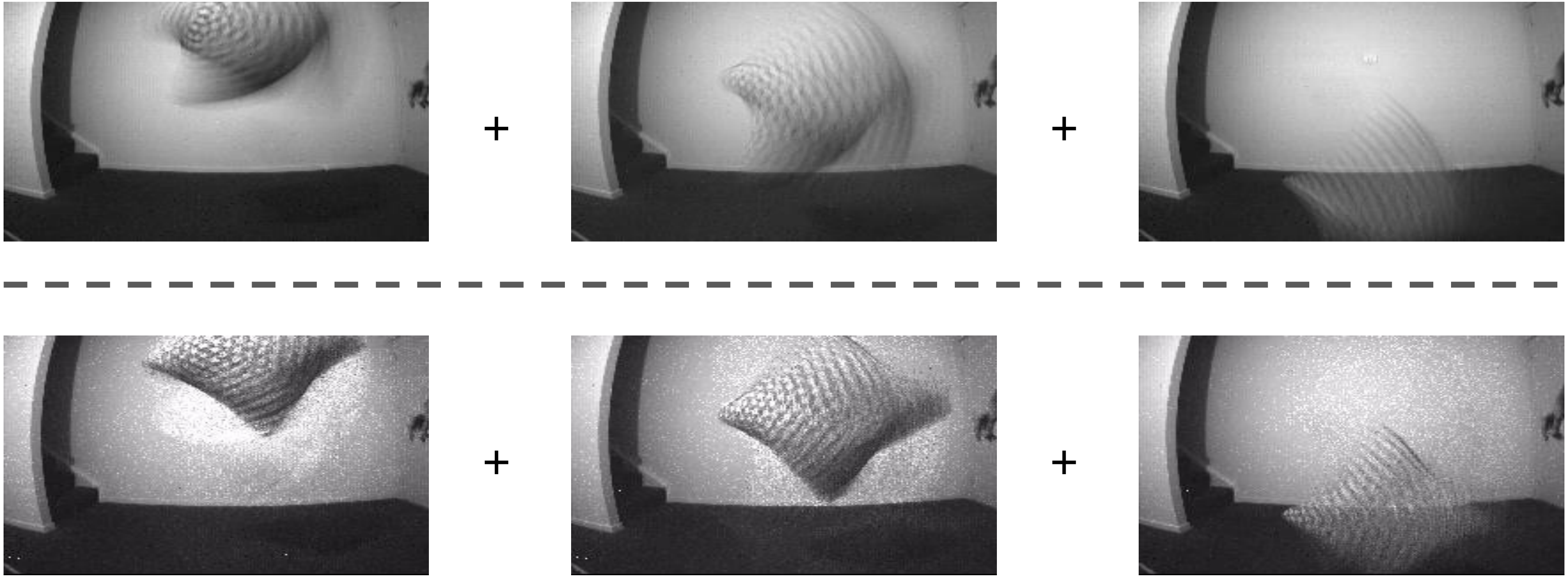


Input blur image | Output sharp video

Results

Input blur image **Output sharp video**

High frame rate video generation



t = 1 t = 2 t = 3

Results

Average result of the reconstructed videos on dataset[4]

	Baseline 1	Baseline 2	Scheerlinck *et al.* [2]	Jin *et al.* [3]	Ours
PSNR(dB)	25.52	26.34	25.84	25.62	**28.49**
SSIM	0.7685	0.8090	0.7904	0.8556	**0.9199**

When the input image is blur, a trivial solution would be:

- **Baseline 1**: Deblurring + Reconstruction
- **Baseline 2**: Reconstruction + Deblurring

[4]. S. Nah. Deep multi-scale convolutional neural network for dynamic scene deblurring. CVPR, 2017.

Results

Baseline 1

Baseline 2

[2]

[3]

t = f - 1

t = f

t = f + 1

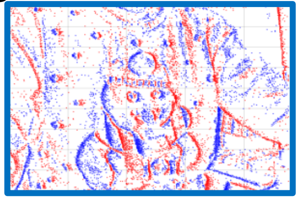
t = f + 2

Our

Thank you
Poster number - 136

Code, Data, Demo, and Extension Work

https://github.com/panpanfei/Bringing-a-Blurry-Frame-Alive-at-High-Frame-Rate-with-an-Event-Camera

log  - ∬  = log