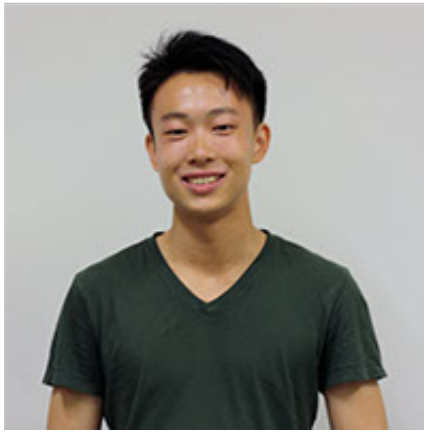
Event-based Feature Tracking and Visual Inertial Odometry



Kostas Daniilidis
with Alex Zhu and Nikolay Atanasov
University of Pennsylvania

Papers at ICRA 2017 and CVPR 2017

www.youtube.com/watch?v=m93XCqAS6Fc

www.youtube.com/watch?v=X3QIFj5Qc4A

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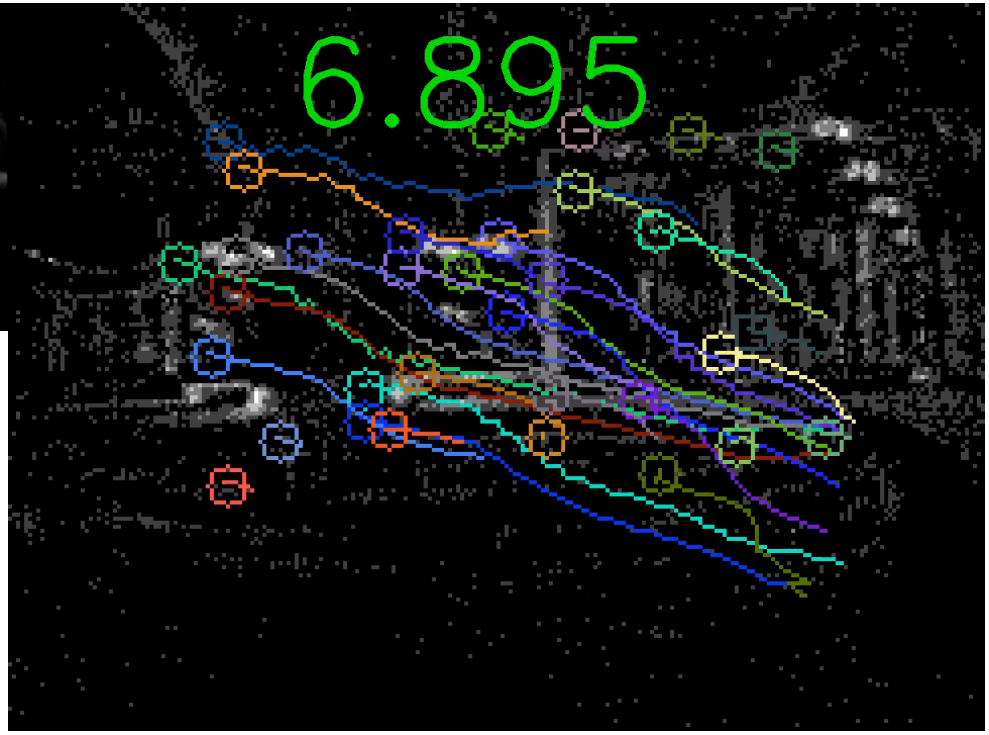
Night Scene, Very Low Lighting
0.1x Real Time

Corresponding grayscale image, 50ms exposure



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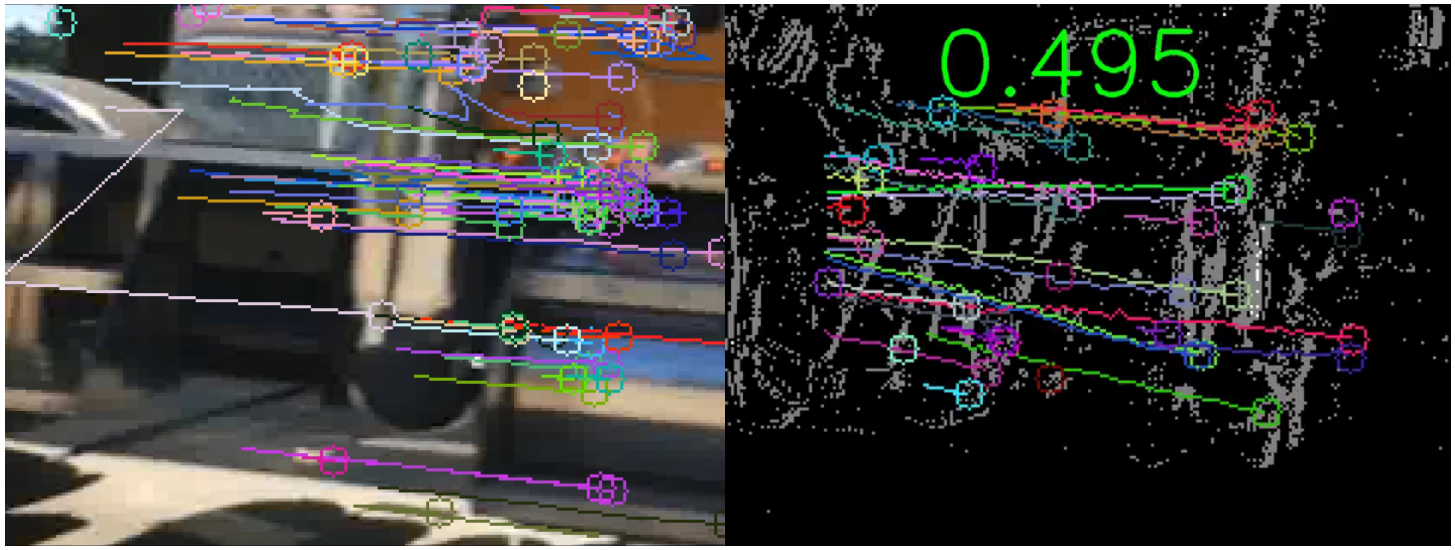
Truck Passing 3m from the Camera at 60 miles/hr, 0.06x Realtime



240FPS iPhone 6 image with KLT.

Event-based tracking on DAVIS 240C.

Optical flow is on the order of 5000 pixels/s.
Sequence is 600ms in realtime.

