Real-Time Intensity-Image Reconstruction for Event Cameras

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Scientific vision days, November 9th, 2016

Joint work with:
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Event Cameras vs. Conventional Cameras

Event cameras are a paradigm shift in digital camera technology

- Low Latency
- Low Bandwidth
- High Dynamic Range

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- High Resolution
- Images

Motivation

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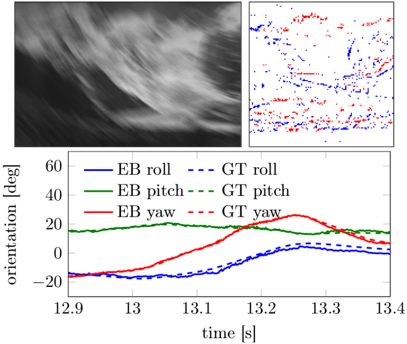
Related Work - Computer Vision with Event Cameras

- Camera Tracking
- Optical Flow
- Image Reconstruction



Event-based, 6-DOF Camera Tracking for High-Speed Applications [Gallego et al. '16]

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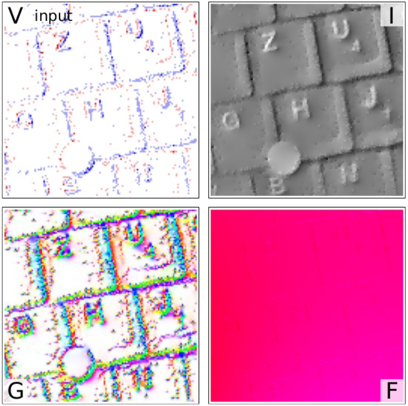

Interacting Maps for Fast Visual Interpretation [Cook et al. '11]

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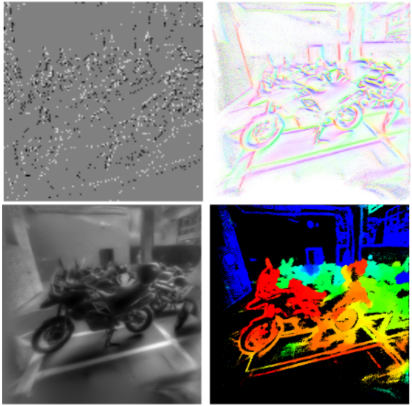

Simultaneous Mosaicing and tracking [Kim et al. '14] and Real-Time 3D Reconstruction and 6-DoF Tracking with an Event Camera [Kim et al. '16]

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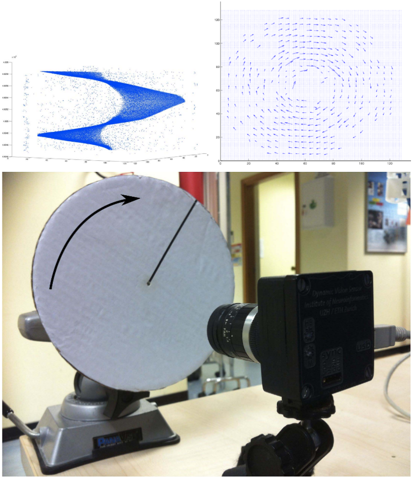

Event-Based Visual Flow [Benosman et al. '14]

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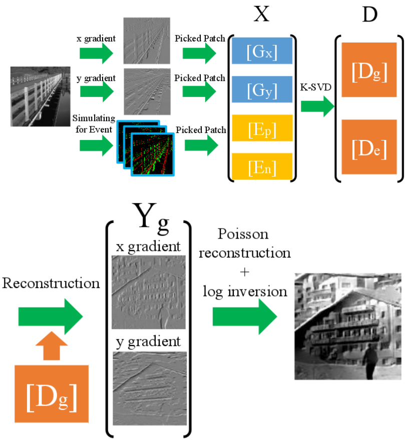

Face Detection and Video Reconstruction from Event Cameras [Miyatani et al. '16]

