

ROBOTICS &
PERCEPTION
GROUP



University of
Zurich^{UZH}

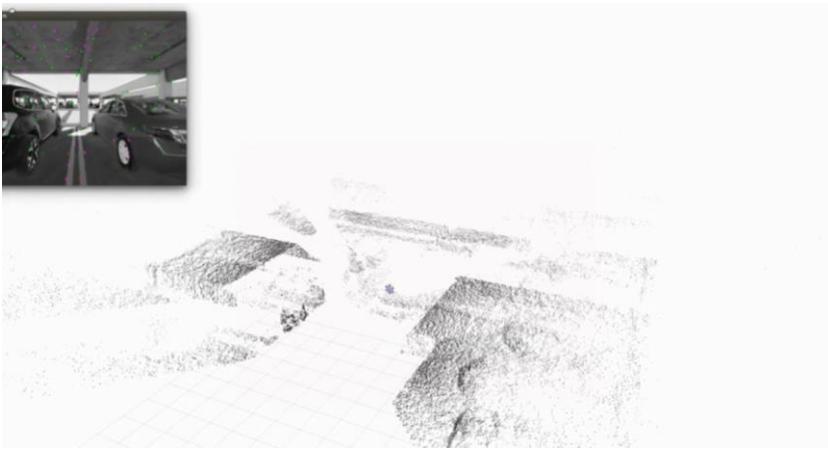
Tutorial on Event-based Vision for High-Speed Robotics

Davide Scaramuzza

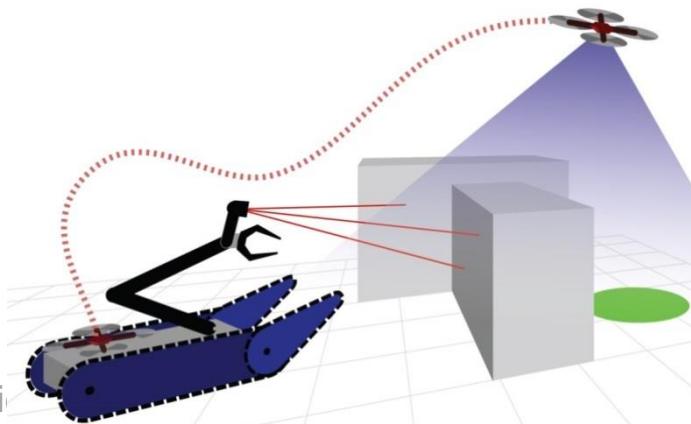
Robotics and Perception Group
<http://rpg.ifi.uzh.ch>
University of Zurich

Current Research

Visual & Inertial State Estimation and Mapping
[T-RO'08, IJCV'11, PAMI'13, RSS'15]



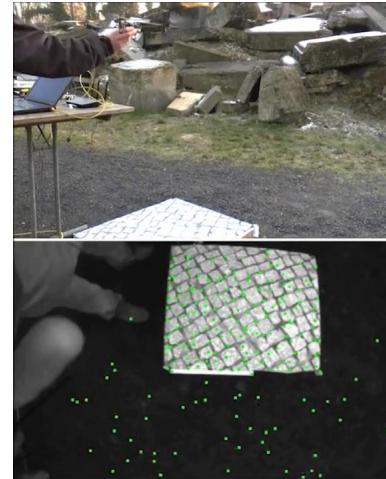
Collaboration of Aerial and Ground Robots
[IROS'13, SSRR'14]



Davi

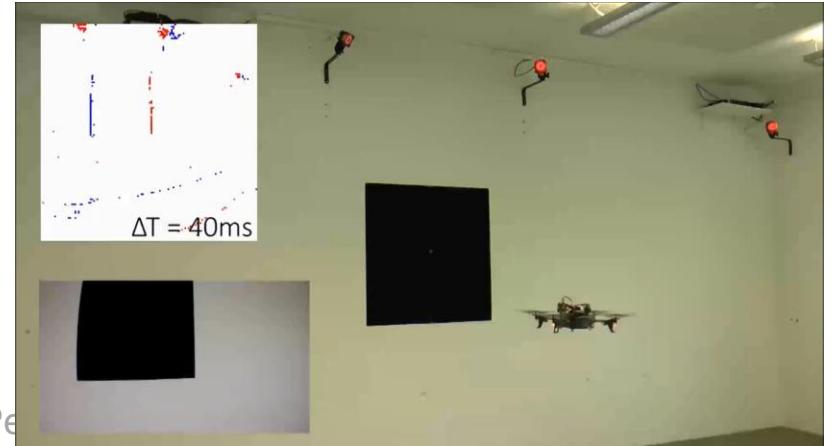
Robotics and Pe

Autonomous Navigation of Flying Robots
[AURO'12, RAM'14, JFR'15a-b]



3x

Event-based Vision for Agile Flight
[IROS'13, ICRA'14-15, RSS'15]



Outline

- Motivation
- Event-based Cameras: DVS and DAVIS
 - Generative model
 - Calibration
 - Visualization
 - Life-time estimation
 - Pose estimation

The Progress of Autonomous Robotics

Past



Kuka KR240

3000 Present

Perception Improvements



KIVA's Robotics Warehouse

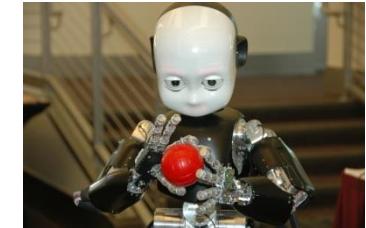


Autonomous Ground Vehicles

Davide Scaramuzza - University of Zurich – Robotics and Perception Group - rpg.ifi.uzh.ch



Google Car



iCub



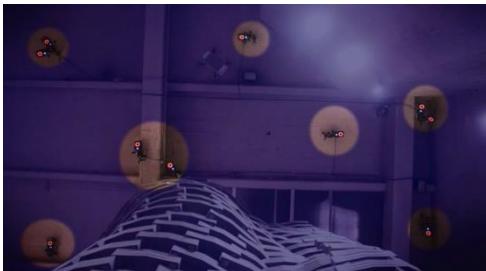
UPenn's
Swarm of Quadcopters

A Comparison between Off-board and On-board sensing

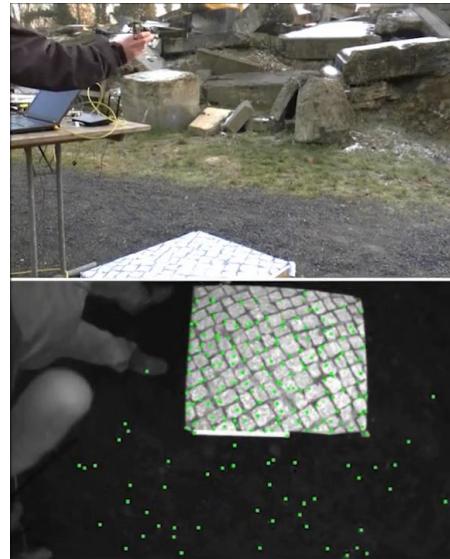
Off-board sensors



VICON-controlled quadcopter
Mueller, Lupashin, D'Andrea



Onboard sensors



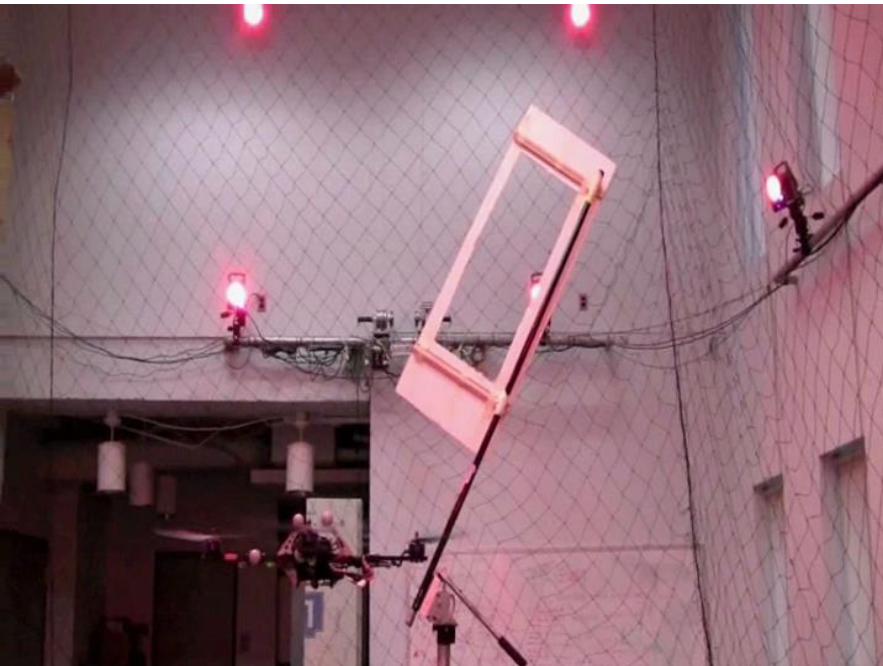
VISION-controlled quadcopter
Fontana, Faessler, Scaramuzza



3x

Open Problems and Challenges with Micro Helicopters

Current flight maneuvers achieved with onboard cameras are **still slow** compared with those attainable with Motion Capture Systems



Mellinger, Kumar



Mueller, D'Andrea

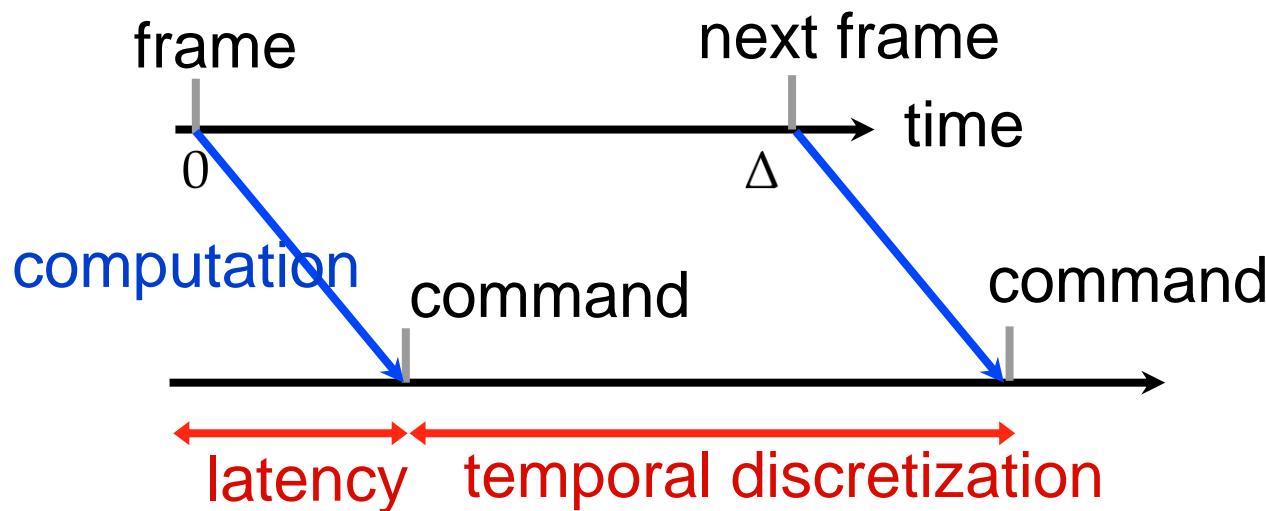
How fast can we go with an onboard camera?

Let's assume that we have perfect perception

*Can we achieve the same flight performances
attainable with motion capture systems or go even faster?*

To go faster, we need faster sensors!

- At the current state, the agility of a robot is limited by the latency and temporal discretization of its sensing pipeline [Censi & Scaramuzza, ICRA'14]
- Currently, the average robot-vision algorithms have latencies of 50-200 ms. This puts a hard bound on the agility of the platform. [Censi & Scaramuzza, ICRA'14]



[Censi & Scaramuzza, *Low Latency, Event-based Visual Odometry*, ICRA'14]

To go faster, we need faster sensors!

- At the current state, the agility of a robot is limited by the latency and temporal discretization of its sensing pipeline.
- Currently, the average robot-vision algorithms have latencies of 50-200 ms. This puts a hard bound on the agility of the platform.
- **Can we create low-latency, low-discretization perception architectures?**

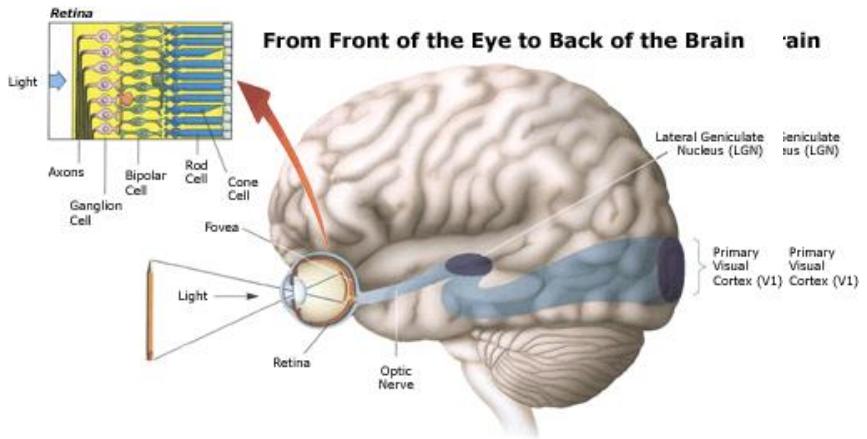
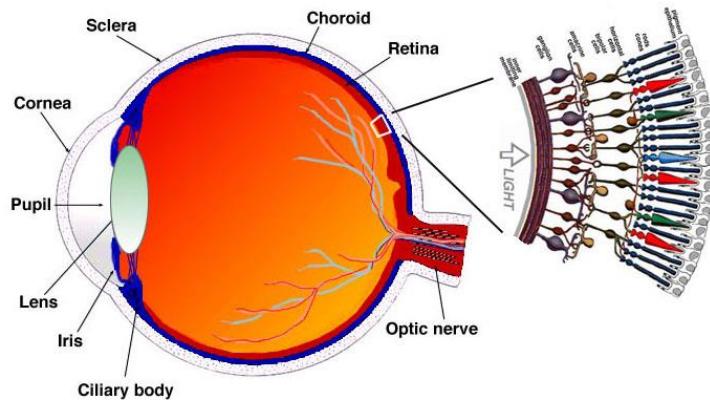
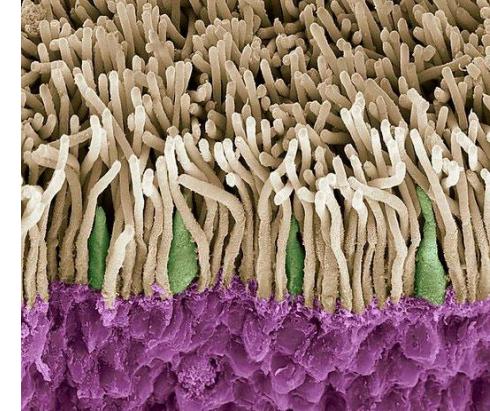
Yes...

...if we use a camera where pixels do not spike all at the same time

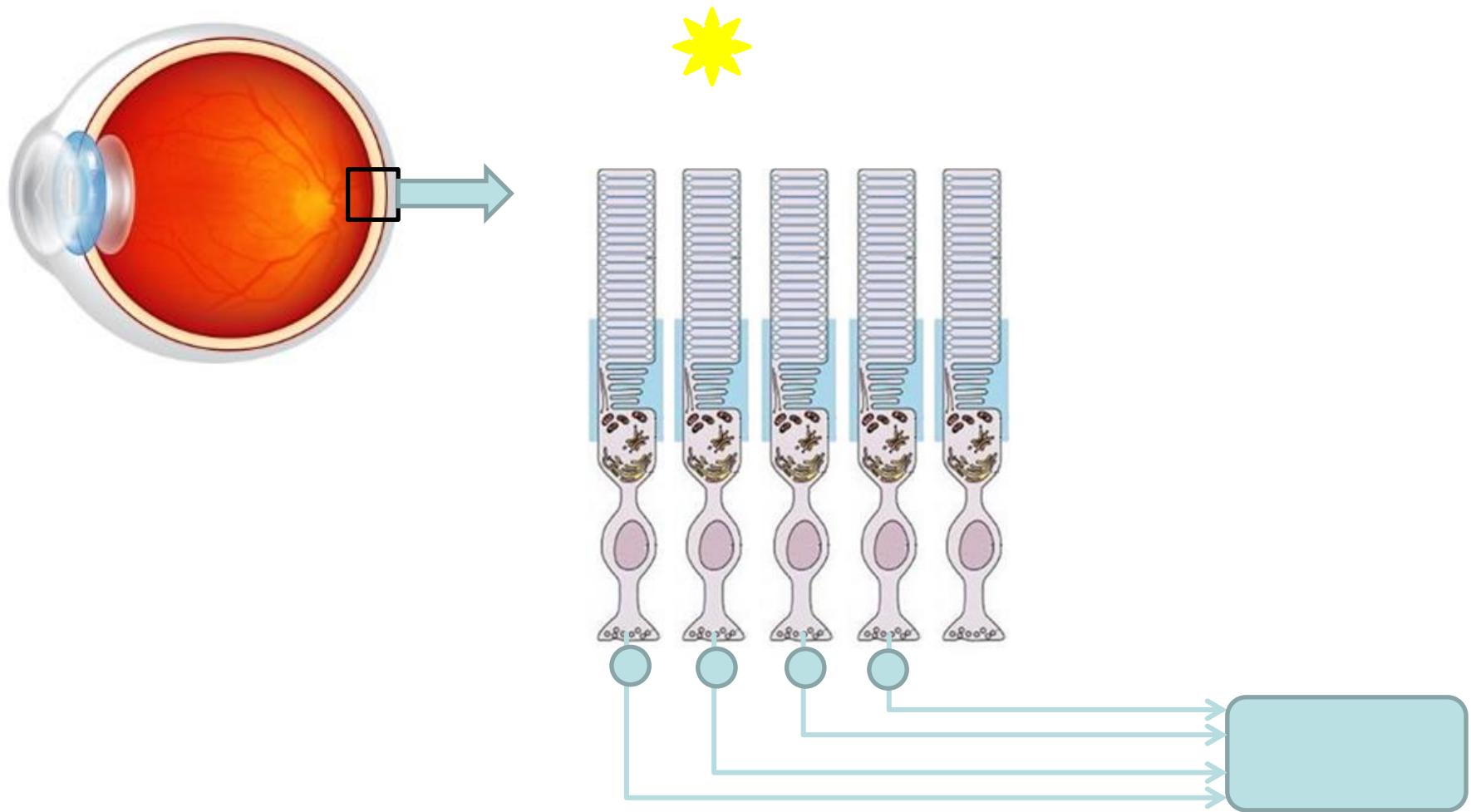
...in a way as we humans do..

Human Vision System

- Retina is ~1000mm²
- 130 million **photoreceptors**
 - 120 mil. rods and 10 mil. cones for color sampling
 - 1.7 million axons



Human Vision System



Dynamic Vision Sensor (DVS)



Event-based camera developed by Tobi Delbrück's group (ETH & UZH).