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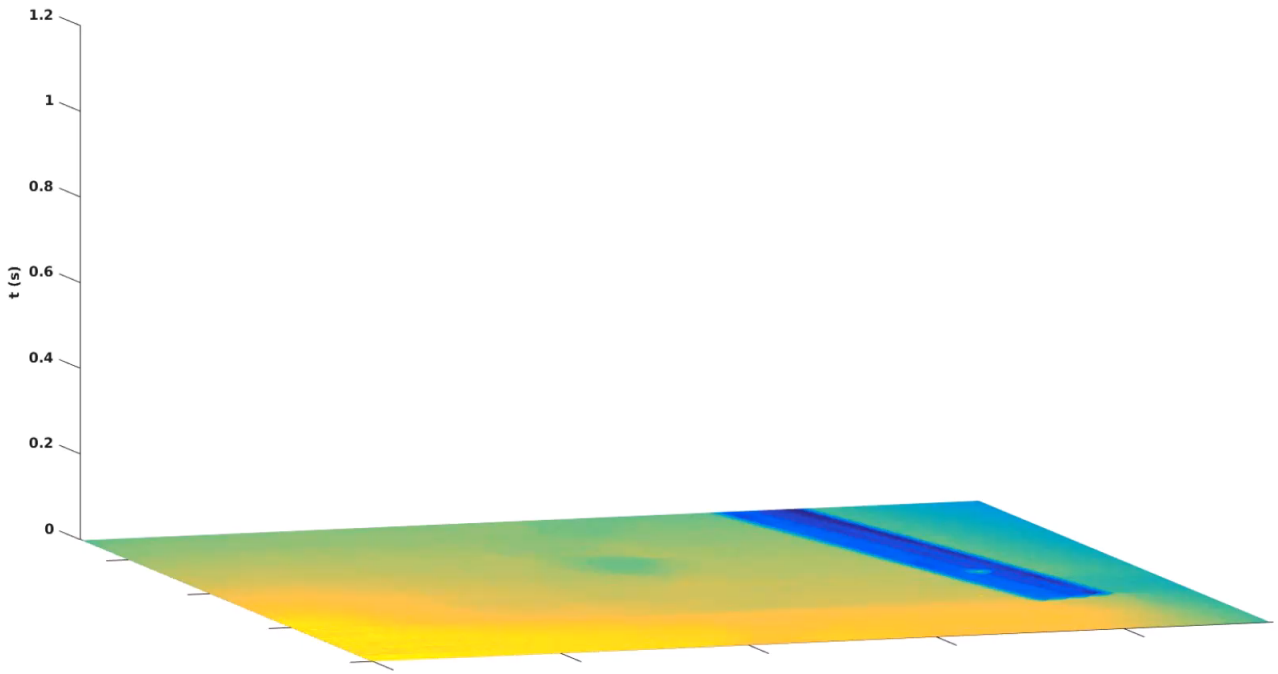
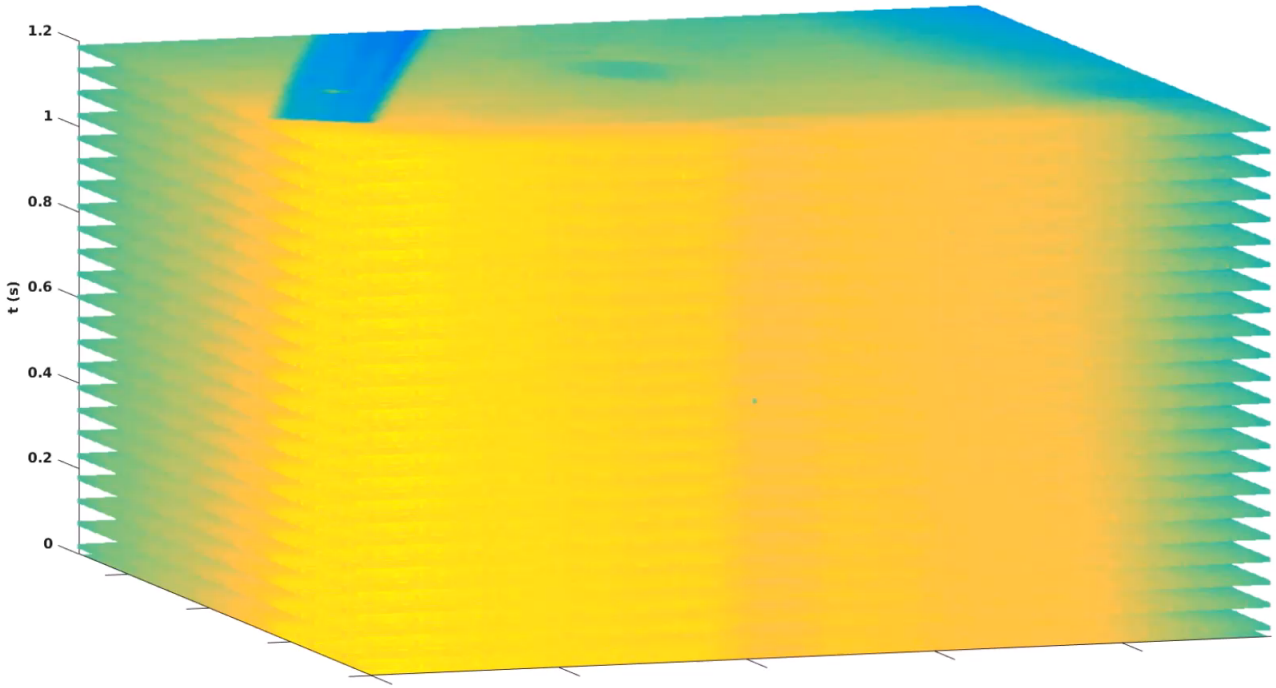
Frame-based Cameras

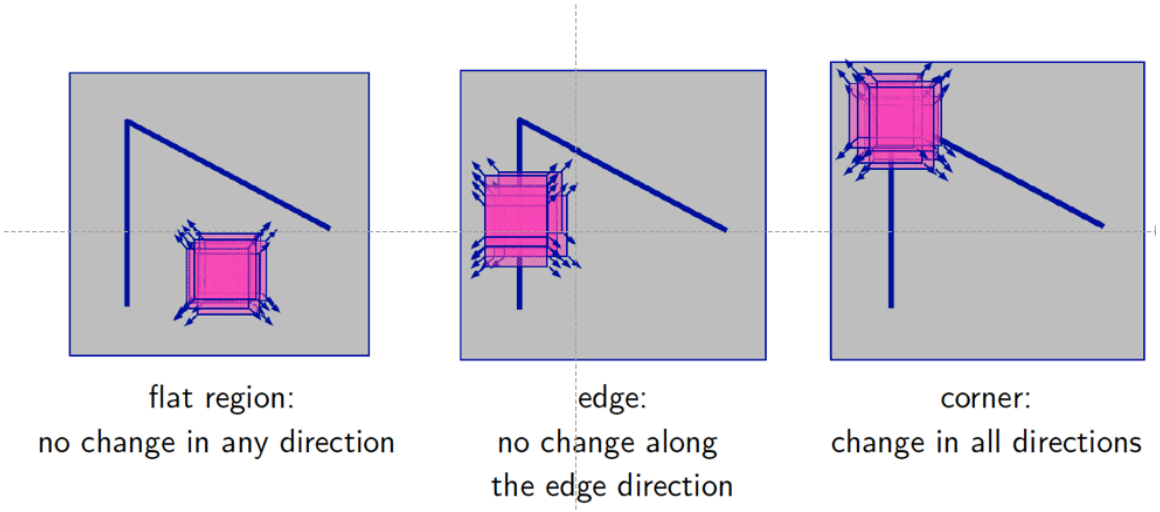


Event-based Cameras



Event-based cameras output asynchronous events (x, y, t, p) at <u>microsecond</u> resolution when $|\log(I(x,t_i)) - \log(I(x,t_{i-1})| \geq \theta$

What is a feature in classic vision?



Features are defined through motion: good flow means good features!

But they defined with a spatial neighborhood!