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- Optical Flow
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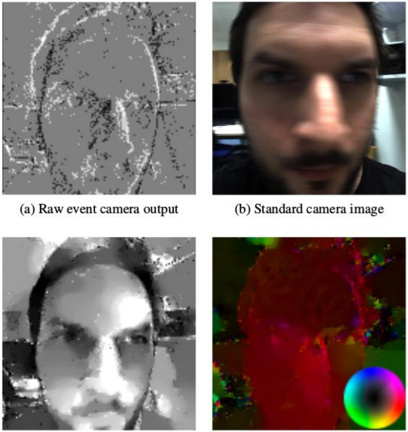

(a) Raw event camera output (b) Standard camera image

(c) Intensity estimate from events (d) Optical flow from events

Simultaneous Optical Flow and Intensity Estimation from an Event Camera [Bardow et al. '16]

Image Formation Process

Event cameras report an event $e^n = \{x^n, y^n, \theta^n, t^n\}$ if pixel intensity at (x^n, y^n) has changed by a threshold $\Delta^{\pm}$ in log-space. For the underlying image in intensity space this means:

$$f^n(x^n, y^n) = u^{n-1}(x^n, y^n) \cdot \begin{cases} c_1 & \text{if } \theta^n > 0 \\ c_2 & \text{if } \theta^n < 0 \end{cases},$$

with $c_1 = \exp(\Delta^+)$, $c_2 = \exp(-\Delta^-)$.

Reconstruction by Denoising

Problems:

- u^0 is unknown and can not be recovered
- Noise in events (possibly not iid)

Goal of this work

Recover a denoised u^n from f^n (fast).

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Our Solution:

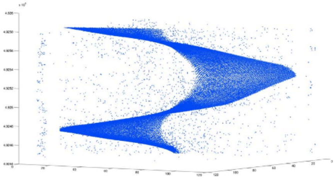
$$u^n = \operatorname*{argmin}_{u \in C^1(\Omega, \mathbb{R}_+)} \left[E(u) = D(u, f^n) + R(u) \right] ,$$

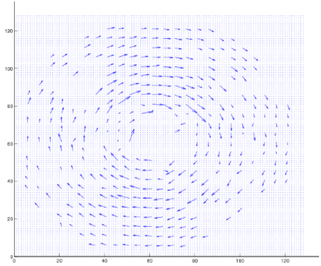
- where $D(u, f^n)$ models camera noise
- and $R(u)$ enforces regularity in the solution

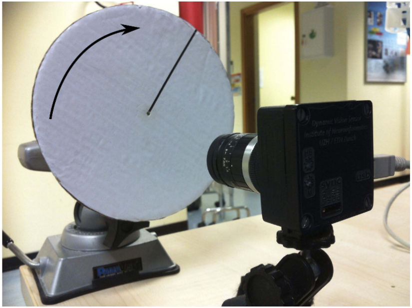
Remaining questions

How to choose D and R and what about the timestamps t^n?

Surface of Active Events

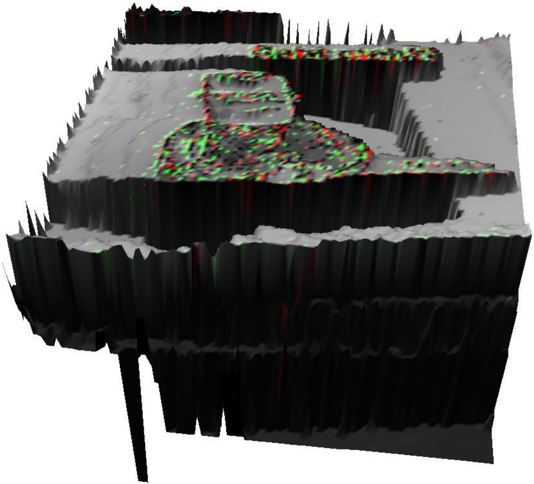






[Benosman et al. '14]