- Temporal resolution: **1 μ s**
- High dynamic range: **120 dB**
- Low transmission bandwidth: ~200Kb/s
- Low power: **20 mW**
- Cost: 2,500 EUR

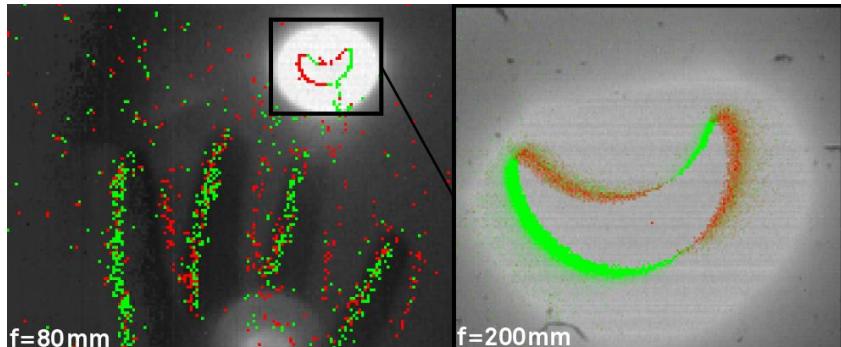
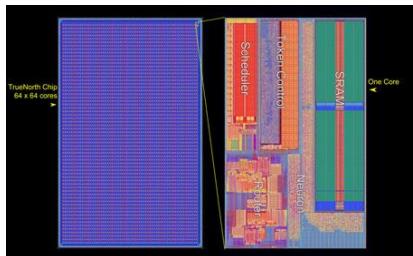
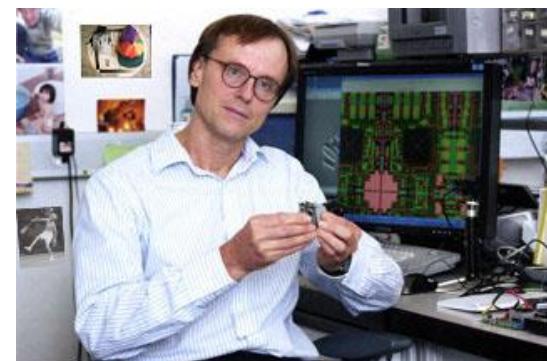


Image of the solar eclipse (March'15) captured by a DVS (courtesy of Sim Bamford by INILabs)



DARPA project Synapse: 1M neuron, brain-inspired processor: IBM TrueNorth



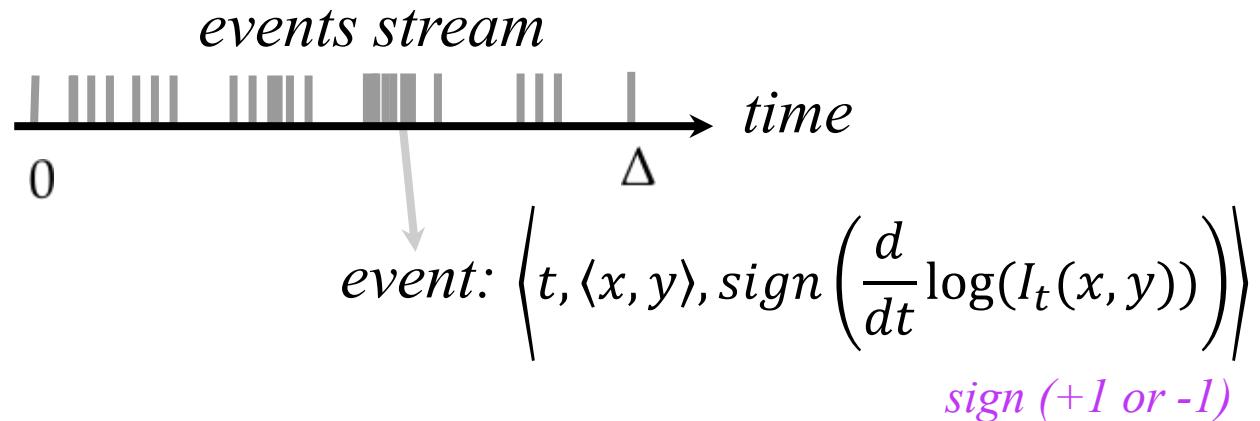
Tobi Delbrück

Camera vs DVS

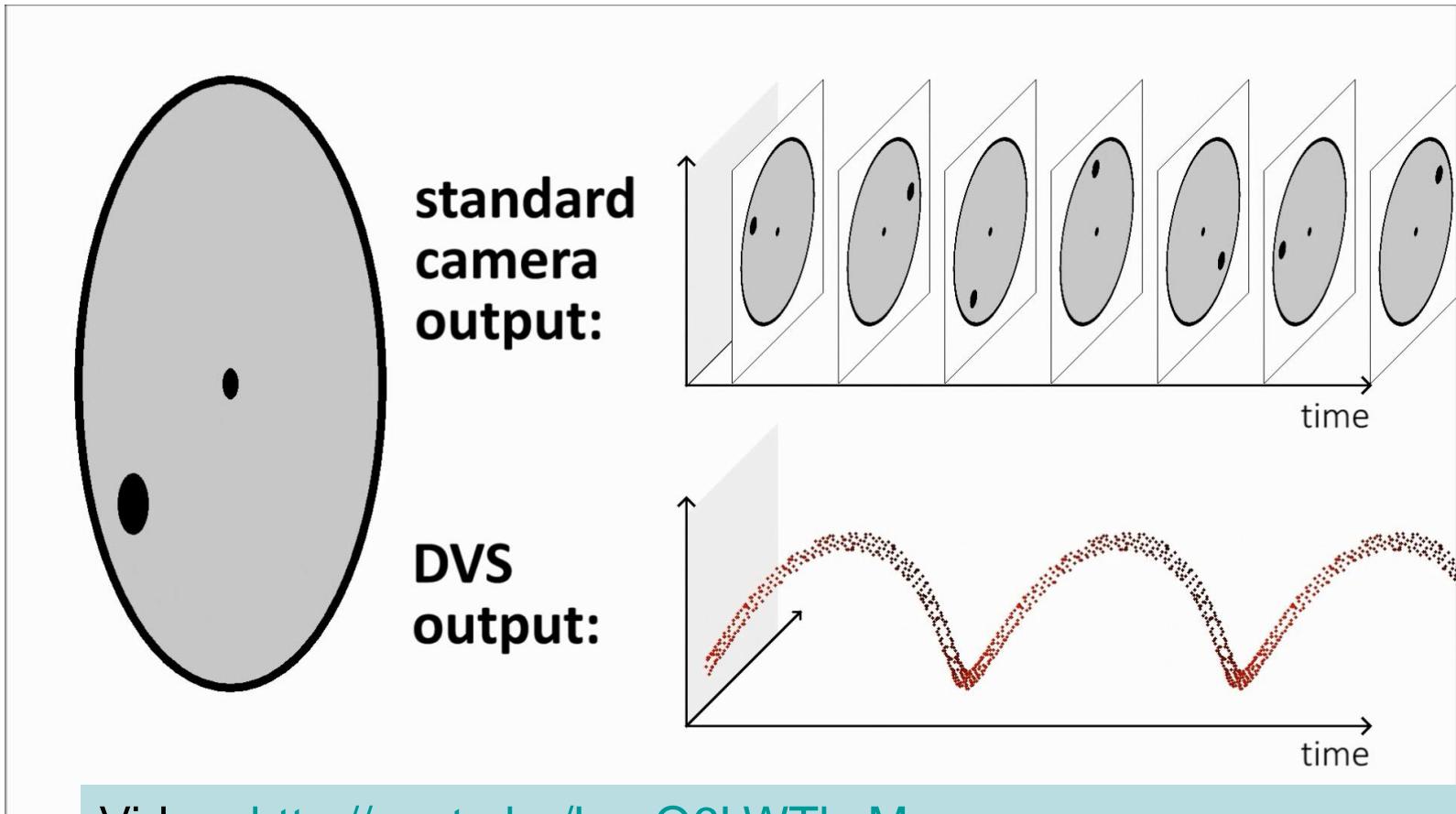
- A traditional camera outputs frames at **fixed time intervals**:



- By contrast, a **DVS** outputs **asynchronous events** at **microsecond resolution**. An event is generated each time a single pixel changes value



Camera vs Dynamic Vision Sensor



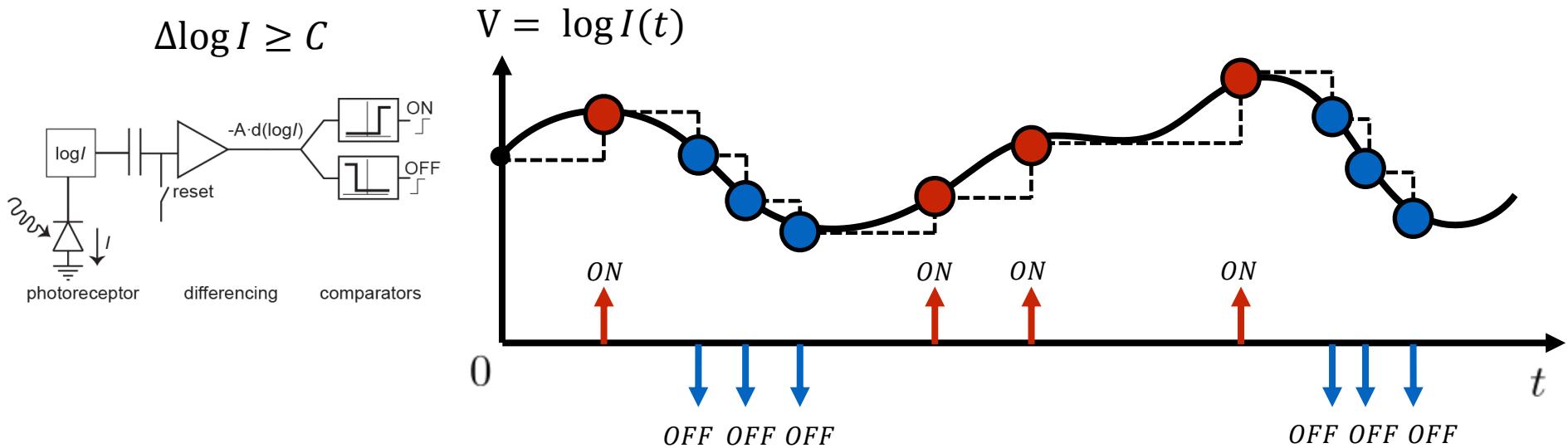
Video: <http://youtu.be/LauQ6LWTkxM>

If you intend to use this video in your presentations, please credit the authors of the paper below, plus the paper.

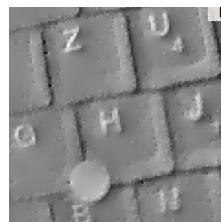


DVS Operating Principle [Lichtsteiner, ISCAS'09]

Events are generated any time a single pixel sees a change in brightness larger than C



The intensity signal at the event time can be reconstructed by integration of $\pm C$



[Cook et al., IJCNN'11]



[Kim et al., BMVC'15]

[Lichtsteiner, Posch, Delbrück. A 128x128 120 dB 15 μ s Latency Asynchronous Temporal Contrast Vision Sensor. 2008]

Dynamic Vision Sensor (DVS)



Advantages

1. **low-latency** (~1 micro-second)
2. **high-dynamic range** (120 dB instead 60 dB)
3. **Very low bandwidth** (only intensity changes are transmitted):
~200Kb/s
4. **Low storage capacity, processing time, and power**

Disadvantages

1. Requires totally **new vision algorithms**
2. **No intensity information** (only binary intensity changes)
3. **Very low image resolution:** 128x128 pixels

Lichtsteiner, Posch, Delbrück. A 128x128 120 dB 15µs Latency Asynchronous Temporal Contrast Vision Sensor. 2008

High-speed cameras vs DVS



	Photron Fastcam SA5	Matrix Vision Bluefox	DVS
Max fps or measurement rate	1MHz	90 Hz	1MHz
Resolution at max fps	64x16 pixels	752x480 pixels	128x128 pixels
Bits per pixels	12 bits	8-10	1 bits
Weight	6.2 Kg	30 g	30 g
Active cooling	yes	No cooling	No cooling
Data rate	1.5 GB/s	32MB/s	~200KB/s on average
Power consumption	150 W + llighting	1.4 W	20 mW
Dynamic range	n.a.	60 dB	120 dB

Related Work (1/2)

➤ Event-based Tracking

- Conradt et al., ISCAS'09
- Drazen, 2011
- Mueller et al., ROBIO'11
- Censi et al., IROS'13
- Delbruck & Lang, Front. Neuros.'13
- Lagorce et al., T-NNLS'14

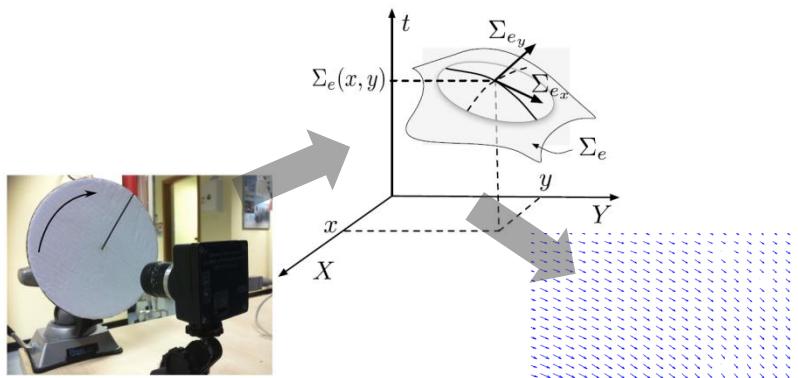


➤ Event-based Optic Flow

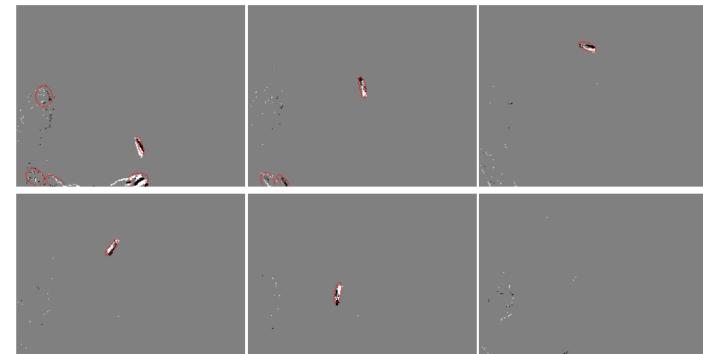
- Cook et al, IJCNN' 11
- Benosman, T-NNLS'14

➤ Event-based ICP

- Ni et al., T-RO'12

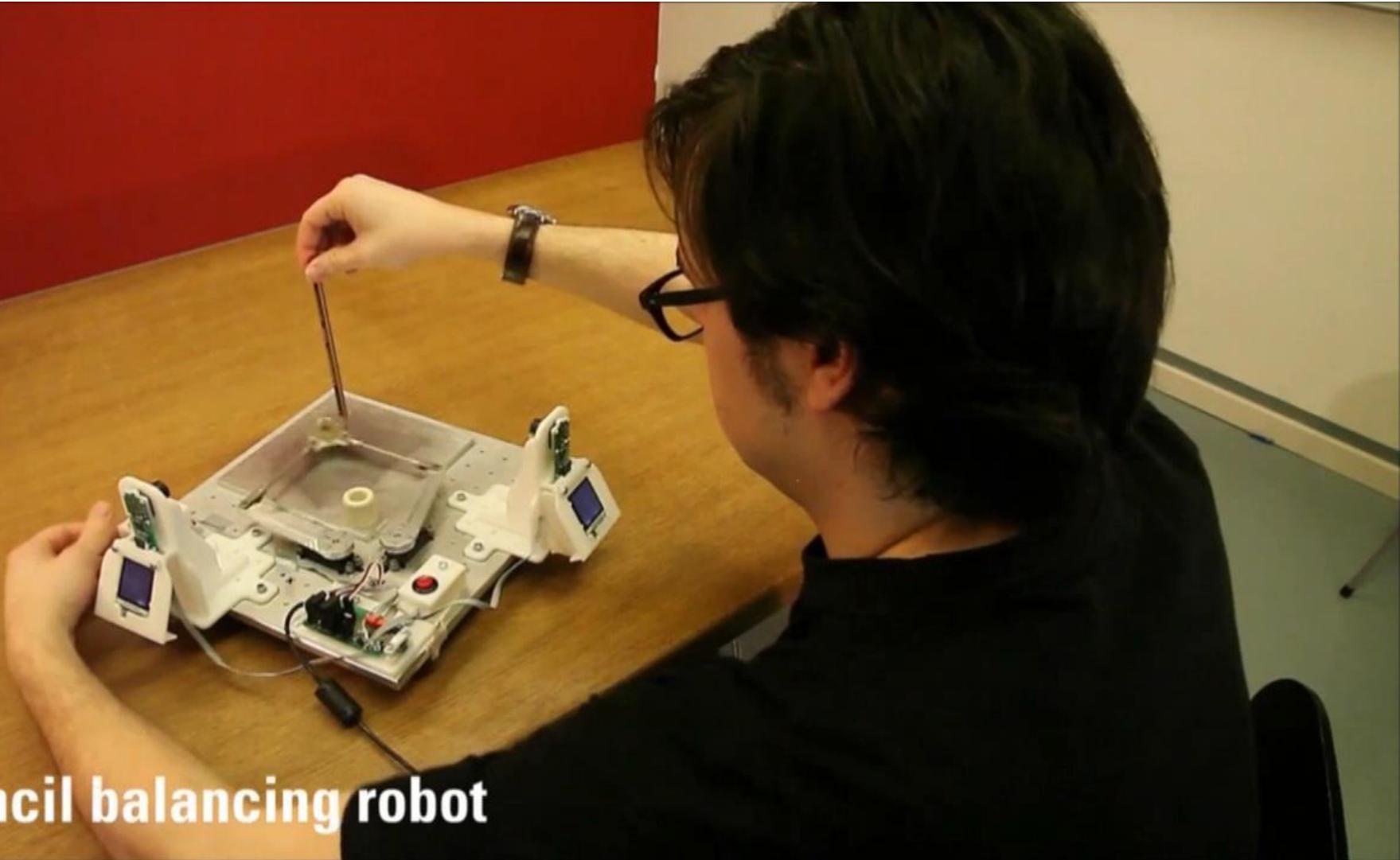


Event-Based Visual Flow [Benosman, TNNLS' 14]



Asynchronous Event-Based Multikernel Algorithm for High-speed Visual Features Tracking [Lagorce et al., TNNLS' 14]
Perception Group - rpg.mpi-inf.mpg.de

Related Work (1/2)

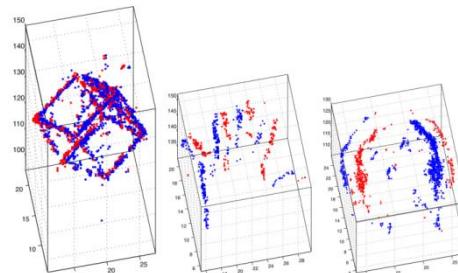


Pencil balancing robot

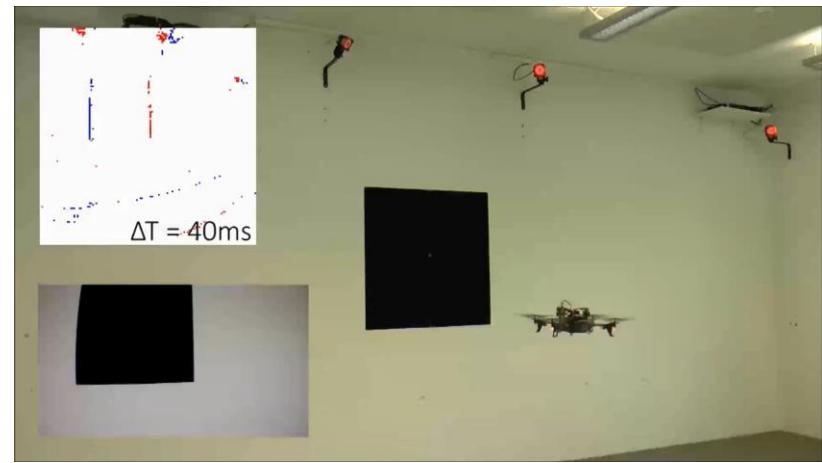
Conradt, Cook, Berner, Lichtsteiner, Douglas, Delbrück, **A pencil balancing robot using a pair of AER dynamic vision sensors**, IEEE International Symposium on Circuits and Systems. 2009

Related Work (2/2)