Speed is dealt with multiple scales

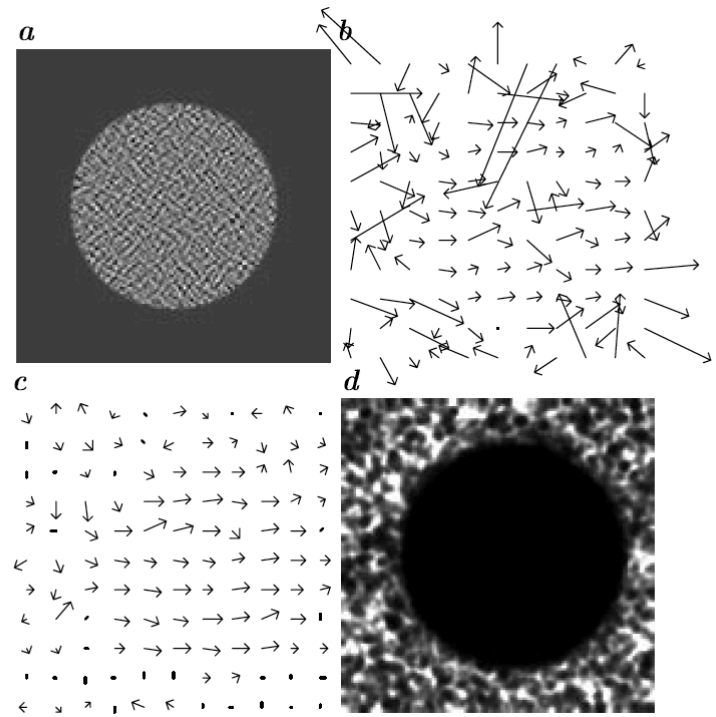
Published in: Handbook of Computer Vision and Applications, eds. B Jähne, H Haussecker, and P Geissler, volume 2, chapter 14, pages 297-422, Academic Press, Spring 1999.

Last modified: 28 Dec 1998.

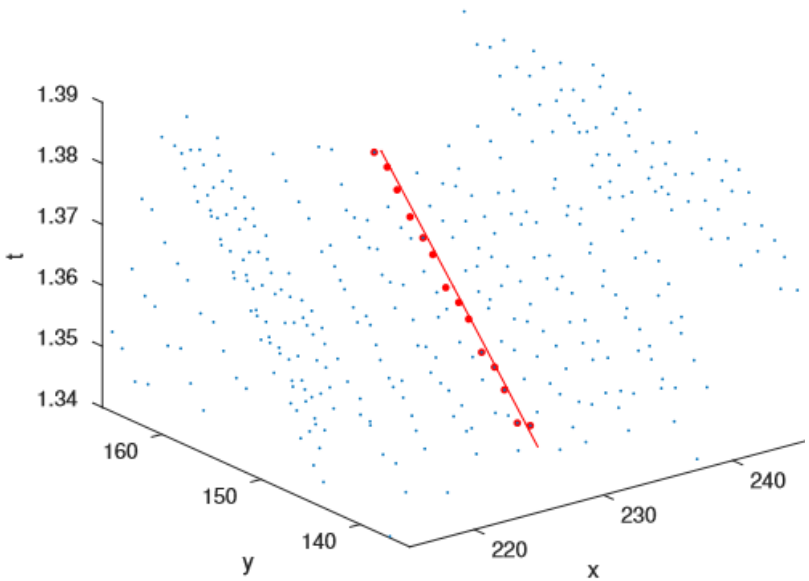
14 Bayesian Multi-Scale Differential Optical Flow

Eero P. Simoncelli

Center for Neural Science, and
Courant Institute of Mathematical Sciences
New York University

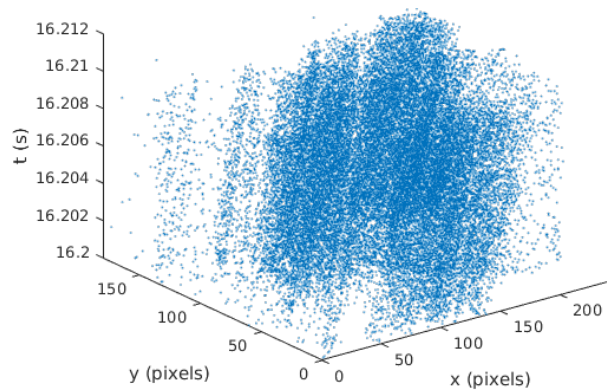


A feature is a set of 2D events induced by the same point in 3D.



$$\begin{pmatrix} f(t) \\ 1 \end{pmatrix} \sim K \begin{bmatrix} R(t) & T(t) \end{bmatrix} \begin{pmatrix} F \\ 1 \end{pmatrix}$$

A feature is a set of 2D noisy events induced by the same point in 3D.

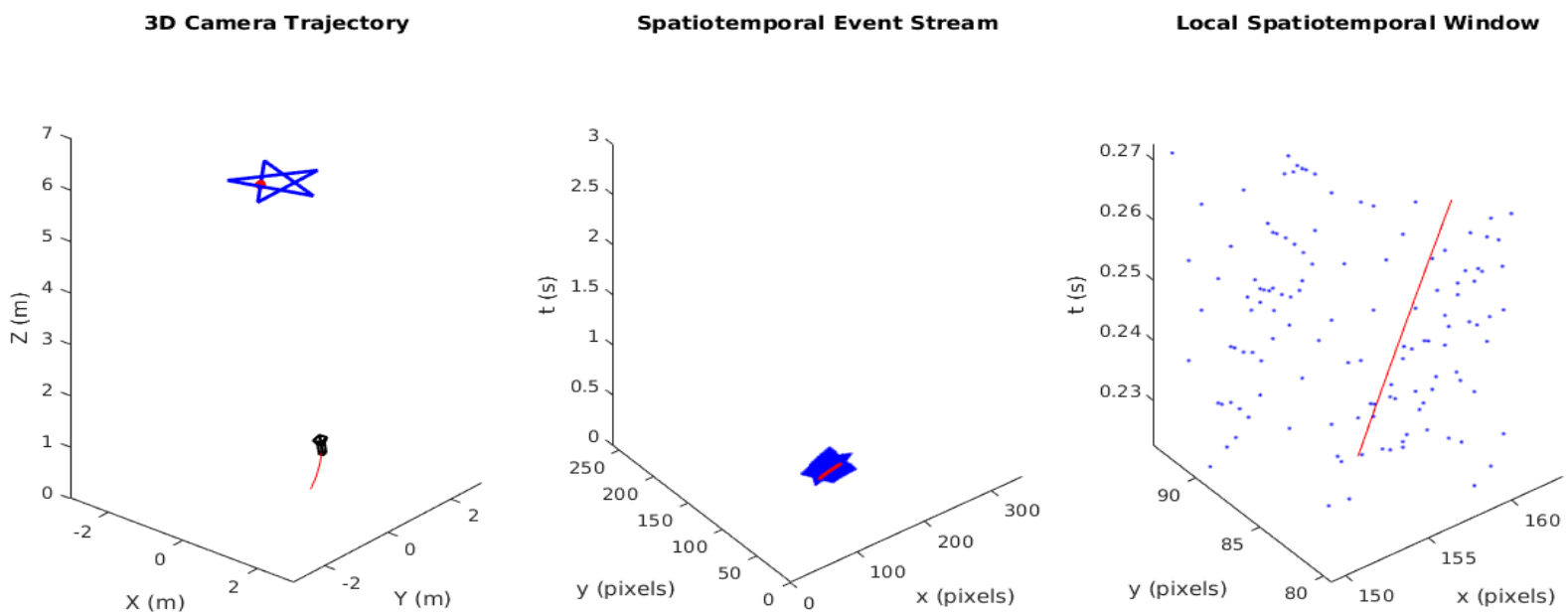


Our measurements are events $\{e_i := (x_i, t_i)\}_{i=1}^{n}$, where

$$x_i := p_{\pi(i)}(t_i) + \eta(t_i), \quad \eta(t_i) \sim \mathcal{N}(0, \Sigma), \quad \forall i$$

$\pi : \{1, \ldots, n\} \to \{1, \ldots, m\}$ is an unknown many-to-one function representing the *data association* between the events $\{e_i\}$ and projections $\{p_j\}$ that generate them.