Surface of Active Events



surface $S \subset \mathbb{R}^3$ as the graph of a scalar function $t(x, y)$

$$X = \varphi(x, y) = \begin{bmatrix} x, & y, & t(x, y) \end{bmatrix}^T$$

Defining a Regulariser on the SAE

Given a smooth function $s \in C^1(S, \mathbb{R})$ on the manifold, we can define $\mathrm{d}s(Y) = \langle \nabla_g s, Y \rangle_g \quad \forall Y \in T_X\mathcal{M}$ [Lee et al. '97], with

$$\nabla_g s = \left(g^{11} s_x + g^{12} s_y\right) \varphi_x + \left(g^{21} s_x + g^{22} s_y\right) \varphi_y,$$

where g^{ij} denotes the components of the inverse of g, the metric tensor

$$g = \begin{bmatrix} \langle \varphi_x, \varphi_x \rangle & \langle \varphi_x, \varphi_y \rangle \\ \langle \varphi_x, \varphi_y \rangle & \langle \varphi_y, \varphi_y \rangle \end{bmatrix}.$$

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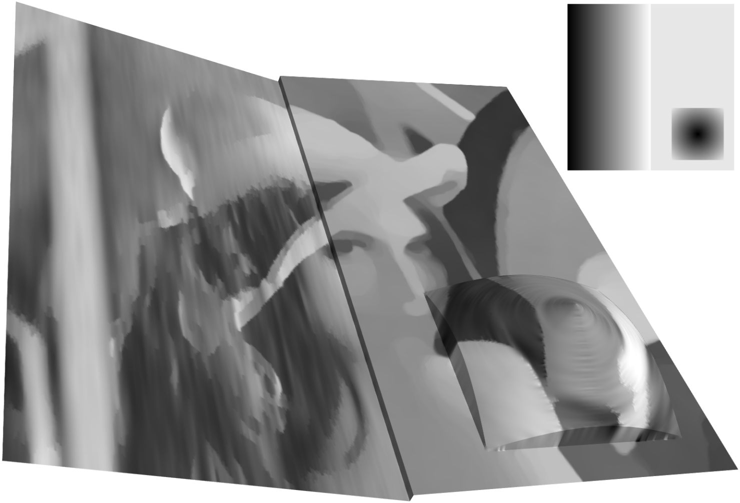
This allows us to define the TV norm on S as

$$TV_g(s) = \int_S |\nabla_g s| \, \mathrm{d}s = \int_\Omega |\nabla_g s| \sqrt{det(g)} \, \mathrm{d}x\mathrm{d}y.$$

Effect of Regularization on a Surface

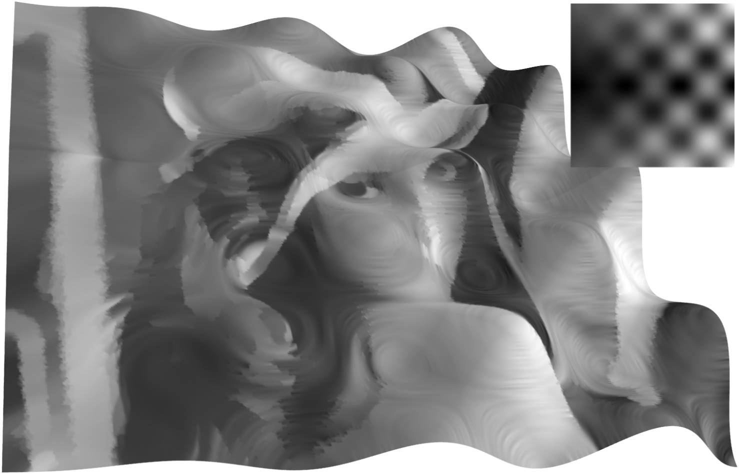
ROF denoising on a flat surface

Effect of Regularization on a Surface



ROF denoising on a ramp

Effect of Regularization on a Surface



ROF denoising on a sine wave

Data Term

Measures the distance of the optimized image u to the current data f^n under some camera noise model assumptions.