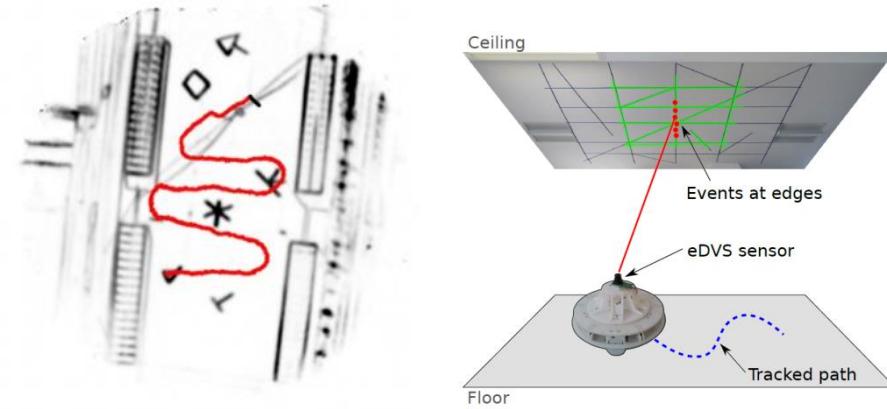
- **Event-based 6DoF Localization**
 - Weikersdorfer et al., ROBIO'12
 - Mueggler et al., IROS'14
- **Event-based Rotation estimation**
 - Cook et al, IJCNN' 11
 - Kim et al, BMVC'15
- **Event-based Visual Odometry**
 - Censi & Scaramuzza, ICRA'14
- **Event-based SLAM**
 - Weikersdorfer et al., ICVS'13
- **Event-based 3D Reconstruction**
 - Carneiro'13



Event-based 3D reconstruction from neuromorphic retinas [Carneiro et al., NN'13]



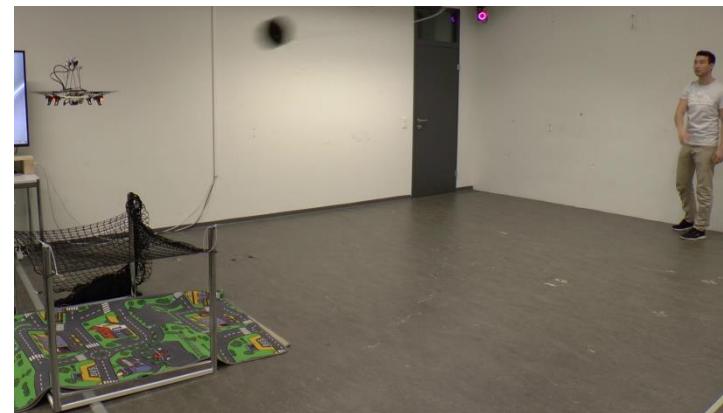
Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, [Mueggler et al., IROS'14]



Simultaneous Localization and Mapping for Event-Based Vision Systems [Weikersdorfer et al., ICVS'13]

Related Work: Event-based Tracking

- **Collision avoidance**
 - Guo, ICM'11
 - Clady, FNS' 14
 - Mueggler, ECMR'13
- **Estimating absolute intensities**
 - Cook et al, IJCNN' 11
 - Kim et al, BMVC'15
- **HDR panorama & Mosaicing**
 - Kim et al, BMVC'15
 - Belbachir, CVPRW'14, Schraml, CVPR'15

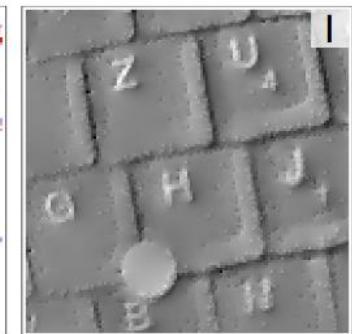
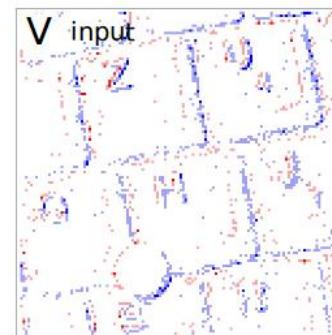


Towards Evasive Maneuvers with Quadrotors
using Dynamic Vision Sensors [Mueggler et al., ECMR'15]



Simultaneous Mosaicing and Tracking with an
Event Camera [Kim et al., BMVC'15]

Brighter
Darker



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

Live Demos

A Simple Use Case:

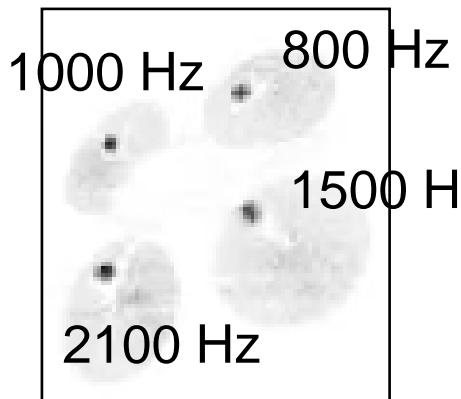
Active LED marker Tracking

[IROS'13]

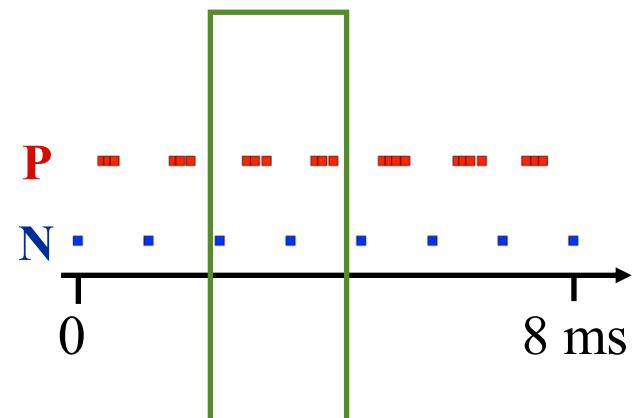
[Censi, Brandli, Delbruck, Scaramuzza, Low-latency localization by Active LED Markers tracking using a Dynamic Vision Sensor , IROS'13]

Low-latency Active LED Tracking [IROS'13]

- Active LED blinking at a high frequency (>1 KHz).
- A DVS can detect the LED position and discriminate frequency
- Advantages:
 - simple
 - low latency
 - robust to interferences



Time slice = blinking period \times 2



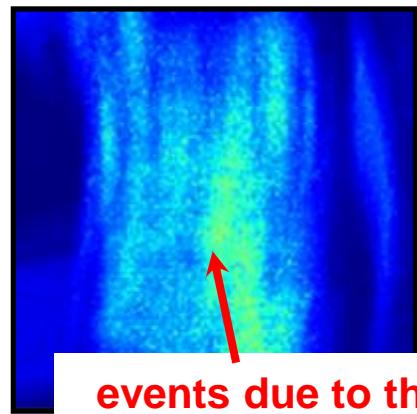
Blinking LEDs with different frequency act as uniquely identifiable markers

[Censi, Brandli, Delbrück, Scaramuzza, Low-latency localization by Active LED Markers tracking using a Dynamic Vision Sensor , IROS'13]

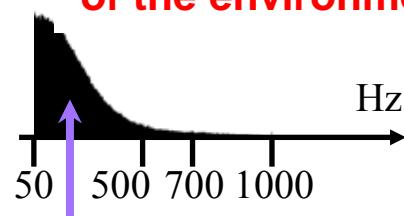
Low-latency Active LED Tracking [IROS'13]

- Robust to the camera motion

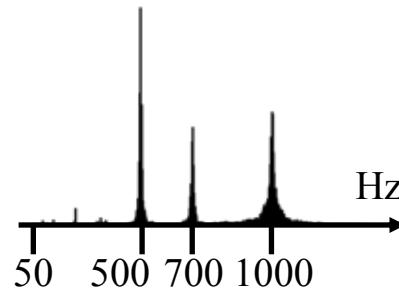
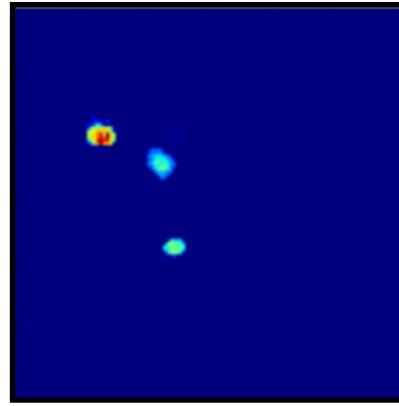
no LEDs, with motion



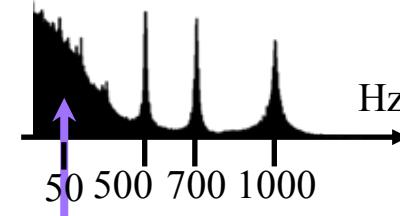
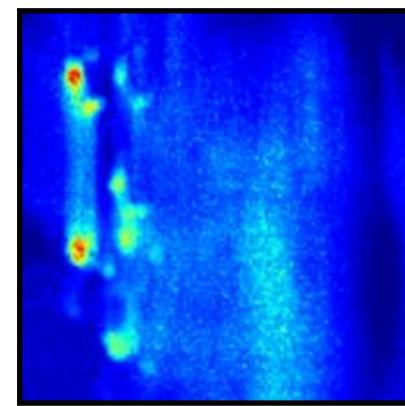
events due to the
apparent motion
of the environment



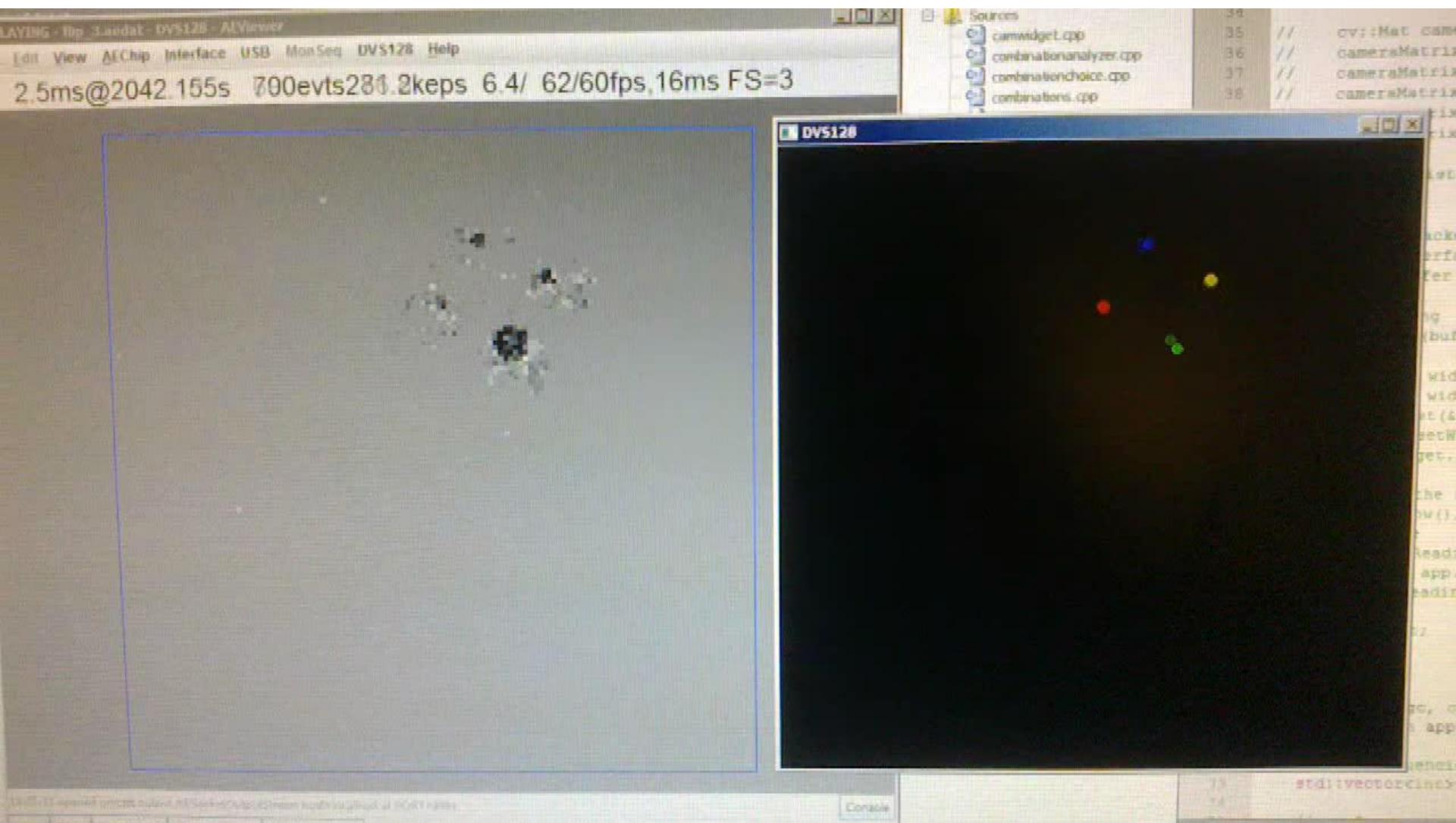
with LEDs, no motion



LEDs + motion



Results: Flip



[Censi, Brandli, Delbruck, Scaramuzza, Low-latency localization by Active LED Markers tracking using a Dynamic Vision Sensor , IROS'13]

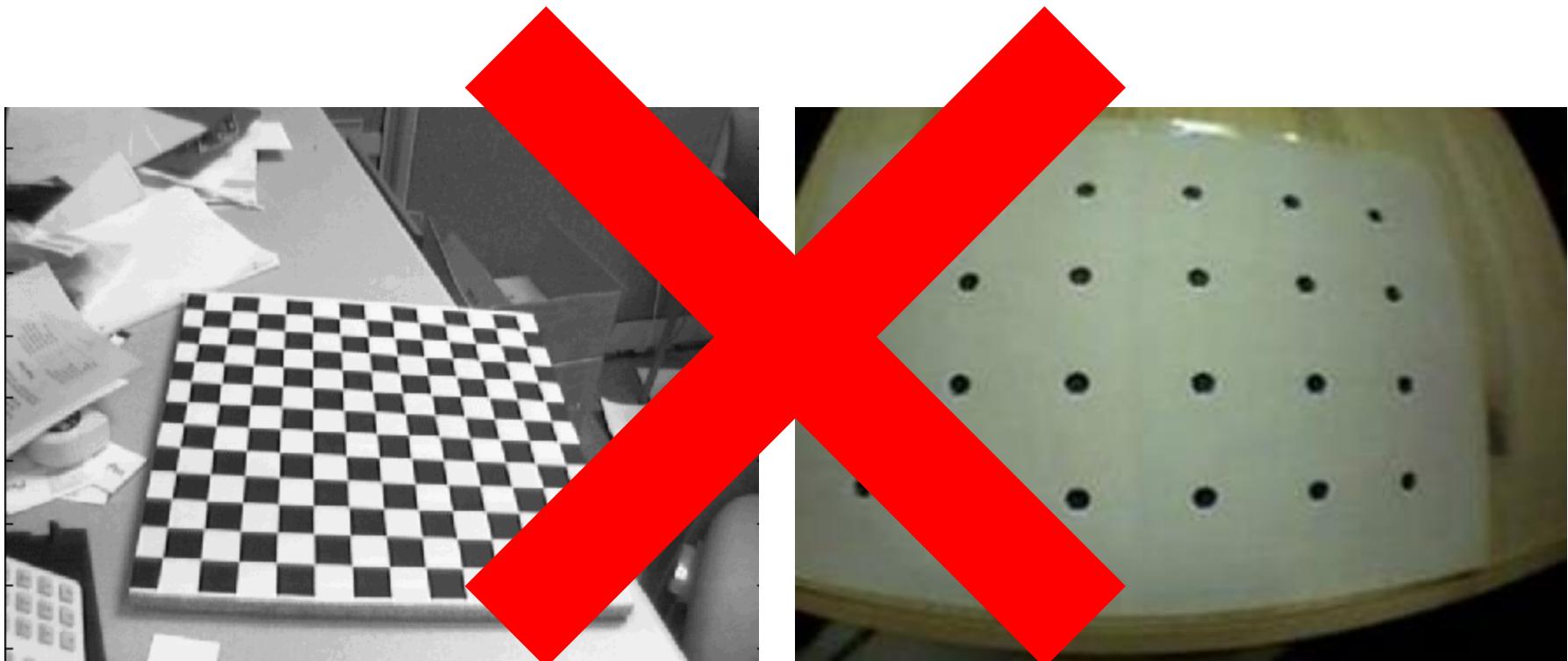
Calibration

[IROS'14]

[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]

Calibration of a DVS [IROS'14]

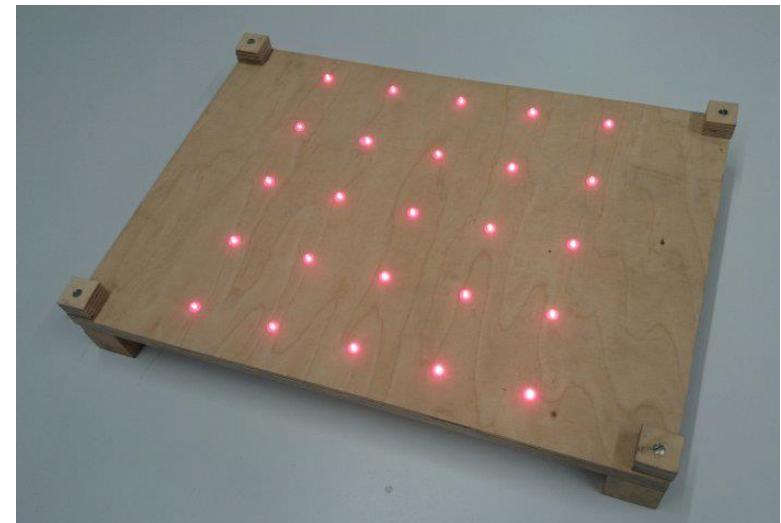
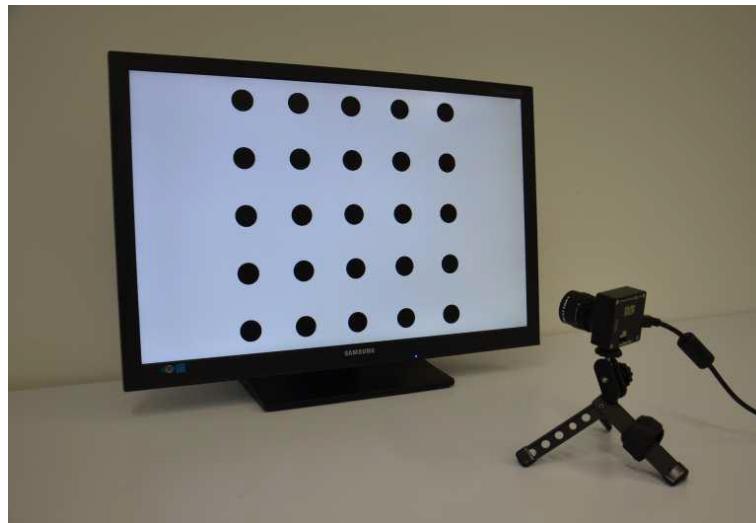
- Standard **pinhole camera model** still valid (same optics)
- Standard passive calibration patterns **cannot be used**
 - need to move the camera → inaccurate corner detection



[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]

Calibration of a DVS [IROS'14]

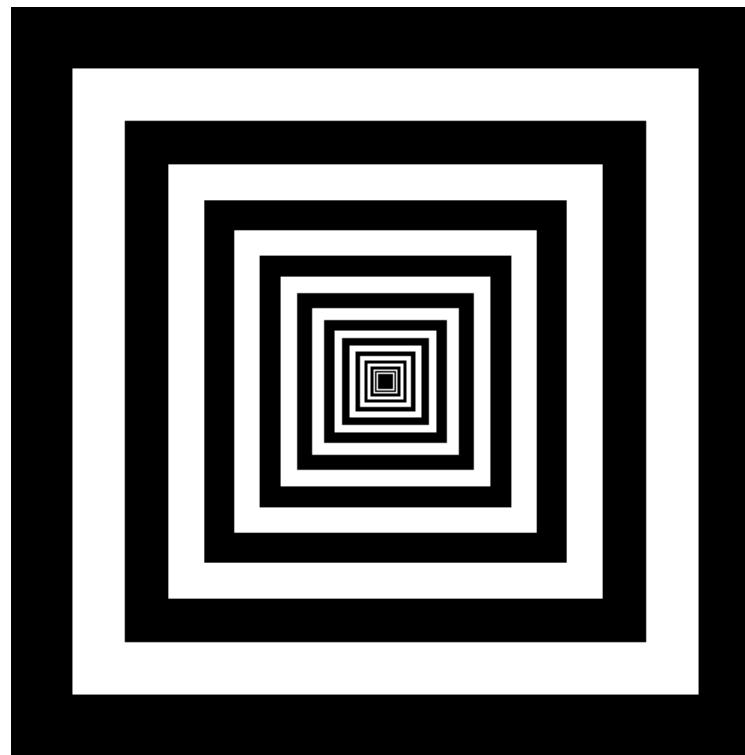
- Standard **pinhole camera model** still valid (same optics)
- Standard passive calibration patterns **cannot be used**
 - need to move the camera → inaccurate corner detection
- **Blinking patterns** (computer screen, LEDs)
- ROS DVS driver + intrinsic and extrinsic stereo calibration **open source**:
https://github.com/uzh-rpg/rpg_dvs_ros



[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]

Calibration of a DVS [IROS'14]

- How to adjust the focus?
 - Use screen blicking pattern such as concentric, logarithmically-spaced, B&W squares



Event-based Vision

Why is Event-based Vision challenging?