A feature is a set of events with same flow



$$\|(x_i - t_i v) - (x_k - t_k v)\|^2 \mathbb{1}_{\{\pi(i)=\pi(k)=j\}} = 0, \quad \forall\, i, k \in [n]$$

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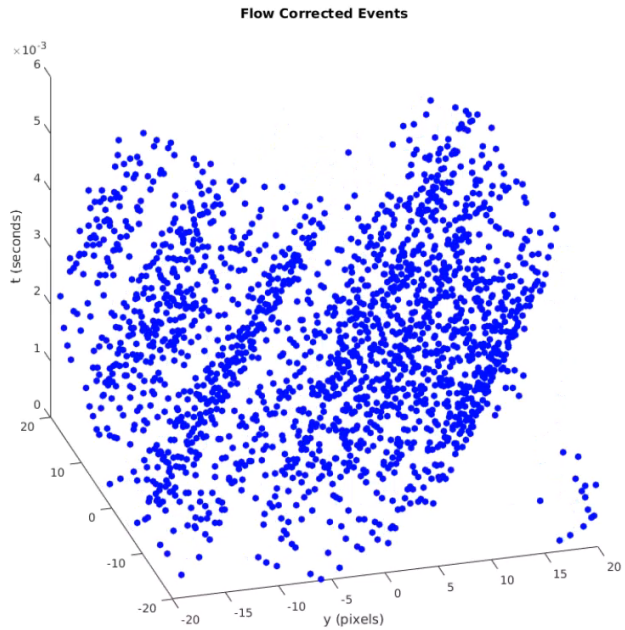
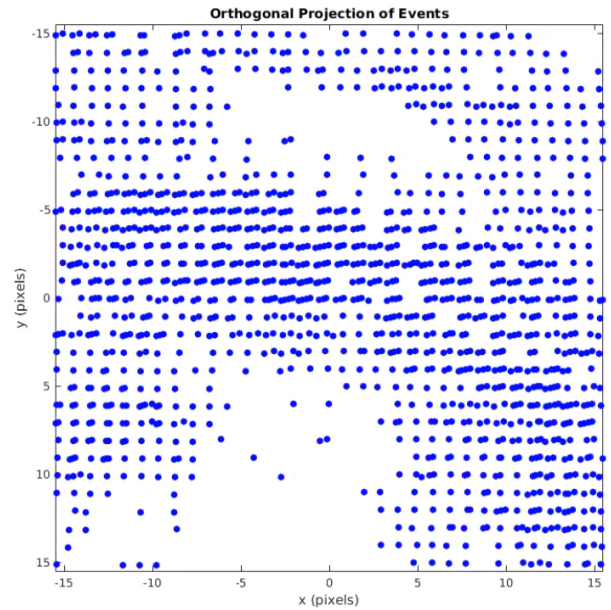
But we do not know the association so we will take the expectation

$$\mathbb{E}_{\pi(i),\pi(k)}\|(x_i - t_i v) - (x_k - t_k v)\|^2 \mathbb{1}_{\{\pi(i)=\pi(k)=j\}}$$

Optical Flow Estimation





Data association probability

Propagated events through time

$$\min_{r,v} \sum_{i=1}^{n} \sum_{k=1}^{n} \left[\sum_{j=1}^{m} r_{ij} r_{kj} \right] ||(x_i - t_i v) - (x_k - t_k v)||^2$$

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E-Step

$$r_{ij}(\{p_j\}) := \frac{\phi((x_i - t_i v); p_j, \Sigma)}{\sum_{l=1}^{m} \phi((x_i - t_i v); p_l, \Sigma)}$$

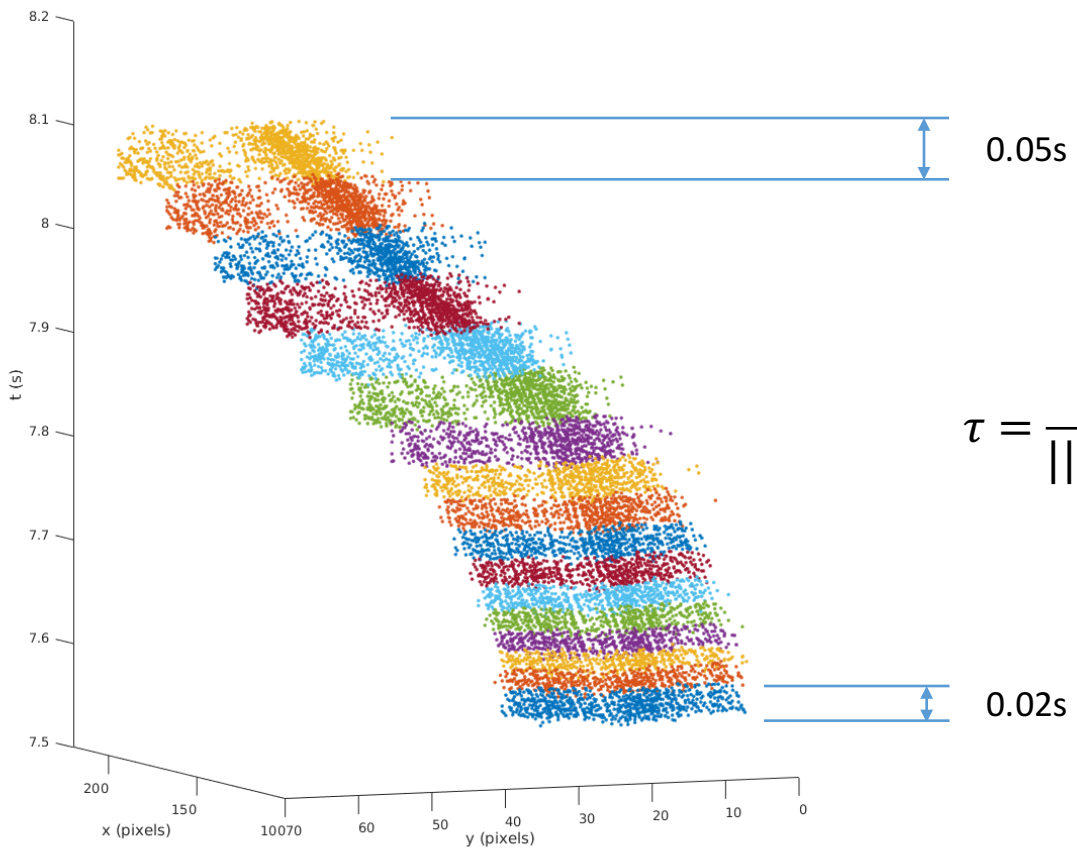
M-Step (linear least squares)

$$\min_{v} \sum_{i=1}^{n} \sum_{k=1}^{n} \left[\sum_{j=1}^{m} r_{ij} r_{kj} \right] \|(x_i - t_i v) - (x_k - t_k v)\|^2$$

How long temporal window?