$\mathbf{D(u, f^n)}$	**Result**	**Convex**
$\|u - f^n\|$	✗	✓

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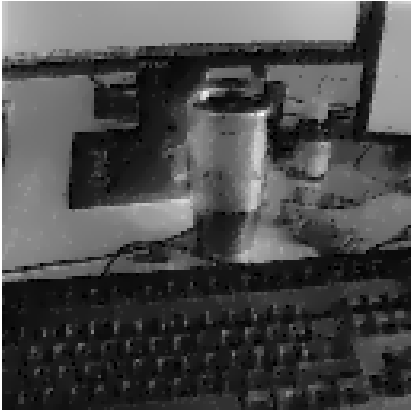

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$\sum_i \log\left(\frac{u_i}{f_i^n}\right)^2$	✓	✗

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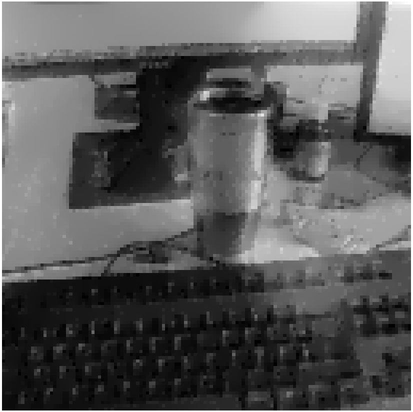

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$\|u - f^n\|^2$	(✗)	✓
$\sum_i \log\left(\frac{u_i}{f_i^n}\right)^2$	✓	✗
$\sum_i u_i - f_i^n \log u_i$	✓	✓

Data Term

We therefore choose:

$$\lambda \int_S (u - f^n \log u)\, \mathrm{d}s = \lambda \int_\Omega (u - f^n \log u) \sqrt{G}\, \mathrm{d}x\mathrm{d}y \ ,$$

known as *generalised Kullback-Leibler divergence*.

- Minimiser is the ML-estimate when assuming Poisson noise between u and f (dependent on the absolute light intensity) [Ratner and Schechner '07]
- Convex $\rightarrow$ easy to minimise

Energy Minimisation

We minimze the original energy using the primal-dual energy formulation

$$\min_u \max_p \left[D(u, f^n) + \langle L_g u, p \rangle - R^*(p) \right], \tag{1}$$

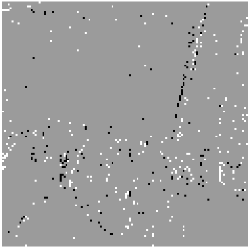
with L_g being the discretised operator ∇_g with the algorithm of [Chambolle and Pock '11].

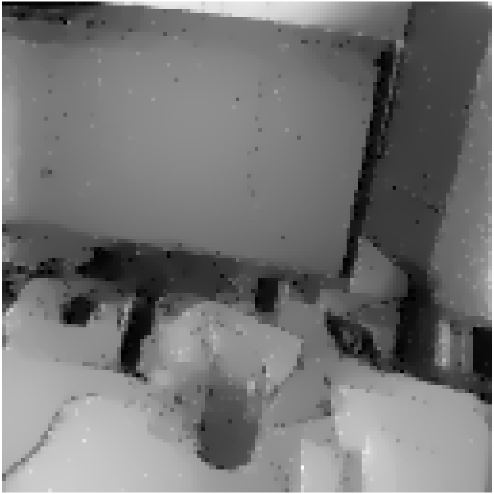
- Algorithm is still defined in pixel-space $\rightarrow$ parallelizable on GPUs
- Converges in less than 50 iterations due to small image size of 128×128

Experiments - Timing

- NVidia GTX 780 ti - TitanX
- $\approx$ 600 frames/sec
- $\approx$ 500.000 events/sec $\rightarrow$ collect 500-1000 events before denoising

Experiments - Influence of Manifold Regularization





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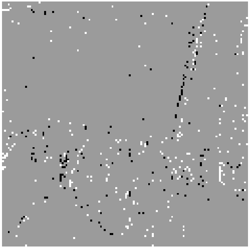