- **DVS output is a sequence of asynchronous events** rather than a standard image => A new *paradigm shift* is needed to deal with these data
- Naive solution: **accumulate events** occurred over a certain time interval and adapt «standard» CV algorithms.
 - Drawback: **it increases latency**
- Instead, we want **each single event** to be used **as it comes!**
 1. **Lifetime:** for how long is an event active?
 2. **How to do asynchronous,** event-based estimation?

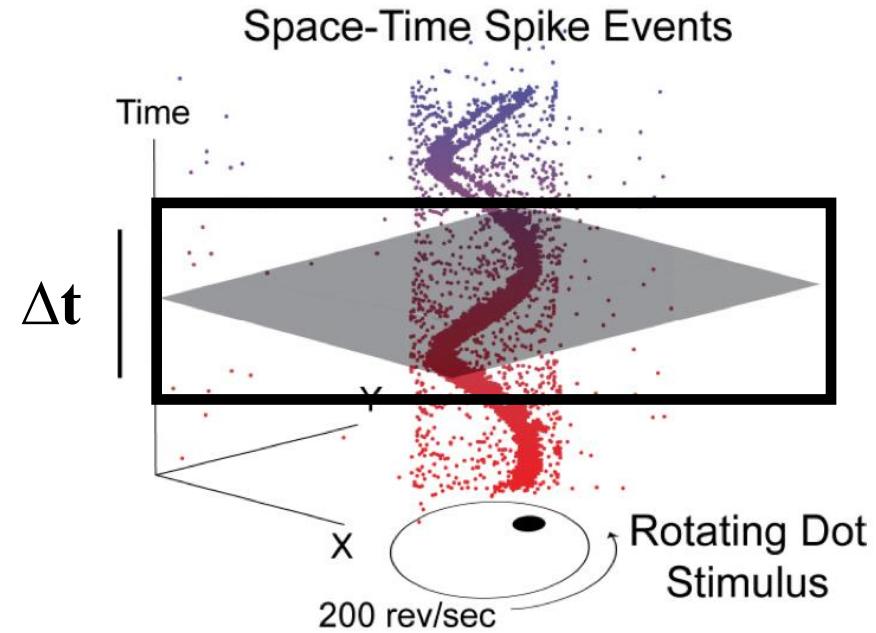
Life-time Estimation

[ICRA'15]

E. Mueggler, C. Forster, N. Baumli, G. Gallego, D. Scaramuzza, **Lifetime Estimation of Events from Dynamic Vision Sensors**, ICRA'15.

How do we Visualize the Event Stream?

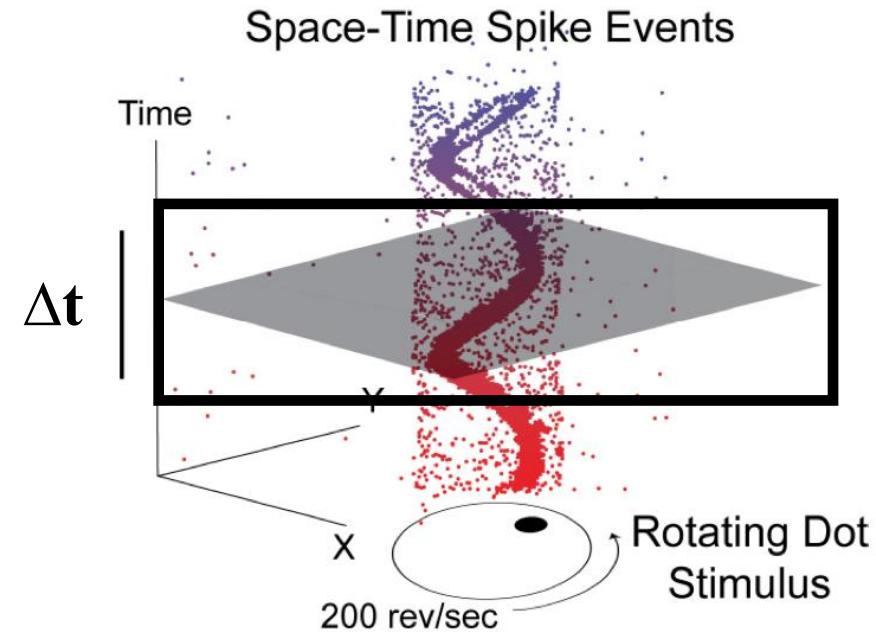
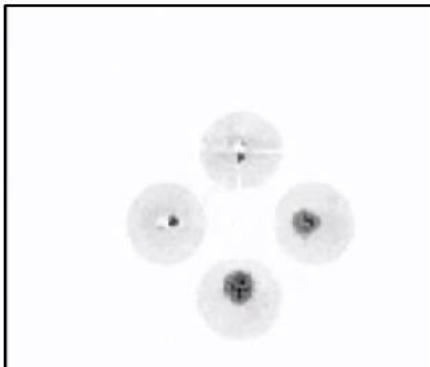
Naive solution: accumulate all events occurred in a time interval Δt



How do we Visualize the Event Stream?

Naive solution: accumulate all events occurred in a time interval Δt

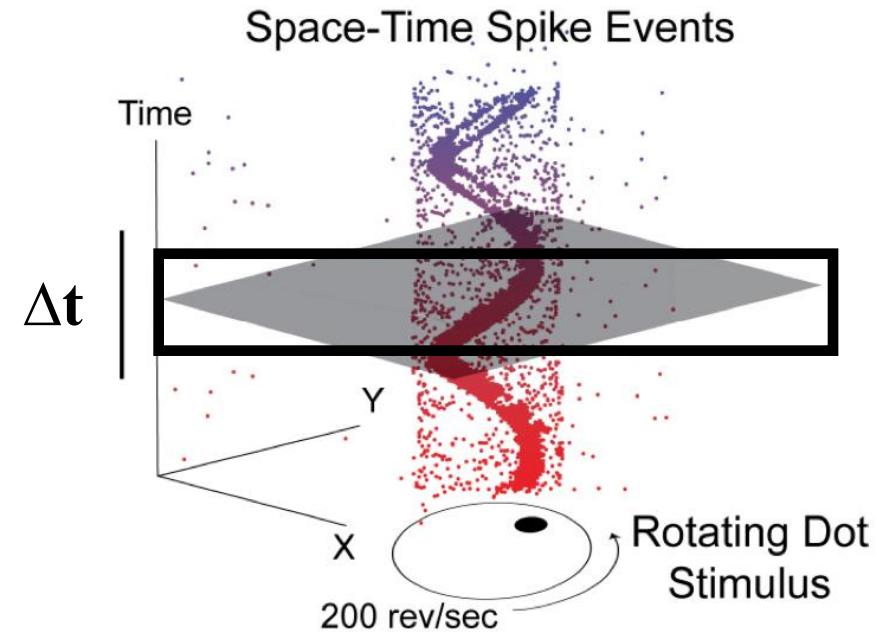
1 video frame = 33 ms (real time)



How do we Visualize the Event Stream?

Naive solution: accumulate all events occurred in a time interval Δt

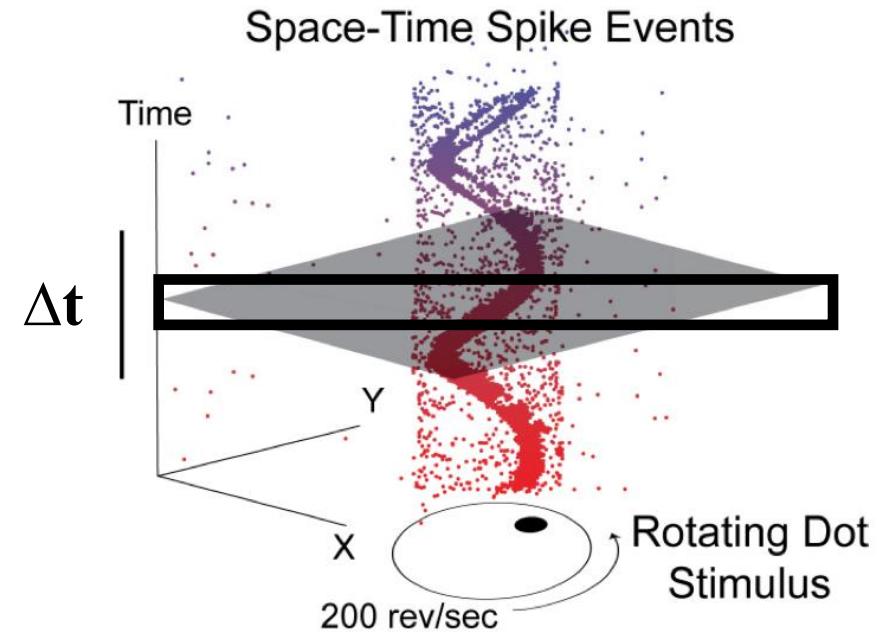
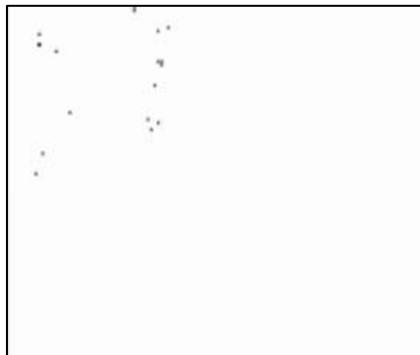
1 video frame = 1 ms



How do we Visualize the Event Stream?

Naive solution: accumulate all events occurred in a time interval Δt

1 video frame = 0.5 ms



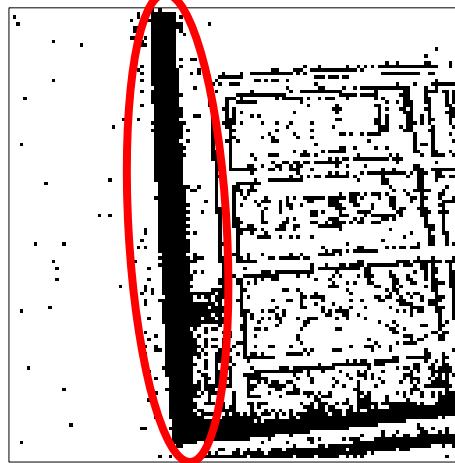
How do we Visualize the Event Stream? [ICRA'15]

Naive solution: accumulate all events occurred in a time interval Δt

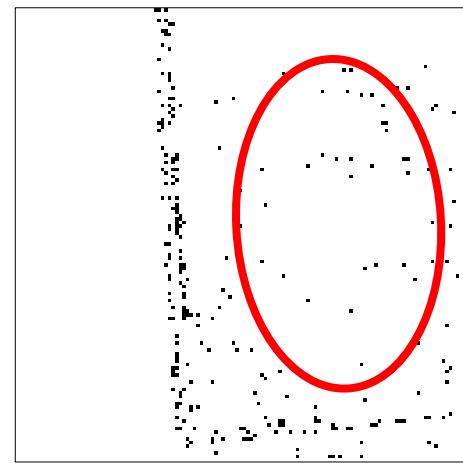
- Large integration time causes motion blur
- Small integration time causes sparsity



$\Delta t = 30\text{ms}$

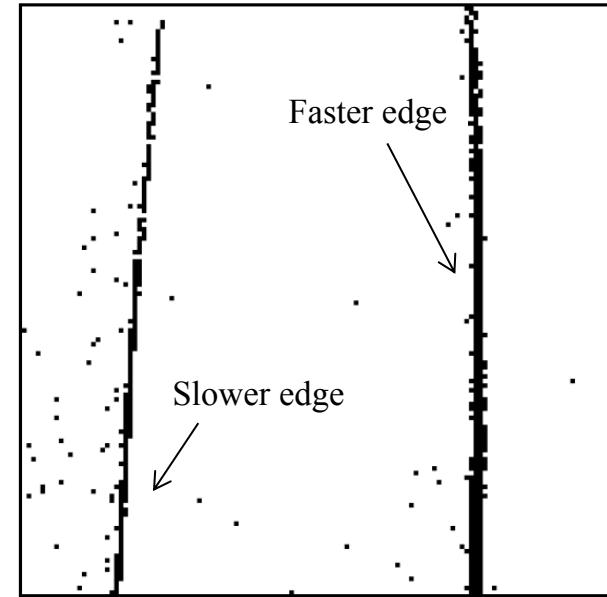
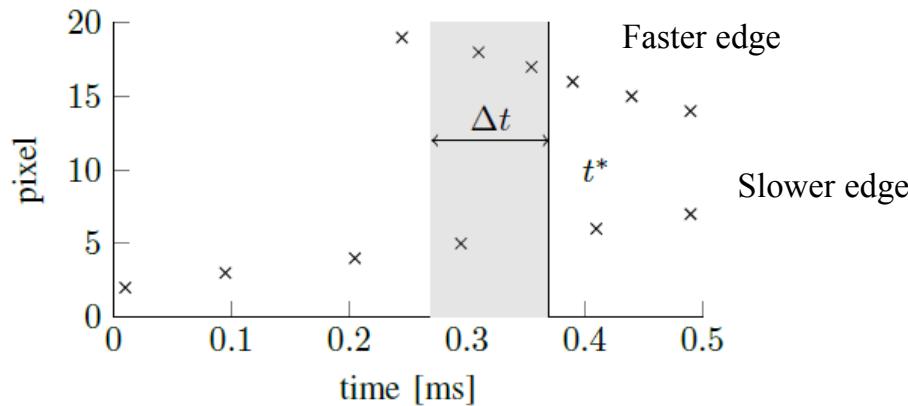


$\Delta t = 1\text{ms}$

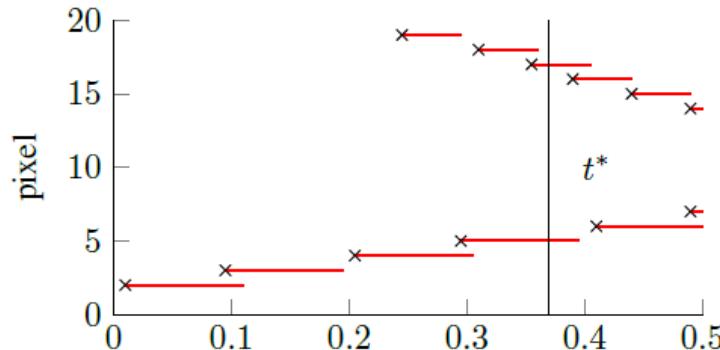


Event Lifetime [ICRA'15]

- Naive method:



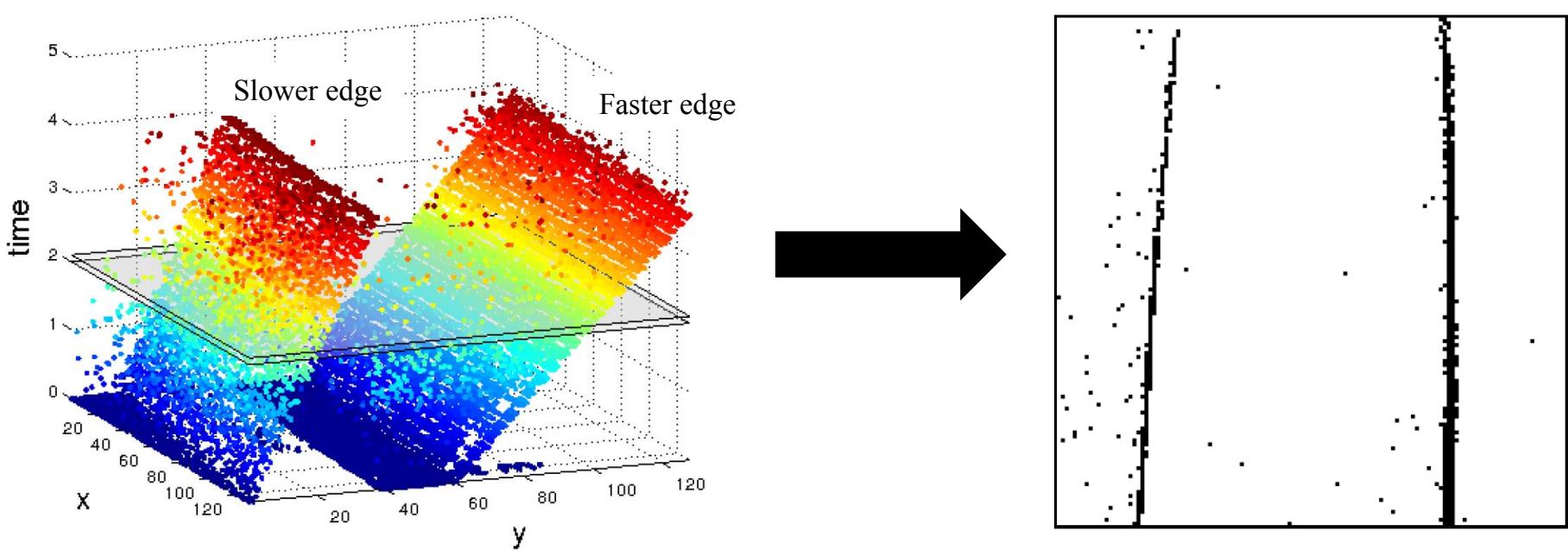
- Lifetime (in red): time needed to trigger an event at adjacent pixel [Mueggler'15]



The event lifetime allows determining all events that are active at a specific time. This allows using standard CV algorithms on an event-based fashion

Surface of Active Events [Benosman, NNL'14]

- Event $e = \langle x, y, p, t \rangle$
- Surface of Active Events $\Sigma_e(x, y) = t$
 - similar to an elevation map