0.5ms window | 2ms window | 5ms window

How do we choose the right temporal window?



$$\tau = \frac{k}{||v||_2}$$

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Over longer time: Monitor quality of feature with an affine motion model!

IEEE Conference on Computer
Vision and Pattern Recognition
(CVPR94) Seattle, June 1994

Good Features to Track

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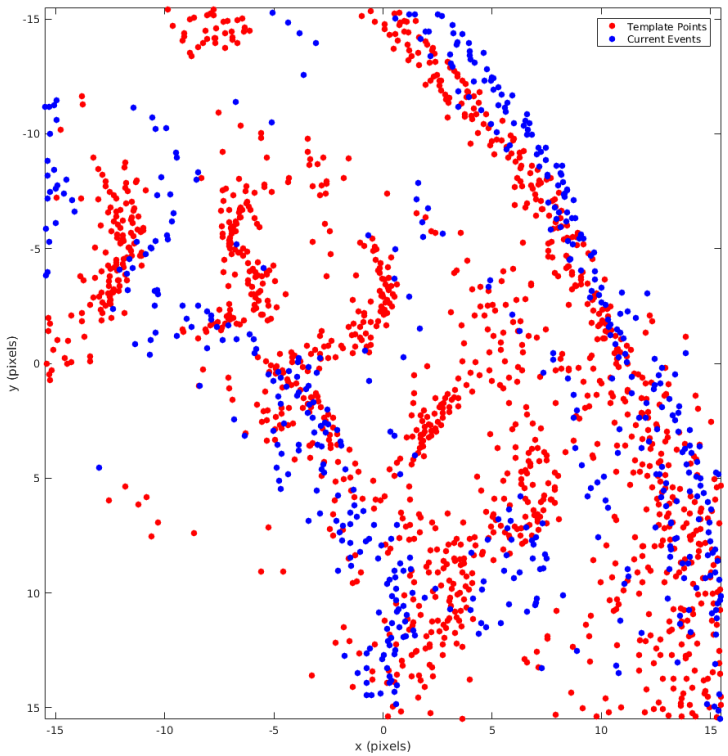
Cornell University
Ithaca, NY 14853

Carlo Tomasi
Computer Science Department
Stanford University
Stanford, CA 94305

Drift Correction - Stabilization



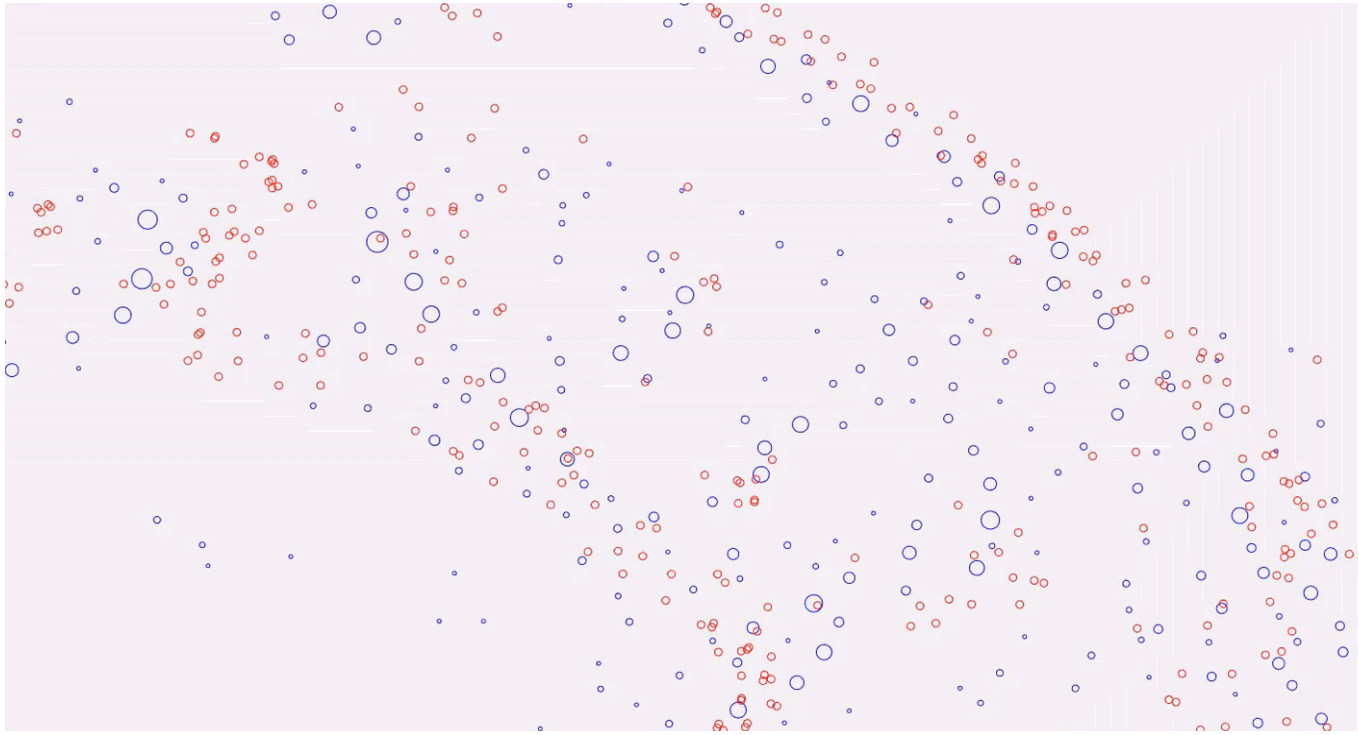
Warped propagated events

Data association

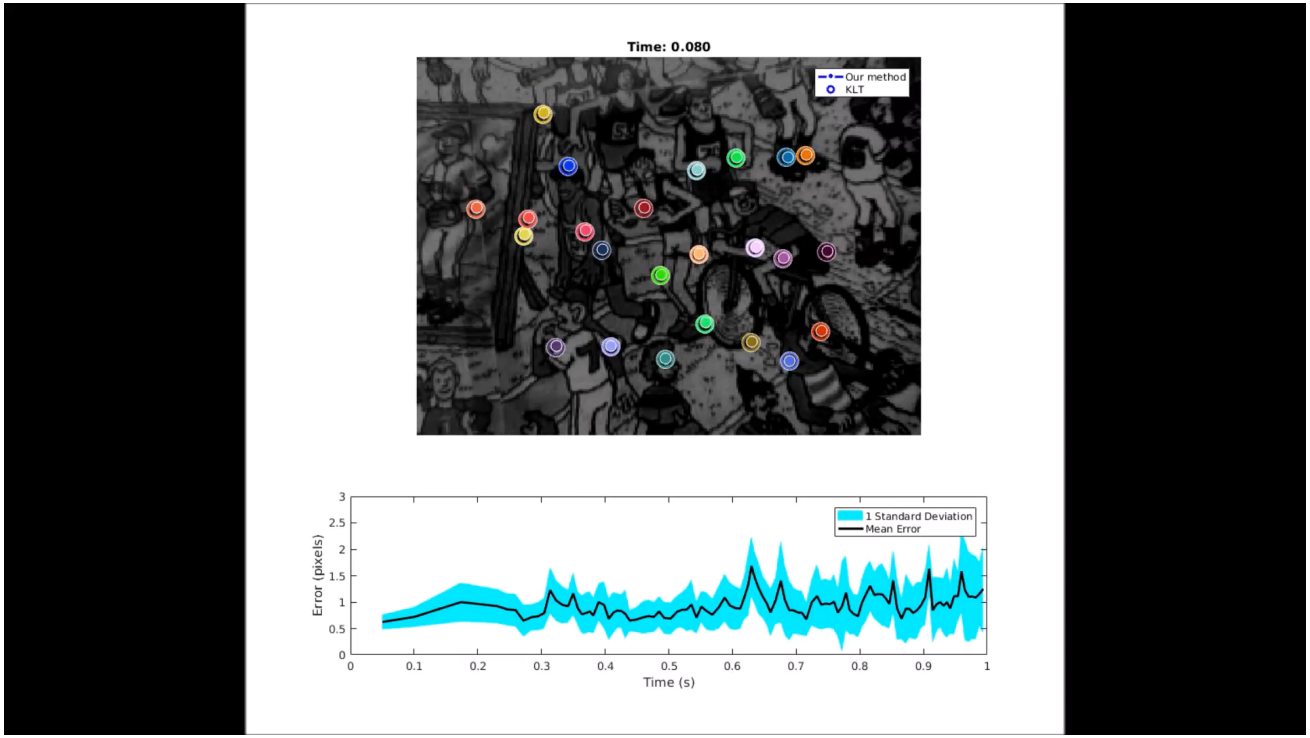
$$\min_{A,b,r} \sum_{i=1}^{n} \sum_{j=1}^{m} r_{ij} \left| A(x_i - t_i v) + b - p_j \right|^2$$