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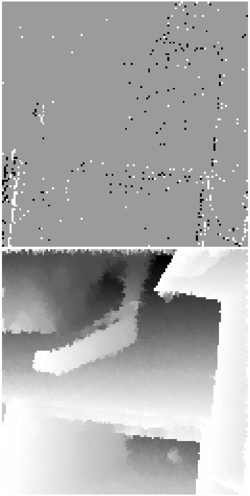

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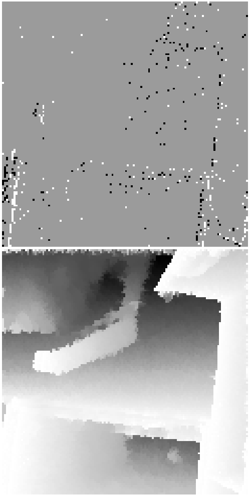
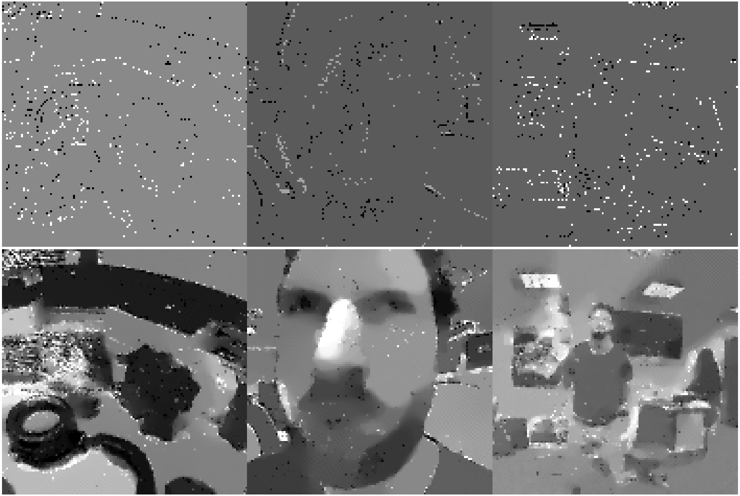


Experiments - Comparison to [Bardow et al. '16]



[Bardow et al. '16]

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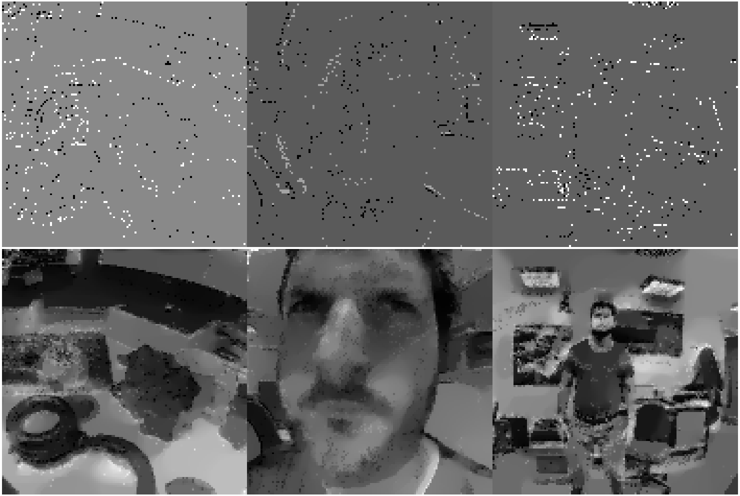

OURS

Experiments - Video

Conclusion

- Image Reconstruction without camera tracking
- Fast enough to achieve Real-Time performance
- Exploitation of the *Surface of Active Events*

Software for DVS128 and DAVIS240 can be downloaded from
https://github.com/VLOGroup

Outlook and Open Questions

- Definition of data term (real camera noise model still unknown)
- Quantitative evaluation of the result (blind Image Quality Analysis or comparison to ground truth)
- Weighting of data term dependent on the number of events per reconstructed image

Thank you for your attention!

Log L2 Data Term

$$\breve{d}(t) = \begin{cases} d(t) & \text{if } \log t < 1 \\ d(e) + d'(e)(t-e) = -\frac{1}{2} + \frac{t}{e} & \text{else} \end{cases}$$