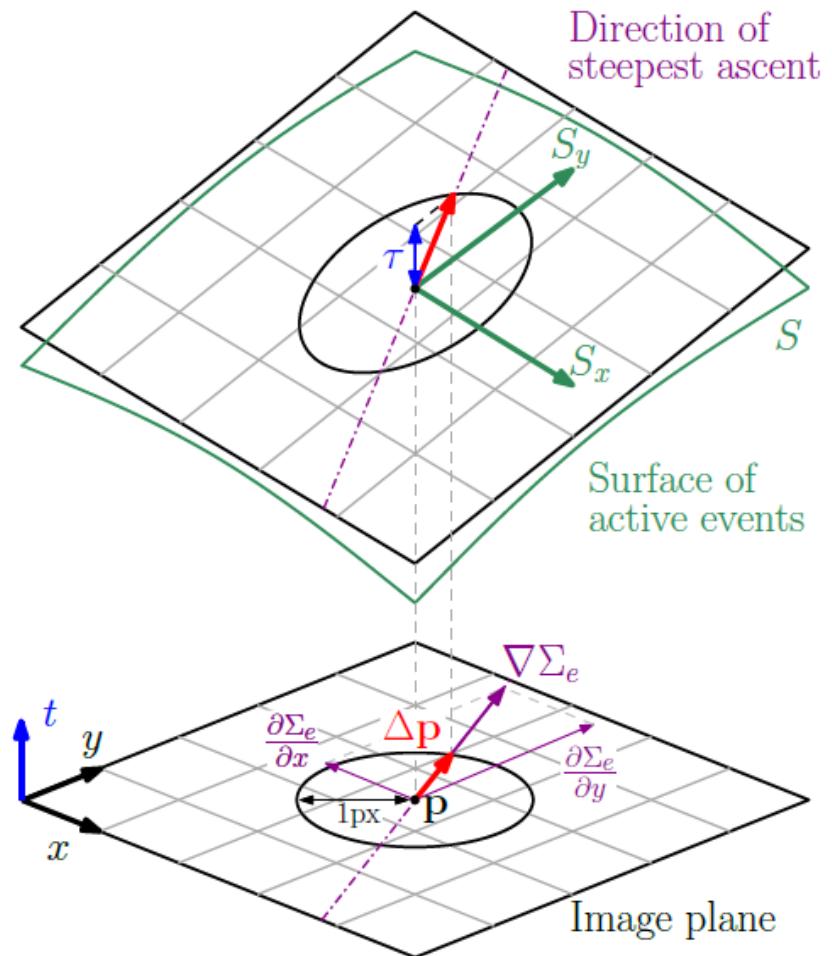
Lifetime estimation of Events [ICRA'15]

- Event velocity on image plane is related to the gradient in the surface of active events:

$$\nabla \Sigma_e(\mathbf{p}) = (v_x^{-1}(\mathbf{p}), v_y^{-1}(\mathbf{p}))^\top$$

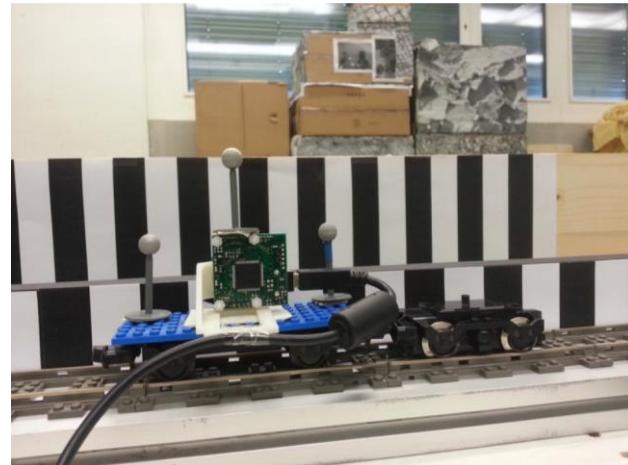
- Lifetime of the event:

$$\tau(\mathbf{p}) = \|\nabla \Sigma_e(\mathbf{p})\| = \sqrt{v_x^{-2} + v_y^{-2}}$$

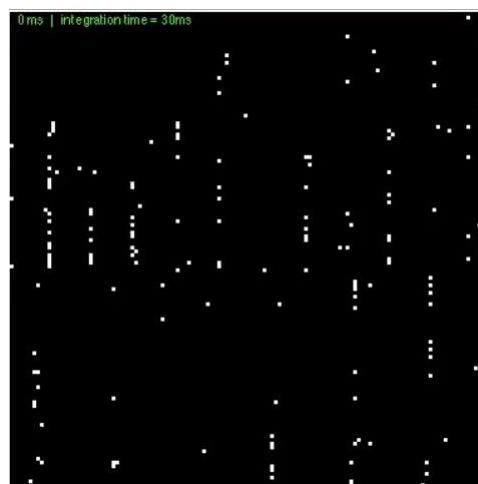


Lifetime estimation: Results with a Stripe Pattern [ICRA'15]

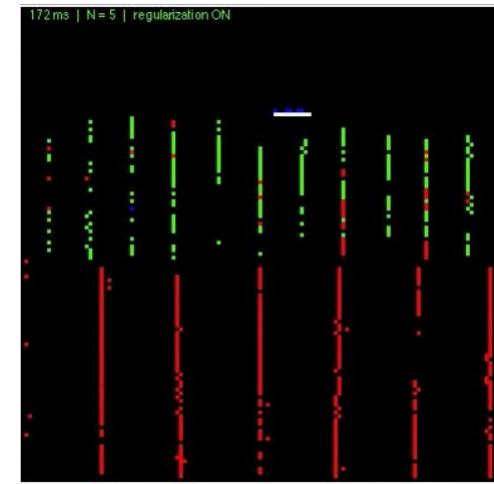
- DVS moving on a model train with constant velocity
- Patterns at $0.1m$, $0.2m$ and $5m$ away from DVS, respectively



$\Delta t = 1\text{ms}$



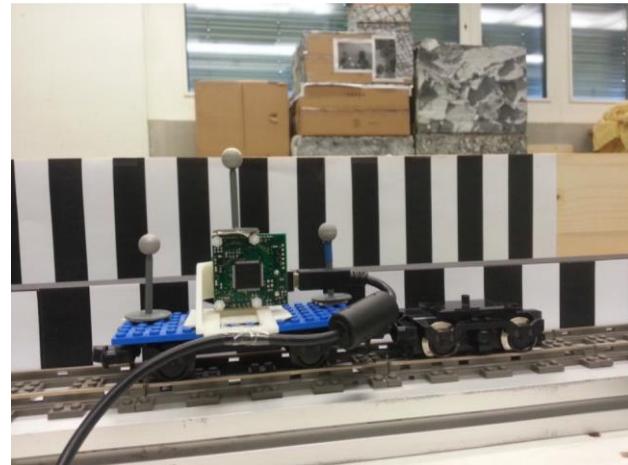
$\Delta t = 30\text{ms}$



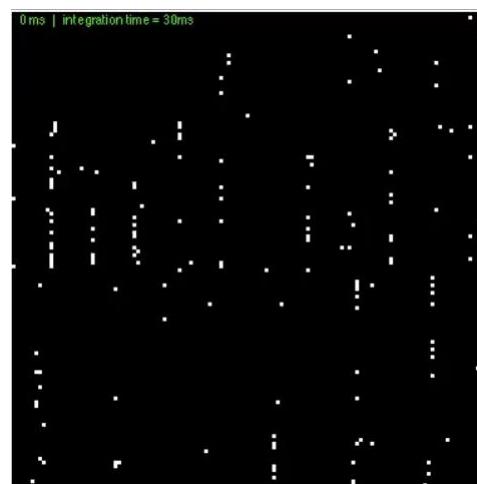
After lifetime estimation

Lifetime estimation: Results with a Stripe Pattern [ICRA'15]

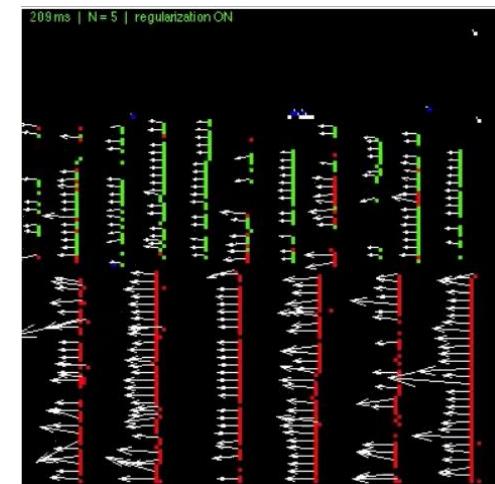
- DVS moving on a model train with constant velocity
- Patterns at $0.1m$, $0.2m$ and $5m$ away from DVS, respectively



$\Delta t = 1\text{ms}$



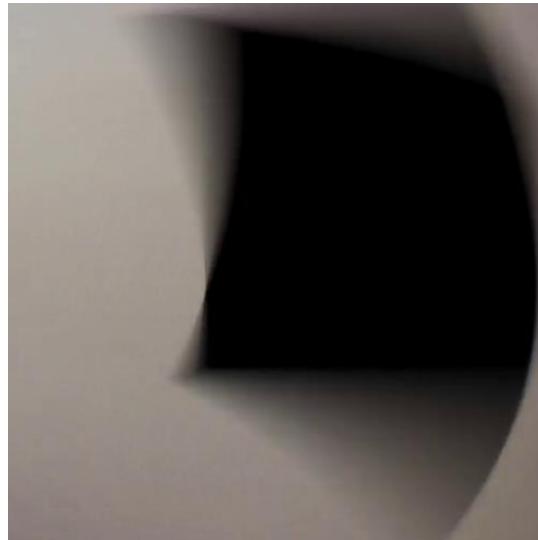
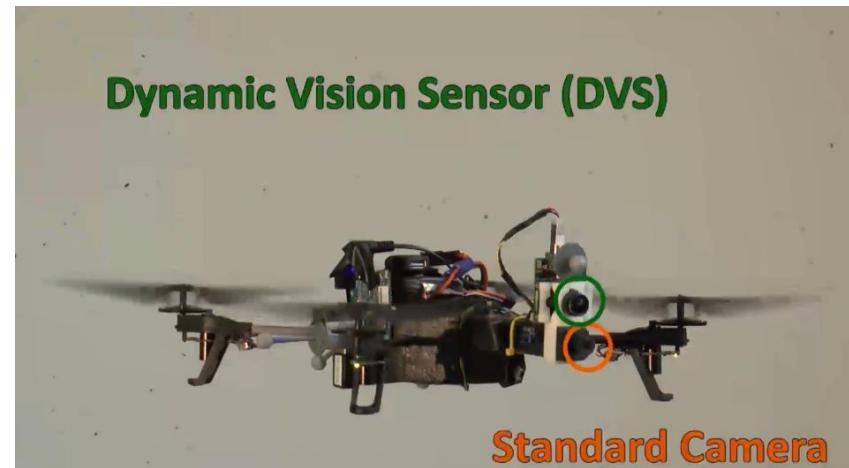
$\Delta t = 30\text{ms}$



Event-based optical flow

Lifetime estimation: Results from a Drone's flip [ICRA'15]

- Quadrotor equipped with DVS and standard camera
- Flips with rotational speeds of 1200 deg/s

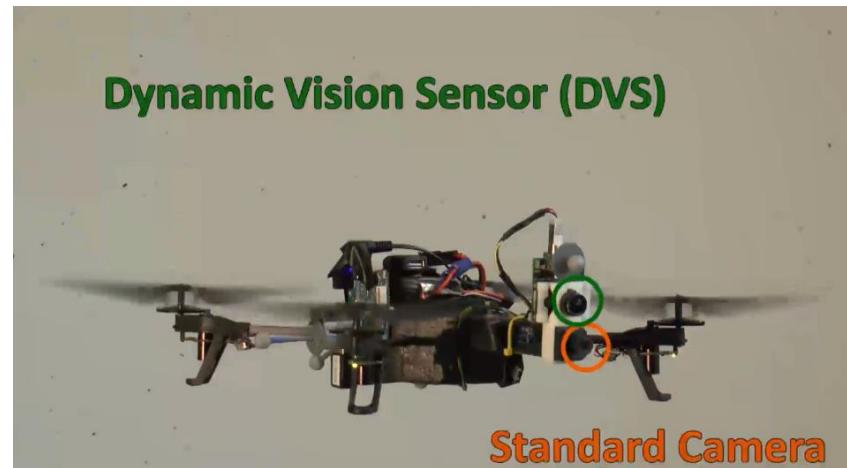


standard camera



Lifetime estimation: Results from a Drone's flip [ICRA'15]

- Quadrotor equipped with DVS and standard camera
- Flips with rotational speeds of 1200 deg/s



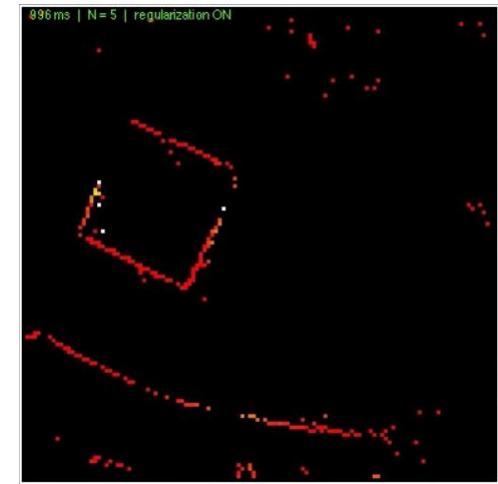
Flip:



$\Delta t = 1\text{ms}$



$\Delta t = 30\text{ms}$



After lifetime estimation

Asynchronous, Event-based Vision

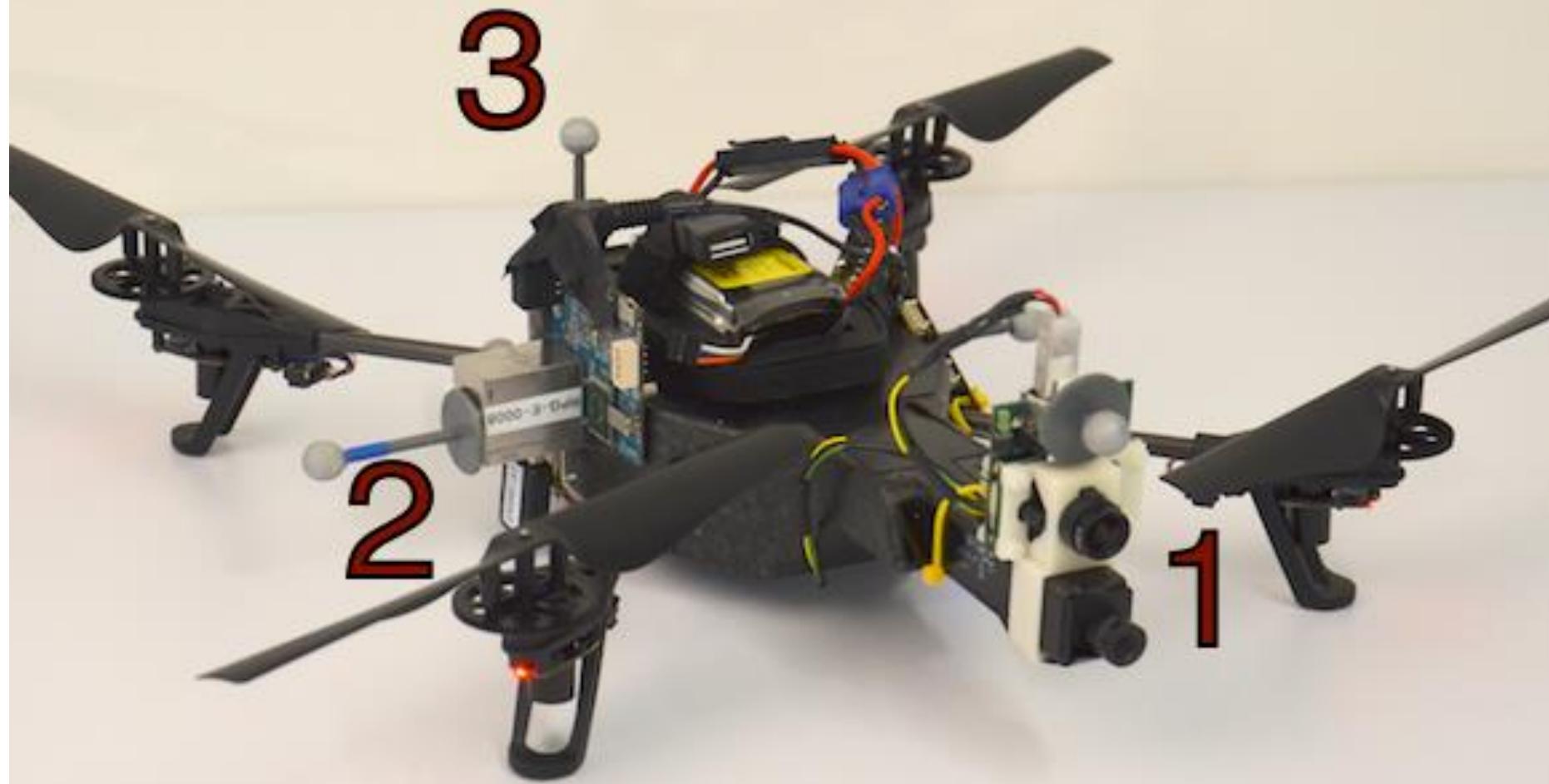
[ICRA'14]

[Censi & Scaramuzza, *Low Latency, Event-based Visual Odometry*, ICRA'14]

Asynchronous, Event-based Vision

- The **event lifetime** is a useful tool to leverage all the events active at a specific time instant
 - Drawback: **it increases latency**
- Instead, we want **each single event** to be used **as it comes!**
 - It allows pose estimation at unprecedented speed, **up to 1MHz!**
- Problem
 - DVS output is a sequence of **asynchronous events** rather than a standard image
 - Thus, a **new paradigm shift** is needed to deal with its data

DVS mounted on a quadrotor AR Drone



[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]. Featured on [IEEE Spectrum](#)

Application Experiment: Quadrotor Flip (1,200 deg/s)

Dynamic Vision Sensor (DVS)



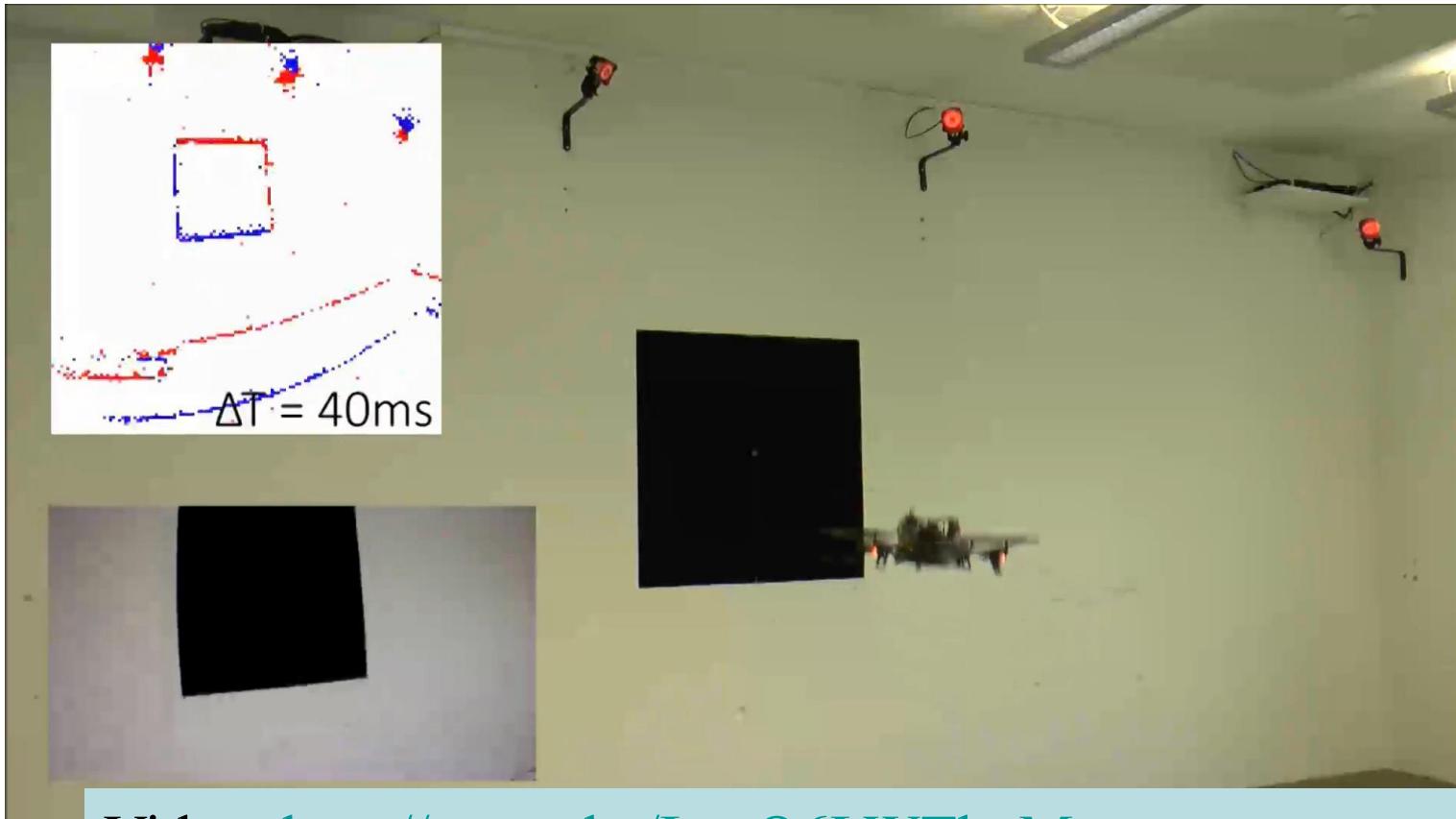
Video: <http://youtu.be/LauQ6LWTkxM>

If you intend to use this video, please credit the authors of the paper below, plus the paper.