Template points

Scope of each feature



Results: KLT Comparison



20 windows initialized, no reacquisition if tracks are discarded. Frame based images from DAVIS.

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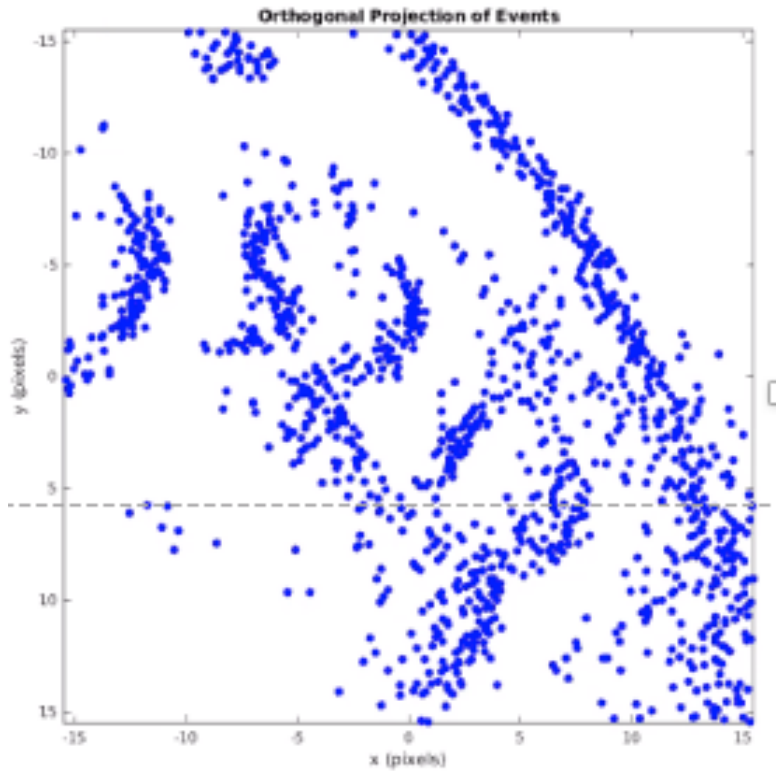
Sparsify and deal with aperture problem: FAST corner selection in the aggregation of warped images



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Visual Inertial Odometry

- Given the event-based feature tracks and a set of IMU observations, how do we obtain an accurate estimate of the camera pose?
- MSCKF (Roumeliotis' group)
- Enforce 3D rotation in 2D tracking

Instead of affine warp…

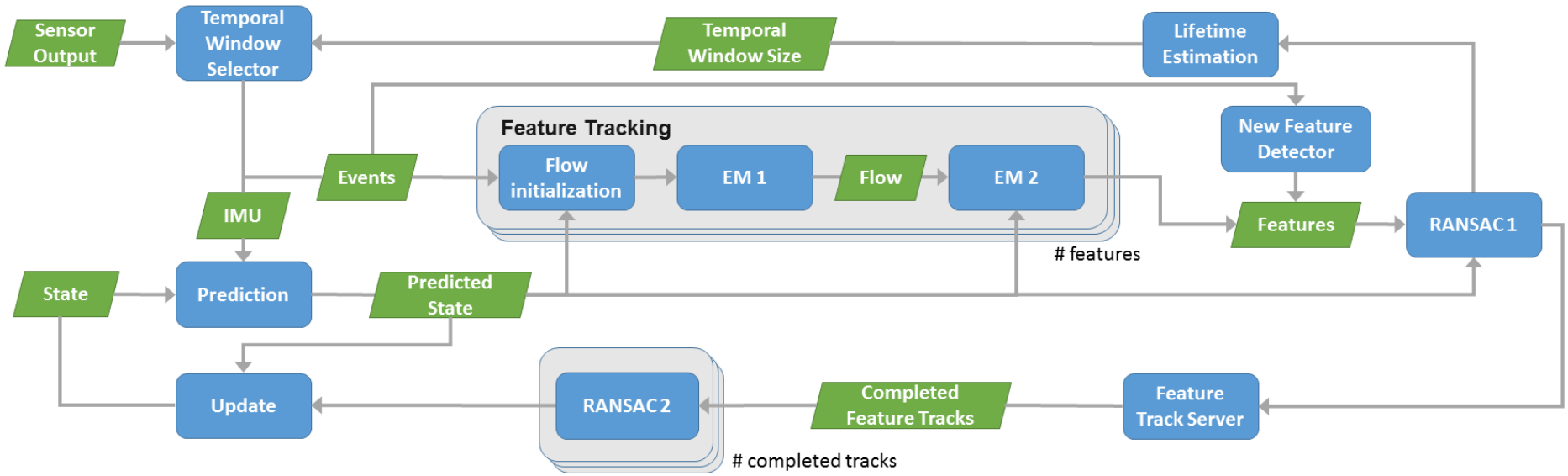
We use the current estimate of rotation and we estimate only scale and local translation

$$y_k^i = \pi\left({}^{i*}R_i \begin{pmatrix} l_k^i \\ 1 \end{pmatrix}\right) - \pi\left({}^{i*}R_i \begin{pmatrix} f(T_i) + u_i dt_i \\ 1 \end{pmatrix}\right)$$

Outlier Rejection

- The EKF uses the L2 loss, and so is very susceptible to outliers in the measurements. To remove these outliers, we apply two RANSAC steps during the tracking.
- RANSAC 1: Pure Translation
  - After each temporal window, two point RANSAC is applied given the rotation estimated from the IMU to reject failed trackers.
- RANSAC 2: Triangulation over frames
  - As each feature track is residualized, a second RANSAC step is applied to find the largest inlier set that agrees on a 3D pose of the feature, given the observations and their corresponding camera poses.