[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]. Featured on [IEEE Spectrum](#)



Application Experiment: Quadrotor Flip (1,200 deg/s)

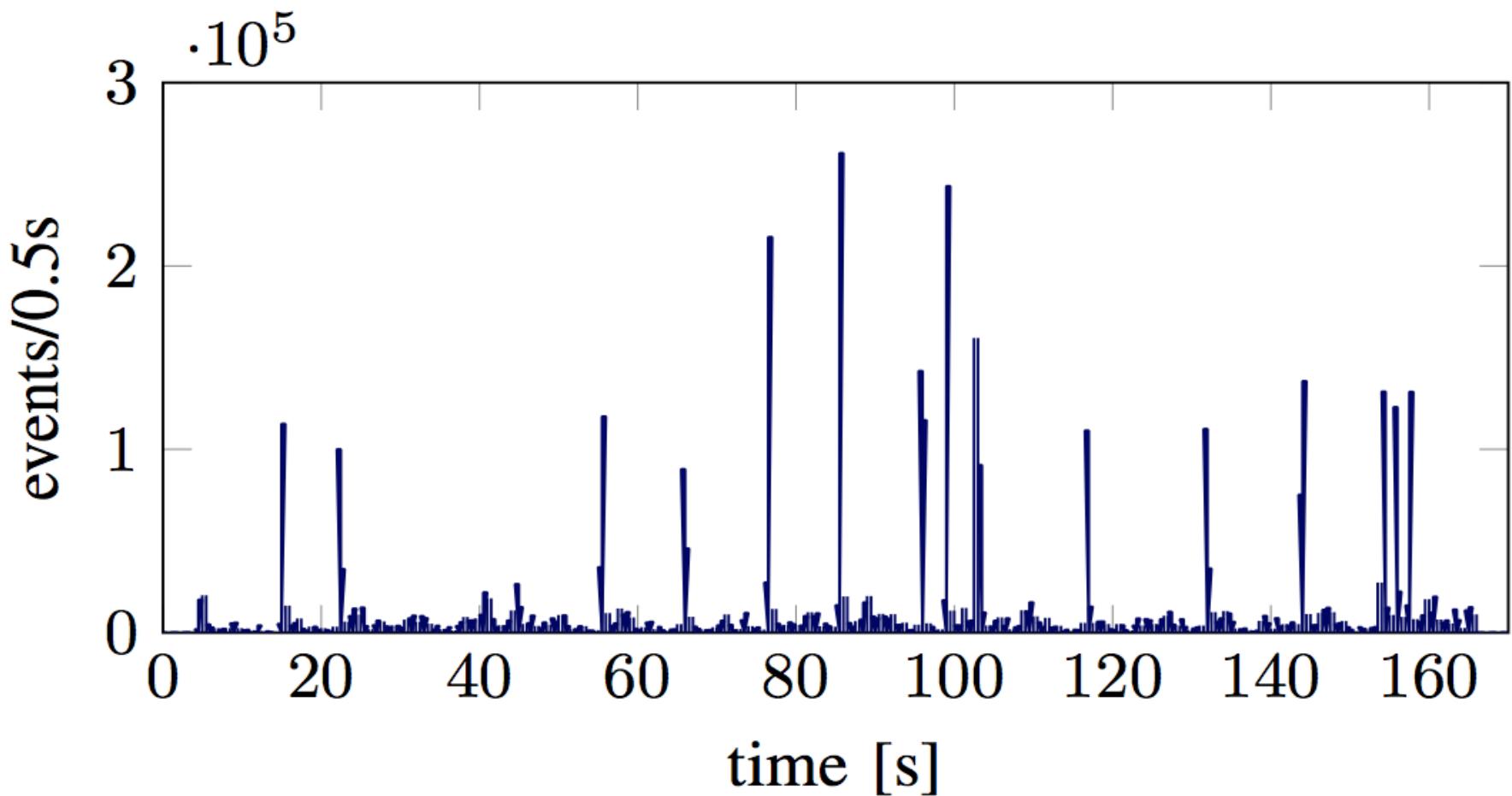


Video: <http://youtu.be/LauQ6LWTkxM>

If you intend to use this video, please credit the authors of the paper below, plus the paper.

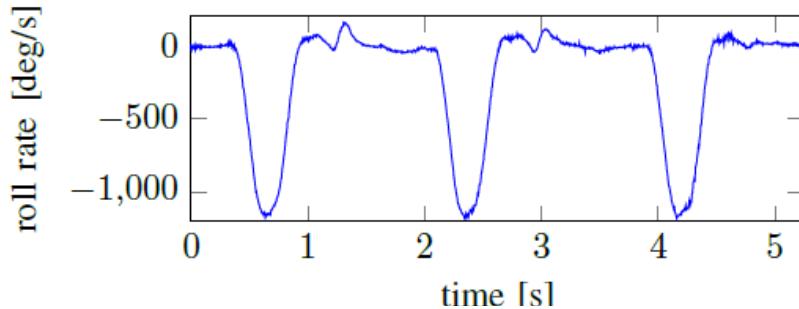
 [Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]. Featured on [IEEE Spectrum](#)

Events per time

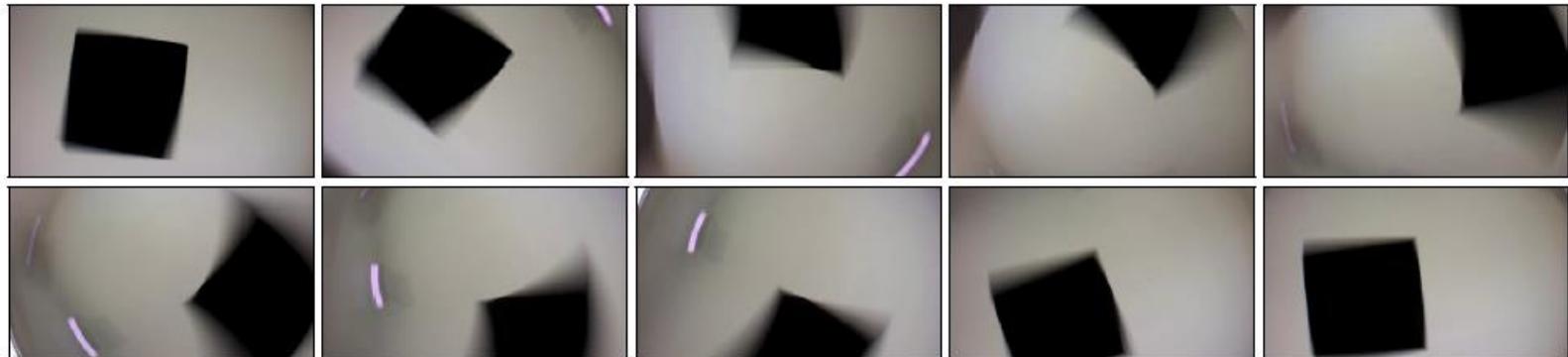
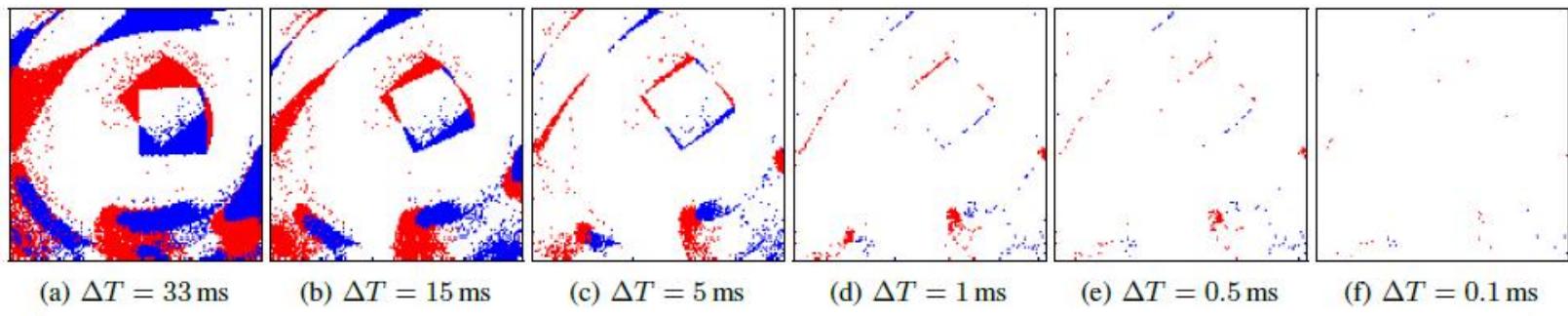


[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]. Featured on [IEEE Spectrum](#)

Camera and DVS renderings



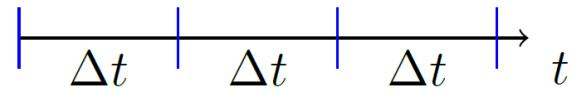
Peak Angular Speed:
1,200 deg/s



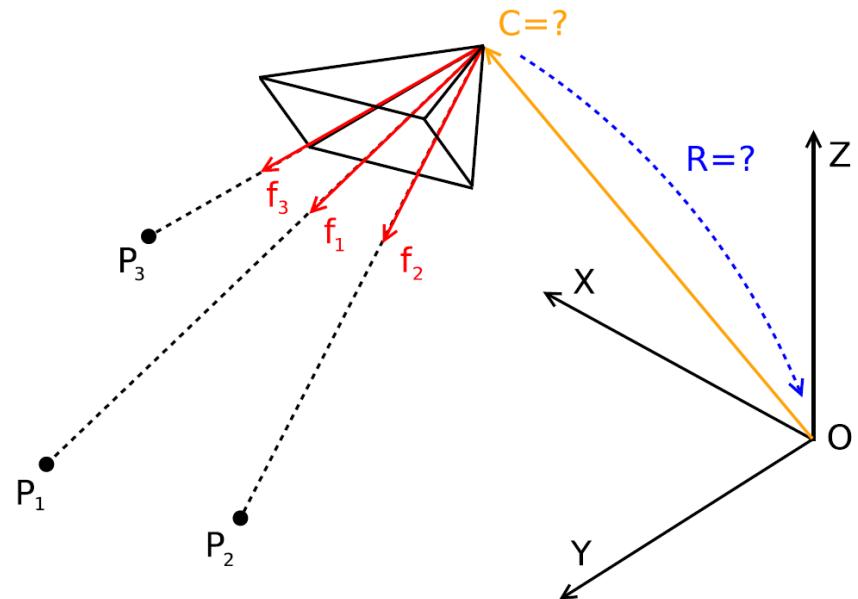
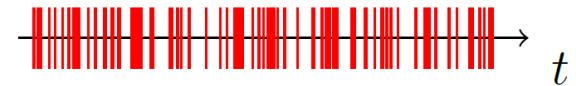
Pose Estimation

- Standard camera: pose at each frame
- DVS: a single event does not provide enough information
 - Need at least 3 events

Standard CMOS camera

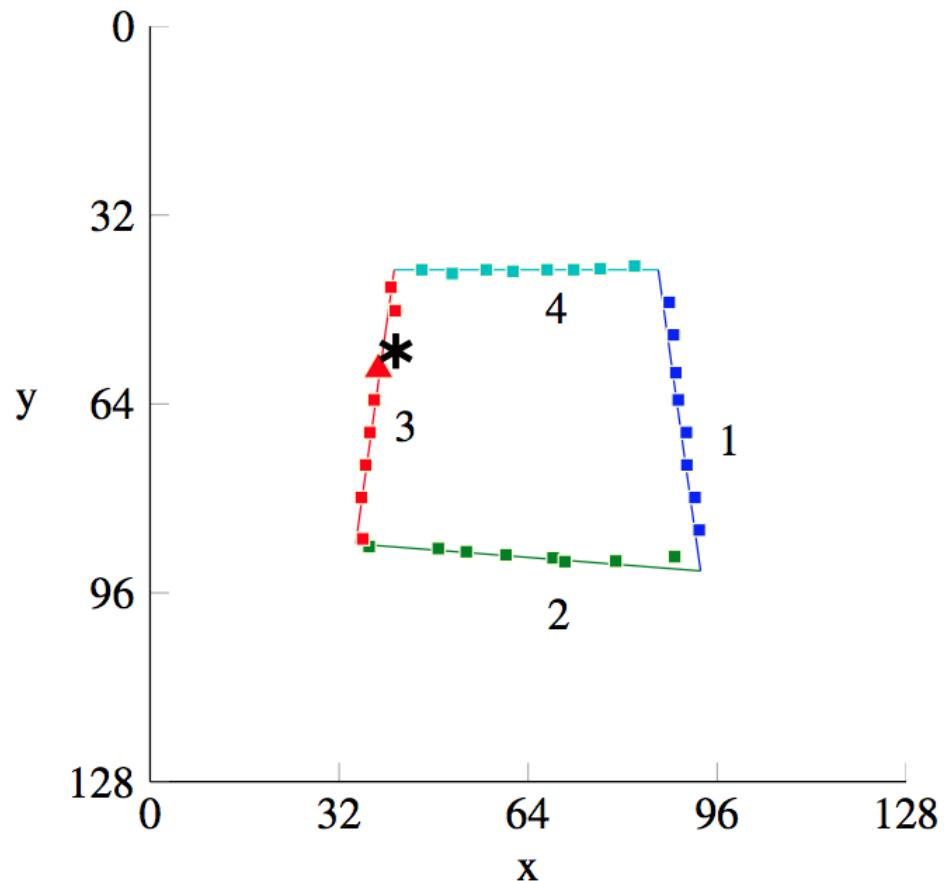


DVS



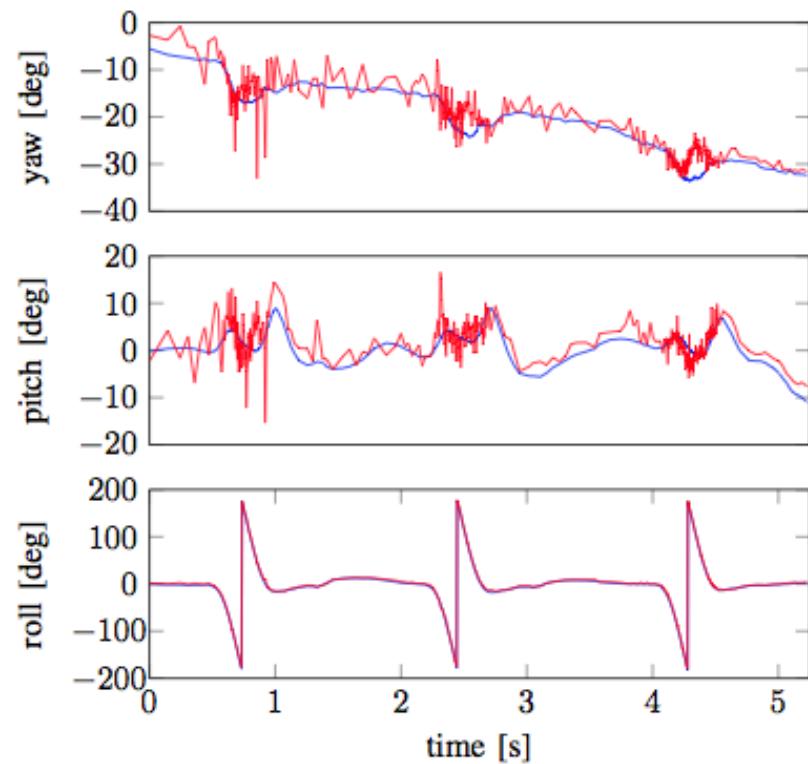
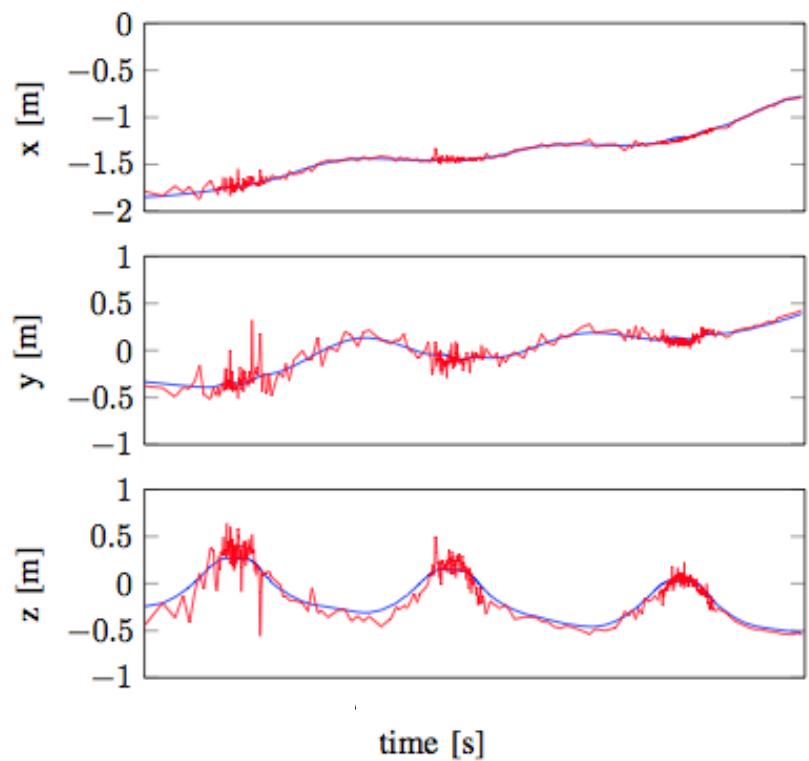
Event-based Tracking Algorithm

- Buffer of n events per side
- When a new event (star) arrives, it replaces the closest event in the buffer (red triangle)
- Reprojection error minimization to estimate new quadrotor pose
- Repeated for every event



$$P^* = \arg \min_P \sum_{l=1}^4 \sum_{i=1}^N \|d(\pi(L_l, P), e_{l,i})\|^2,$$

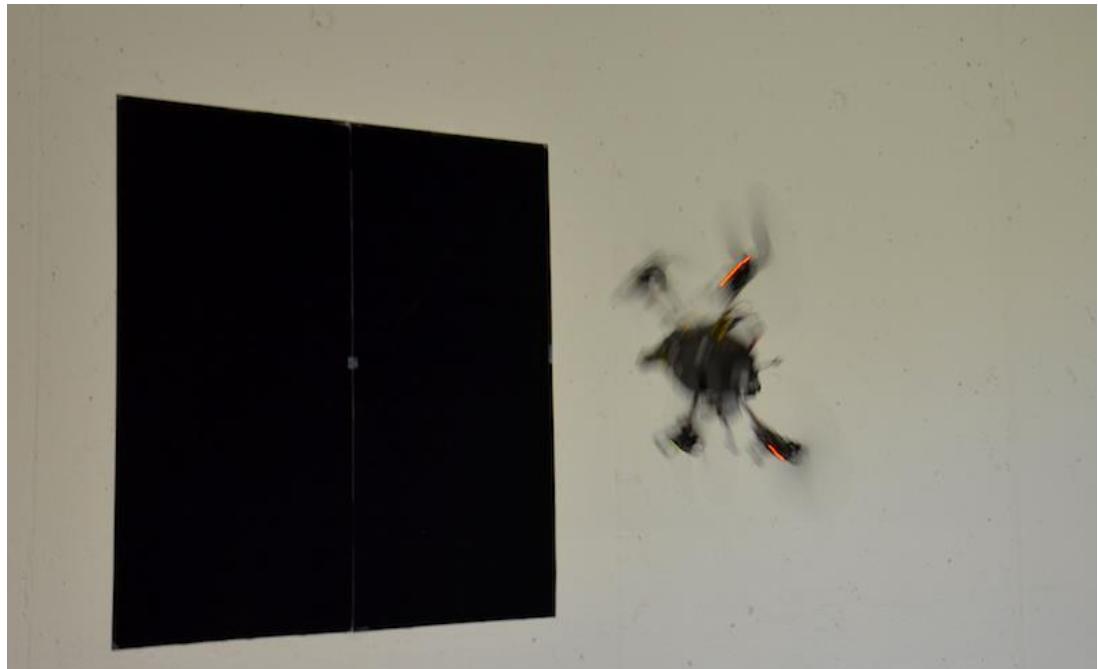
Event-based 6DoF Pose-Estimation Results [IROS'14]



These errors are comparable with those of a frame-based camera with the same resolution of the DVS and infinite frame-rate!

Event-based 6DoF Pose-Estimation Results [IROS'14]

- Successful tracking of 24/25 flips up to 1,200 deg/s
- Mean position error: 10.8cm (standard deviation: 7.8cm)
- Mean orientation error: 5.1° (standard deviation: 2.4°)
- Camera resolution is only 128x128 pixels



[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]. Featured on [IEEE Spectrum](#)

Event-based Pose Estimation from a Photometric Depth Map

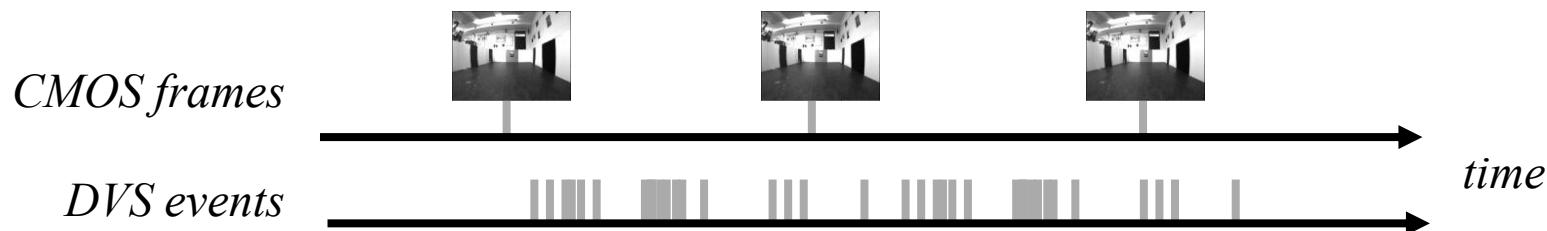
[ICRA'14]

Drawbacks of a DVS

- Currently, only the *sign* of the derivative can be measured, but not its magnitude
- Idea: **Combine a standard camera with a DVS**

DAVIS: Dynamic and Active-pixel Vision Sensor [Brandli'14]

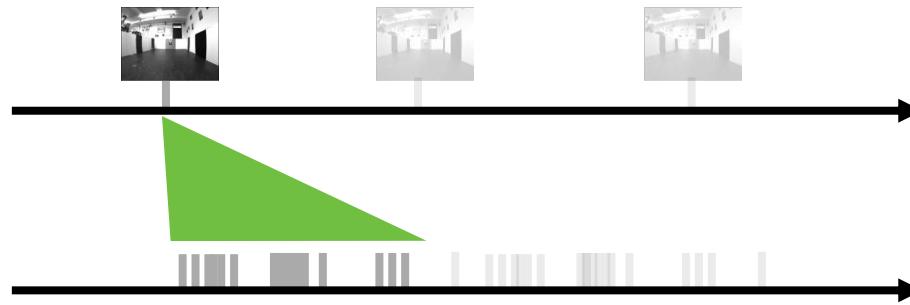
Combines the event-driven activity output of the DVS with conventional static frame output of CMOS active-pixel sensors.



Brandli, Berner, Yang, Liu, Delbruck, "A 240×180 130 dB 3 μ s Latency Global Shutter Spatiotemporal Vision Sensor." IEEE Journal of Solid-State Circuits, 2014.

Inter-frame, Event-based Pose Estimation [ICRA'14]

- Idea: reduce the problem to “localization” with respect to the previous CMOS frame; assume known depth map

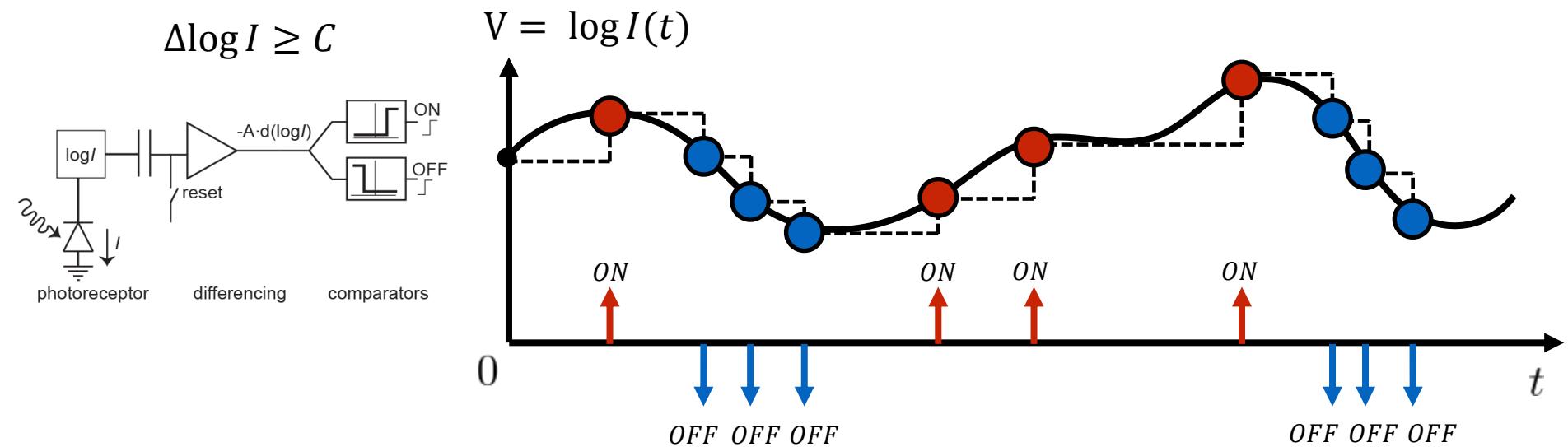


- Solution: Use Bayesian localization
 - Prob. Measurement Model $p(e_{t,u,v}) \propto |\langle \nabla I, \dot{\mathbf{u}} \Delta t \rangle|$
 - Motion model: we use a constant velocity $(\mathbf{v}, \boldsymbol{\omega})$ model $\dot{\mathbf{u}} = \frac{\mathbf{v}}{d} \times \mathbf{p} + \boldsymbol{\omega}$

[Censi & Scaramuzza, «Low Latency, Event-based Visual Odometry», ICRA'14],
Featured on [MIT News](#)

DVS Operating Principle [Lichtsteiner, ISCAS'09]

Events are generated any time a single pixel sees a change in brightness larger than C



Generative Model [Gallego'15] [Censi'14]

Events are generated any time a single pixel sees a change in brightness larger than C in a time interval Δt

$$|\Delta \log I| \geq C$$

$$\Delta \log I \approx \frac{\partial \log I}{\partial t} \Delta t$$

If $I(\mathbf{u}, t)$ is the intensity function measured by the DVS at a pixel $\mathbf{u} = (u, v)$ at time t , from the constant-brightness constraint, we have

$$\frac{\partial I}{\partial u} u + \frac{\partial I}{\partial v} v + \frac{\partial I}{\partial t} \Delta t = 0 \Rightarrow \frac{\partial I}{\partial t} + \langle \nabla_{\mathbf{u}} I, \dot{\mathbf{u}} \rangle = 0$$

$$|\Delta \log I| \approx |\langle \nabla_{\mathbf{u}} \log(I), \dot{\mathbf{u}} \Delta t \rangle| \geq C$$

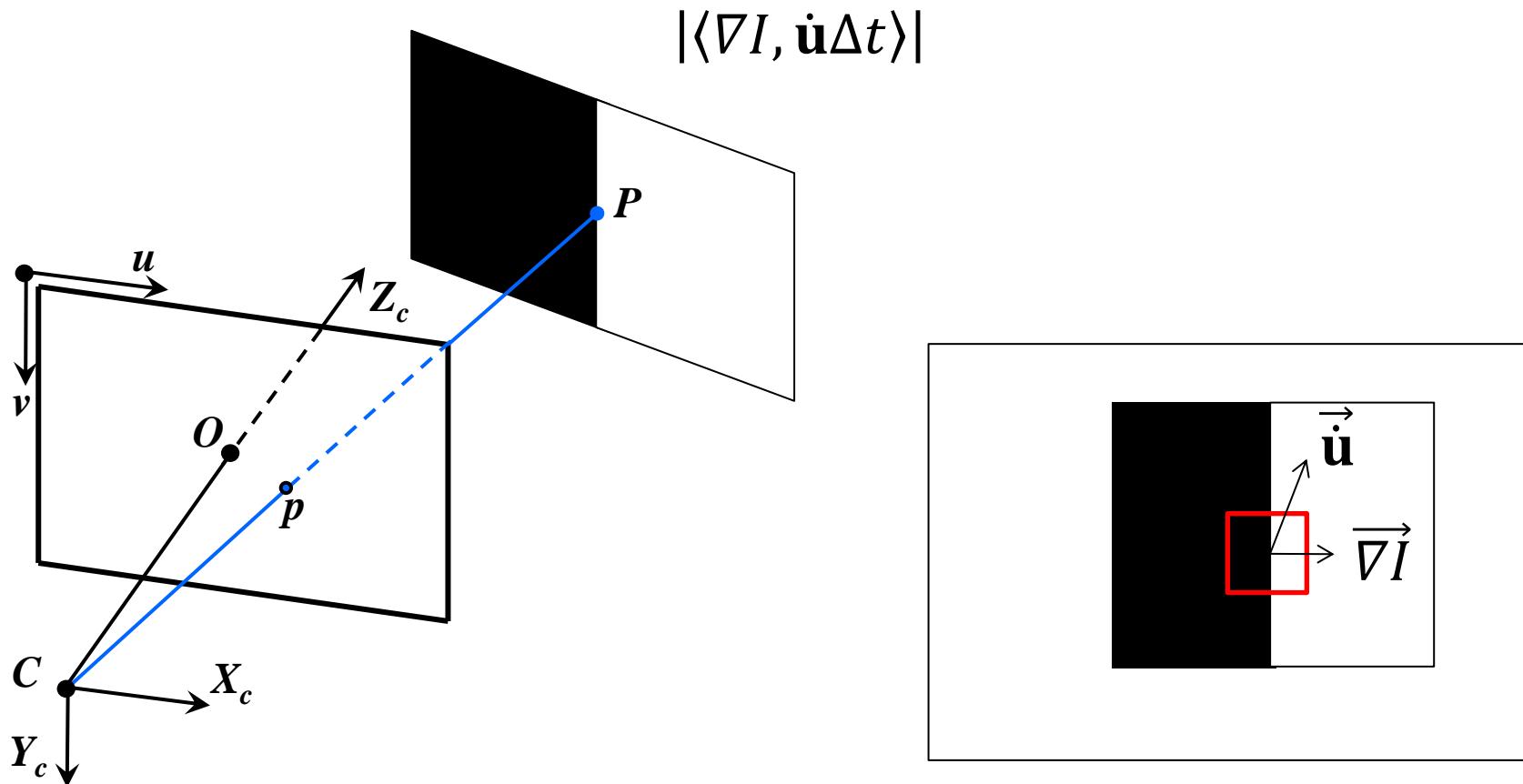
\downarrow
image
gradient \downarrow
pixel
velocity

[Gallego, Forster, Mueggler, Scaramuzza, Event-based Camera Pose Tracking using a Generative Event Model, 2015, ArXiV preprint]

[Censi & Scaramuzza, Low Latency, Event-based Visual Odometry, ICRA'14]

Generative Model [Censi & Scaramuzza, ICRA'14]

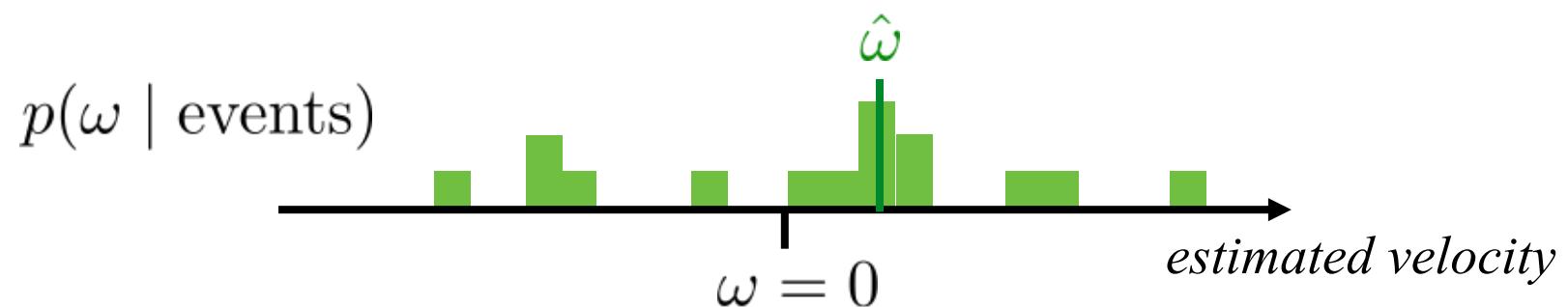
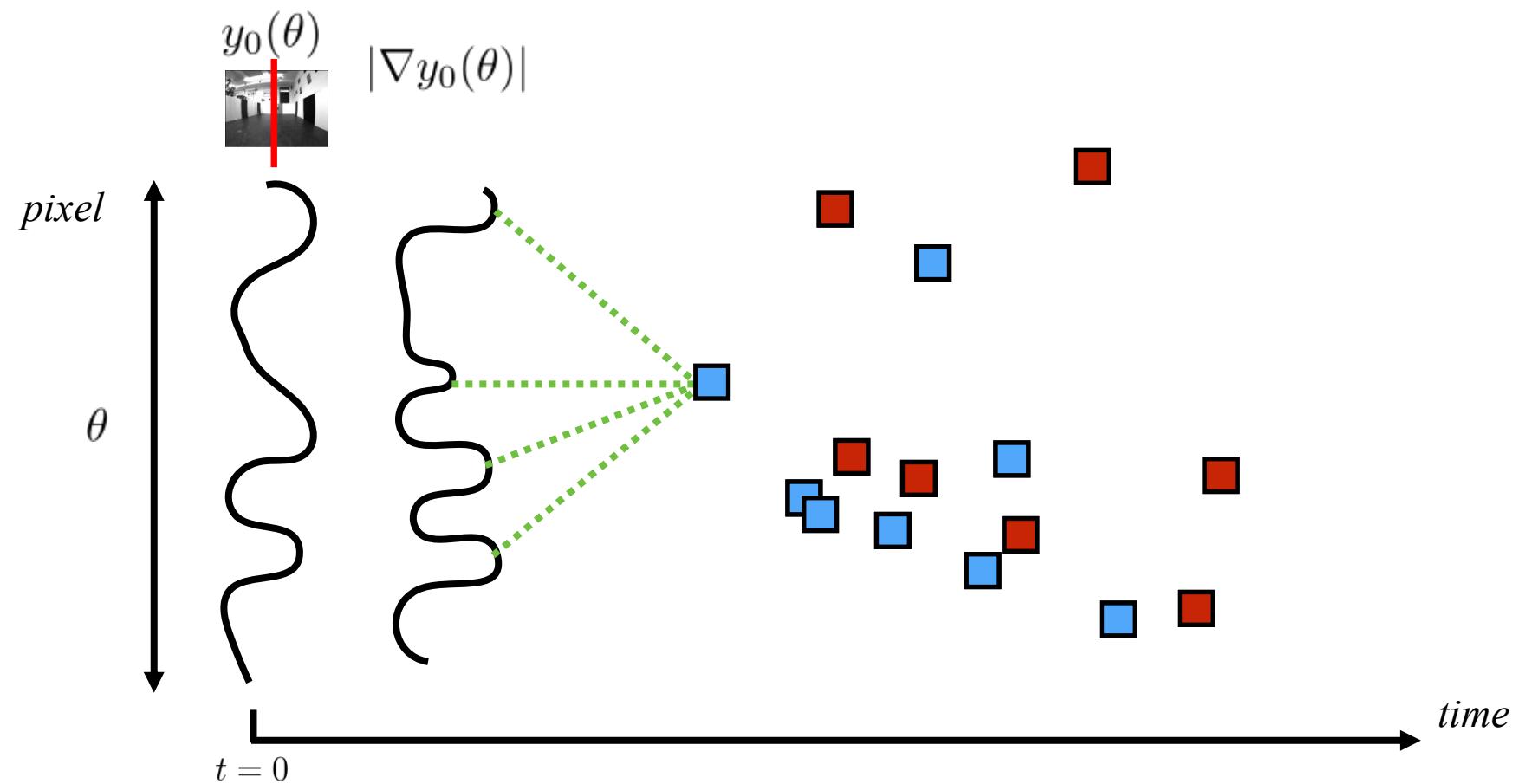
Intuitively, the generative model tells us that the **probability** that an event is generated depends on the **scalar product** between the gradient ∇I and the apparent motion $\dot{\mathbf{u}}\Delta t$



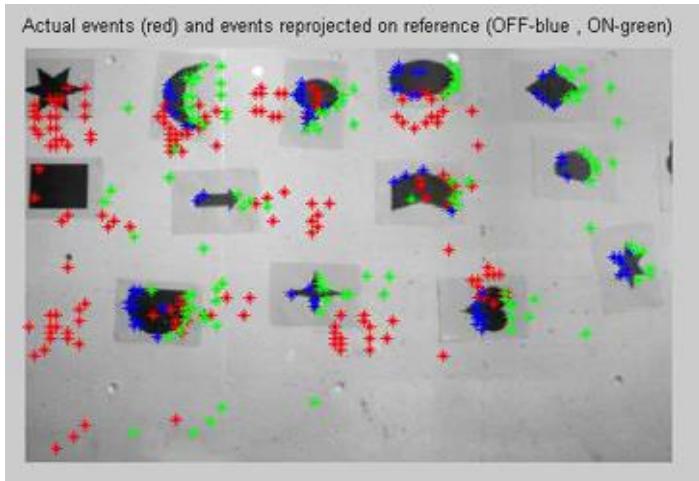
[Gallego, Forster, Mueggler, Scaramuzza, Event-based Camera Pose Tracking using a Generative Event Model, 2015, ArXiV preprint]

[Censi & Scaramuzza, Low Latency, Event-based Visual Odometry, ICRA'14]