EVIO Summary



Zhu A., Atanasov N., and Daniilidis D. "Event-based Visual Inertial Odometry", *Submitted to Computer Vision and Pattern Recognition (CVPR) 2017.*

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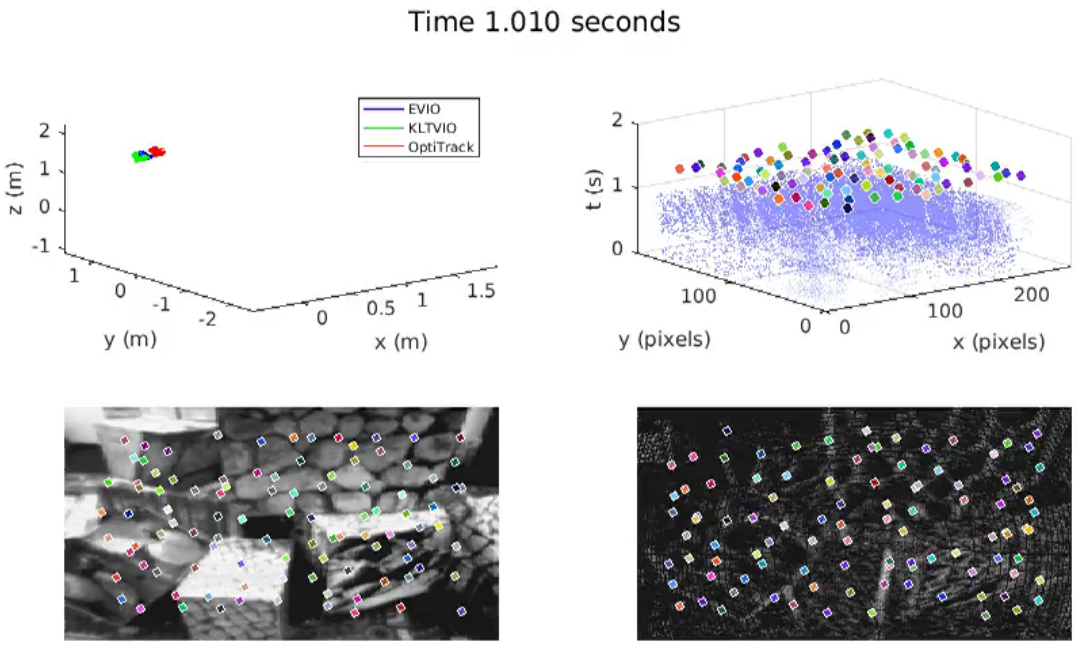
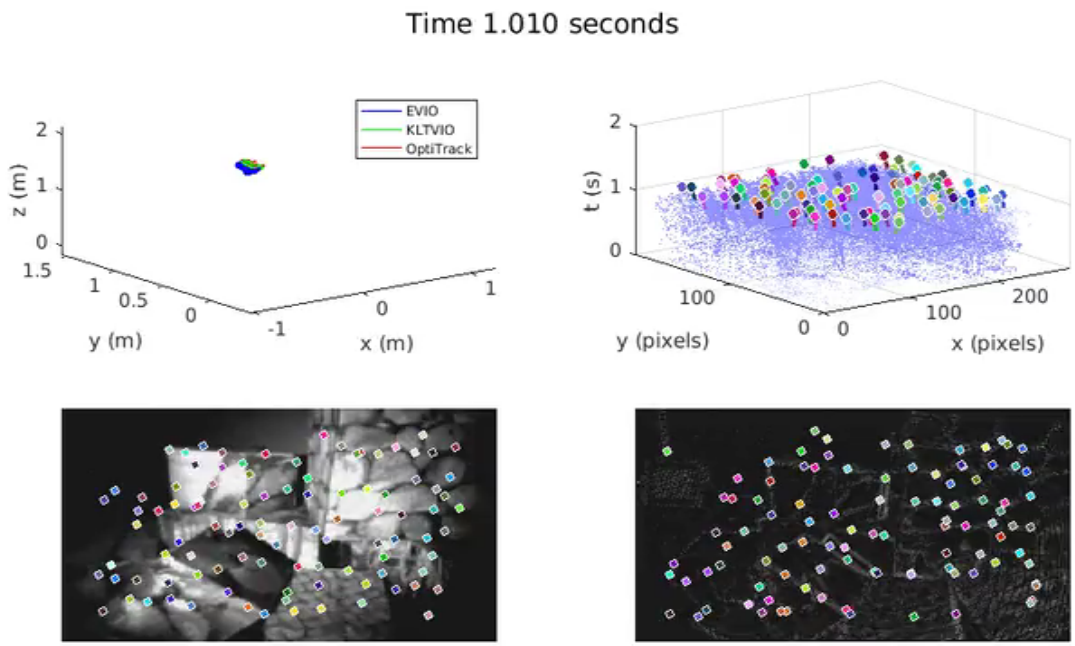
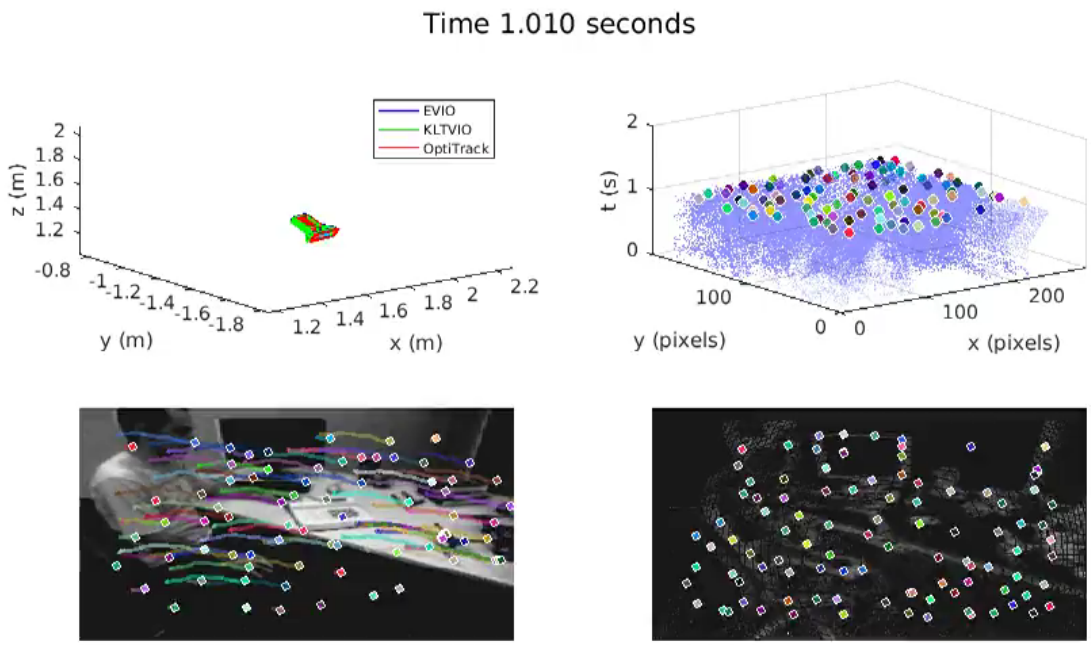
Results: General Scene