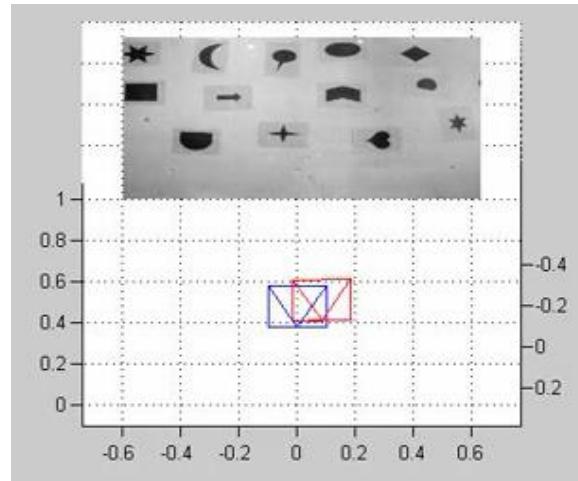
Event-based Pose Estimation, 1D Example (pure rotation)



Event-based 6DoF Pose Estimation Results



RED: observed events;
GREEN, BLUE: reprojected events (ON, OFF)



Estimated 6DoF pose

[Gallego, Forster, Mueggler, Scaramuzza, Event-based Camera Pose Tracking using a Generative Event Model, 2015, ArXiV preprint]

[Censi & Scaramuzza, *Low Latency, Event-based Visual Odometry*, ICRA'14]

Continuous-Time Trajectory Estimation for Event-based Vision Sensors

[RSS'15]

Mueggler, Gallego, Scaramuzza, *Continuous-Time Trajectory Estimation for Event-based Vision Sensors*, RSS'15

Continuous-Time Trajectories

➤ Estimate trajectory instead of poses:

- $T_1, T_2, T_3, \dots \rightarrow T(t)$

➤ **Spline Fusion** [Lovegrove, BMVC'13/IJCV'15]

- **Visual-inertial fusion** with rolling-shutter cameras
- Trajectory is represented with **B-splines**
- **Cumulative basis functions** on SE(3), free from singularities:

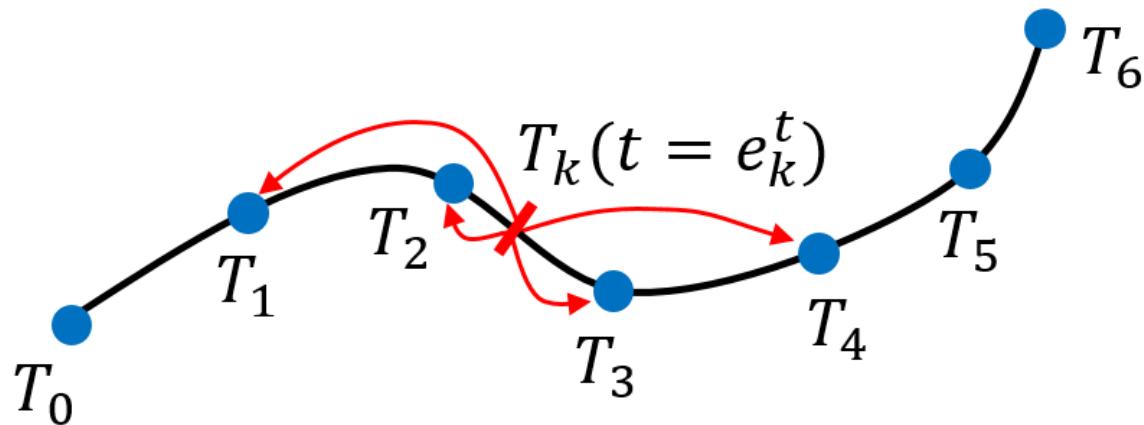
$$T_{w,s}(u(t)) = \underbrace{T_{w,i-1}}_{\text{red}} \prod_{j=1}^3 \exp \left(\tilde{B}_j(u(t)) \Omega_{i+j-1} \right) \quad \begin{array}{c} \text{red} \\ \text{green} \end{array}$$

The diagram shows a trajectory segment starting from a world coordinate frame W (indicated by a red arrow pointing right and a green arrow pointing up). A red curved arrow labeled $T_{w,i-1}$ starts at W and ends at a black dot. From this black dot, a green curved arrow labeled Ω_1 curves upwards and to the right, ending at another black dot. From this second black dot, a green curved arrow labeled Ω_2 curves downwards and to the right, ending at a third black dot. From this third black dot, a green curved arrow labeled Ω_3 curves upwards and to the right, ending at a fourth black dot.

Continuous-Time Trajectories

➤ Advantages of continuous-time trajectories

- **Pose** is well-defined **at any time**
- **Can handle asynchronous, high-frequency** data naturally
- **Local support:** each event only influences a few control poses



Optimization

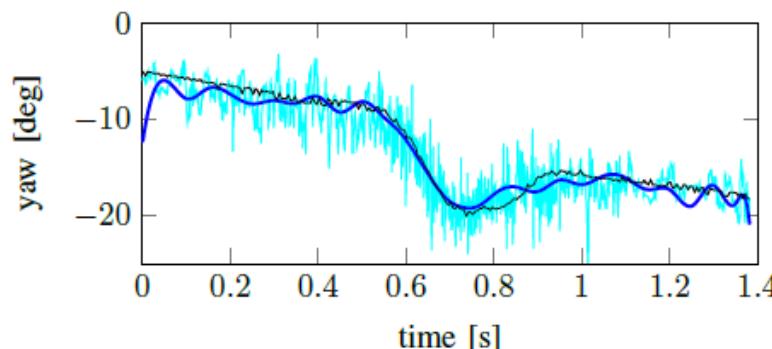
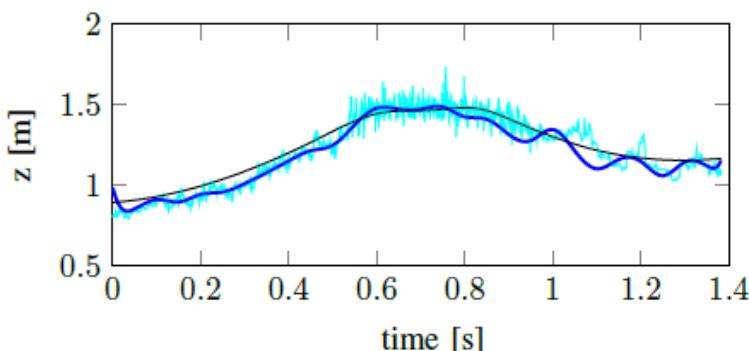
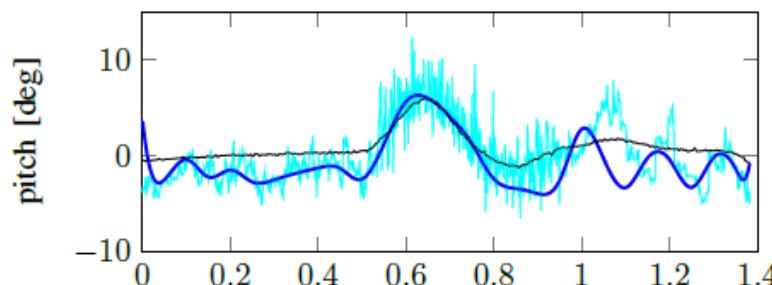
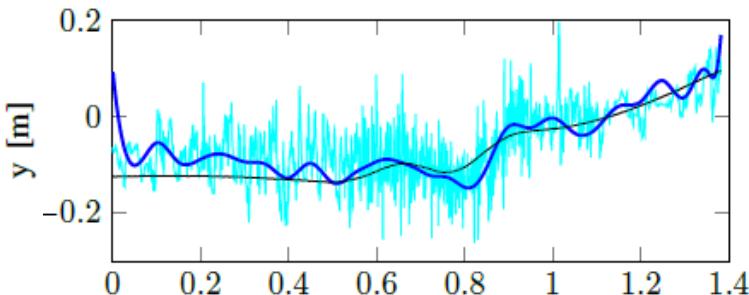
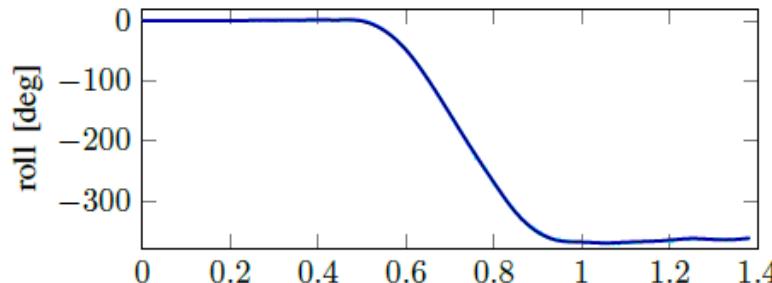
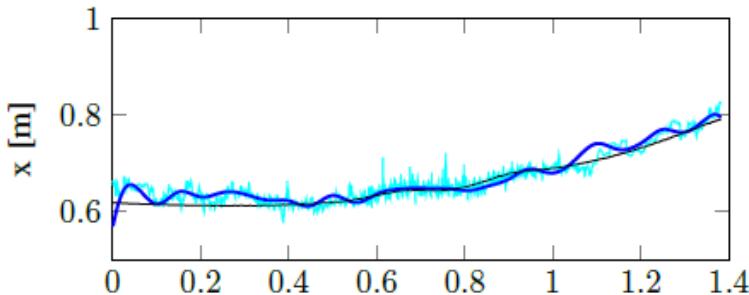
- Find control poses such that reprojection error of all events is minimized:

$$\{\mathbf{T}_{w,i}^*\} = \arg \min_{\mathbf{T}} \sum_k d_{\perp}^2(\mathbf{z}_k, l_j(\mathbf{x}(t_k)))$$

- Few control poses are needed: 1 control pose per 10^4 events

6DoF Experiments

- [IROS'14]: filter
- Batch optimization
- Ground Truth (Vicon)

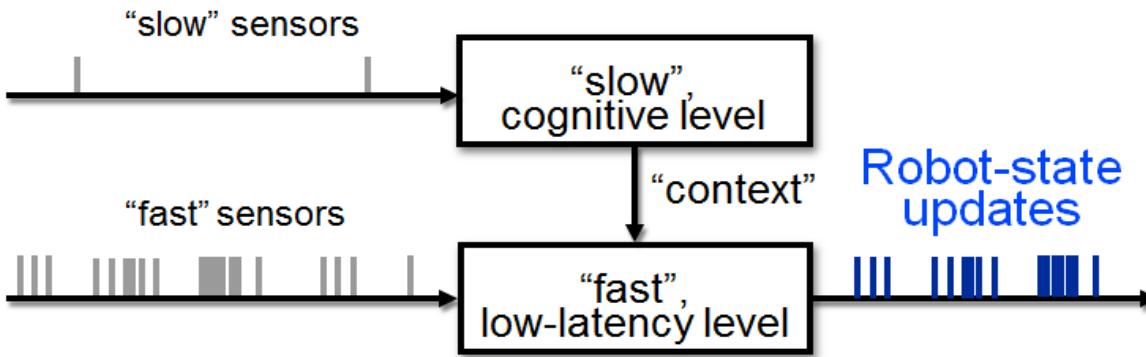


Conclusions

- DVS: **revolutionary sensor** for robotics:
 - **low-latency** (~1 micro-second)
 - Can enable pose estimation at unprecedented speed
 - Event-based, low-latency control
 - **high-dynamic range** (120 dB instead 60 dB)
 - Can enable HDR reconstructions with challenging lighting variations
 - **Very low bandwidth** (only intensity changes are transmitted)
 - Suitable for hardware implementations
- Generative model can be used for filtering-based SLAM solutions
- Currently very low resolution (128x128); however soon overcome
- Suitable for continuous-time batch optimizations
 - The pose can be evaluated at any time!

Outlook

- A two-level sensing pipeline for future **high-speed mobile robotics**:
 - Standard cameras: Localization and Mapping
 - DVS + IMU: agile behavior (evasive maneuver, target tracking, fast re-localization)



Currently working on different problems

- Event-based state-estimation [ICRA’14, IROS’14, RSS’15]
- Tracking [IROS’13, ICRA’15, ECMR’15]
- Collision avoidance [ECMR’15]

DAVIS sensor: combines DVS
and frames in the same
CMOS sensor

Software

➤ From INILabs

- **DVS software for Windows and Linux** (lot of utilities for LED, line, blob tracking, and even processing)
 - <http://sourceforge.net/p/jaer/wiki/jAER%20Installation/>
 - <http://sourceforge.net/p/jaer/wiki/jAER%20USB%20Driver%20Install/>

➤ From my lab

- **ROS DVS driver**
- **Calibration tools** for both intrinsic and stereo calibration:
 - https://github.com/uzh-rpg/rpg_dvs_ros

References for the Sensors

➤ DVS

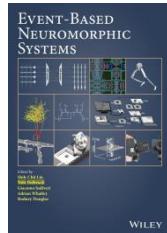
- P. Lichtsteiner, C. Posch, T. Delbrück: **A 128×128 120dB 15us Latency Asynchronous Temporal Contrast Vision Sensor.** IEEE Journal of Solid State Circuits, 2008.

➤ DAVIS

- Brandli, Berner, Yang, Liu, Delbrück: **A 240×180 130 dB 3 μ s Latency Global Shutter Spatiotemporal Vision Sensor,** IEEE Journal of Solid-State Circuits, 2014.

➤ BOOK

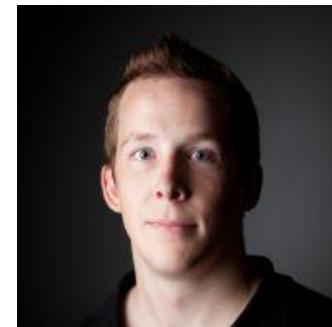
- **Event-based Neuromorphic Systems**, Edited by S.C. Liu, T. Delbrück, G. Indiveri, Whatley, R. Douglas, Wiley, 2014



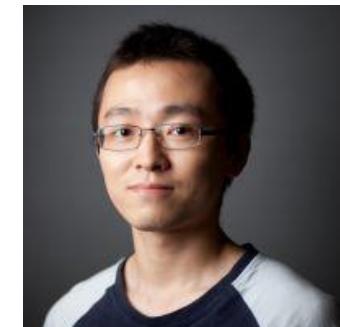
Shih-Chii Liu



Tobi Delbrück



Christian Braendli



Minhao Yang

Algorithms seen in this tutorial

➤ LED Marker Tracking

- A. Censi, J. Strubel, C. Brandli, T. Delbruck, D. Scaramuzza: **Low-latency localization by Active LED Markers tracking using a Dynamic Vision Sensor** IROS'13

➤ Probabilistic model and event-based Bayesian localization

- A. Censi, D. Scaramuzza, **Low-Latency Event-Based Visual Odometry**, ICRA'14

➤ Lifetime estimation

- E. Mueggler, C. Forster, N. Baumli, G. Gallego, D. Scaramuzza, **Lifetime Estimation of Events from Dynamic Vision Sensors**, ICRA'15

➤ Optimization-based localization

- E. Mueggler, B. Huber, D. Scaramuzza: **Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers**. IROS'14

➤ Collision avoidance

- E. Mueggler, N. Baumli, F. Fontana, D. Scaramuzza, **Towards Evasive Maneuvers with Quadrotors using Dynamic Vision Sensors**, ECMR'15

➤ Batch 6DoF localization

- E. Mueggler, G. Gallego, D. Scaramuzza, **Continuous-Time Trajectory Estimation for Event-based Vision Sensors**, RSS'15



Elias Mueggler



Guillermo Gallego



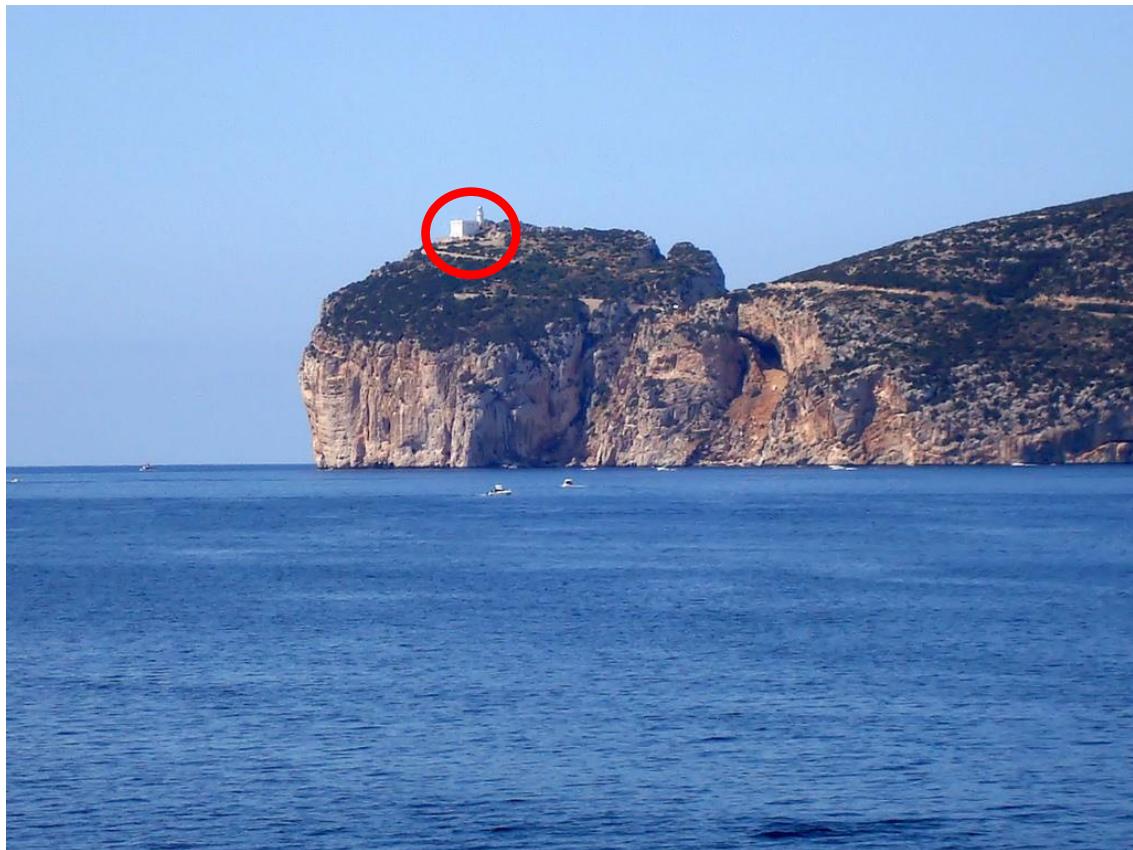
Andrea Censi



Davide Scaramuzza

Cognitive Neuromorphic Engineering Workshop

- <https://capocaccia.ethz.ch/capo/wiki/2015>
- Every year in Capo Caccia, Sardinia, Italy
- 2 weeks
- 12 working hours a day
- Fully hands-on



Questions?

Wrong believes about DVSes:

- “*it’s just another optical-flow sensor*”
 - A DVS is not an optical flow sensor! Optic flow is the velocity of a pixel (two components); a DVS pixel only triggers $\pm 1\text{s}$ if brightness changes
- “*A DVS is a camera with a very-high frame rate*”
 - There are no frames!
 - A DVS is much faster, consumes less power, has a lower data rate, is much smaller
- “*It is of no use because if the scene is very cluttered, all pixels spike*”
 - True. Indeed, an event camera is more suitable, for robotics, for scenes with sparse edges

Thanks! Questions?

Funding

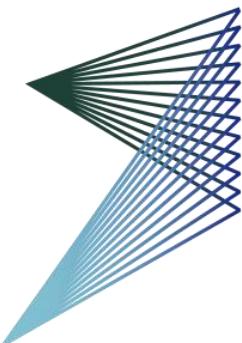


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Kommission für Technologie und Innovation KTI



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