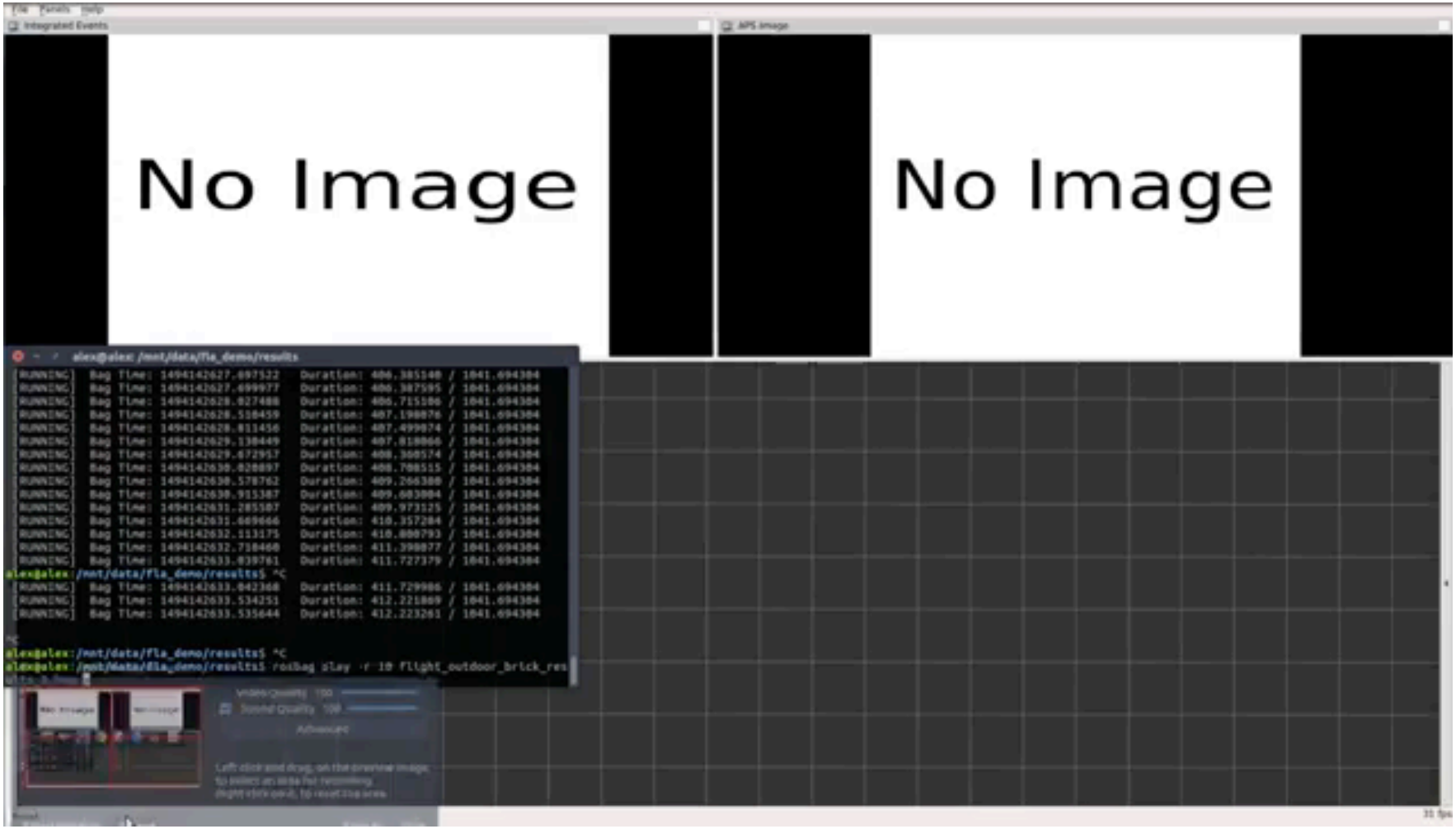


Results: HDR Scene



Results: Motion Independent of Camera





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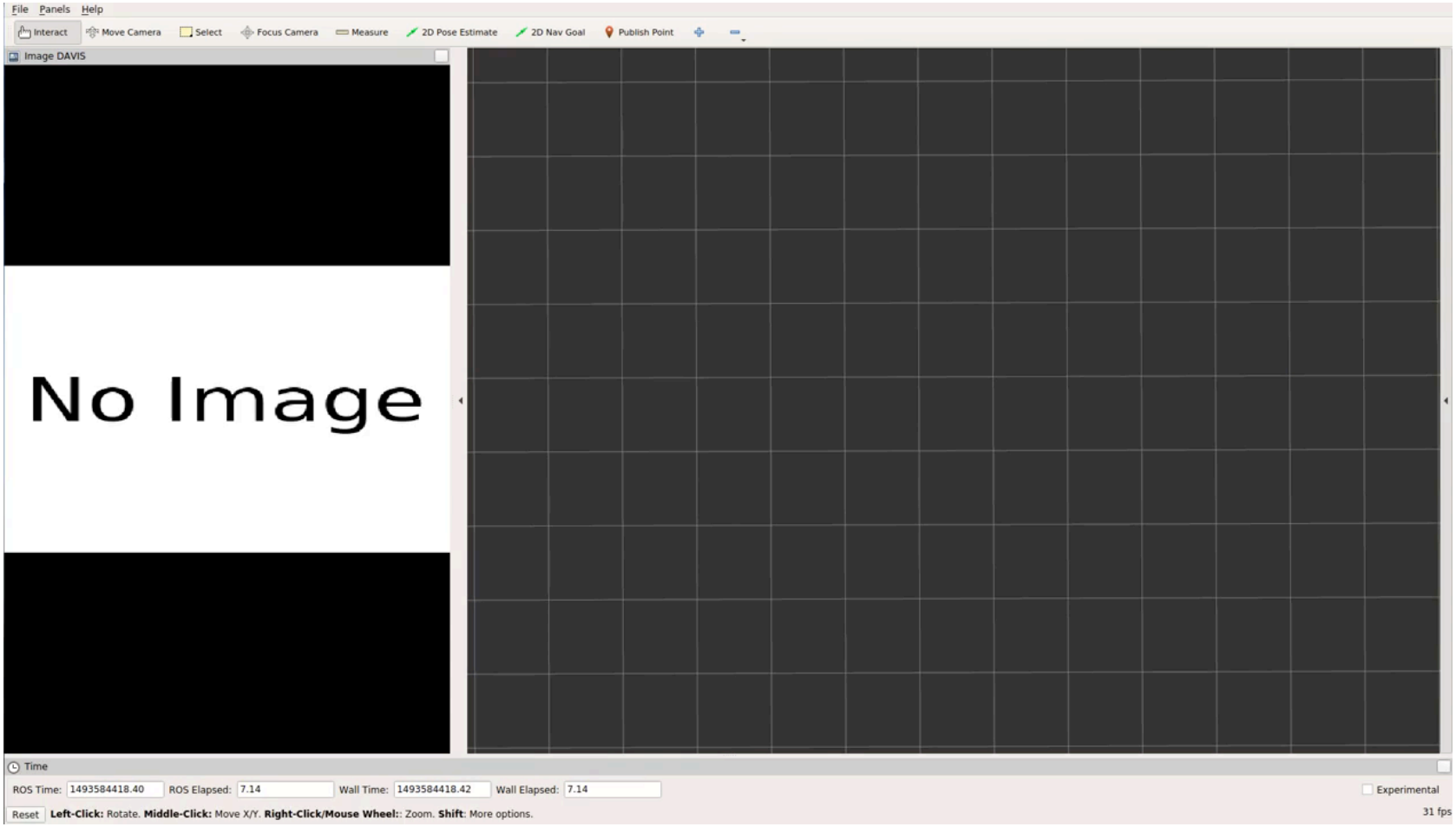

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The future of robot vision is event-based!