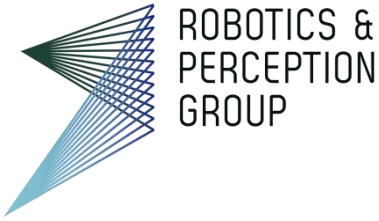
University of Zurich[UZH] | ETH zürich

Institute of Informatics – Institute of Neuroinformatics



Event based vision

Davide Scaramuzza
http://rpg.ifi.uzh.ch

Lab Visit and Exercise - Today

- **Lab visit with live demos** (@Robotics and Perception Group):
  - We will take Tram 10 to Bahnhof Oerlikon Ost
  - Lab address: Andreasstrasse 15, 2nd floor, 2.11
  - Visit starts at 12:30hrs
  - Duration of the visit: 1.5-2 hours (feel free to leave at any time)
  - Afterwards, chocolates and drinks in the lab lounge

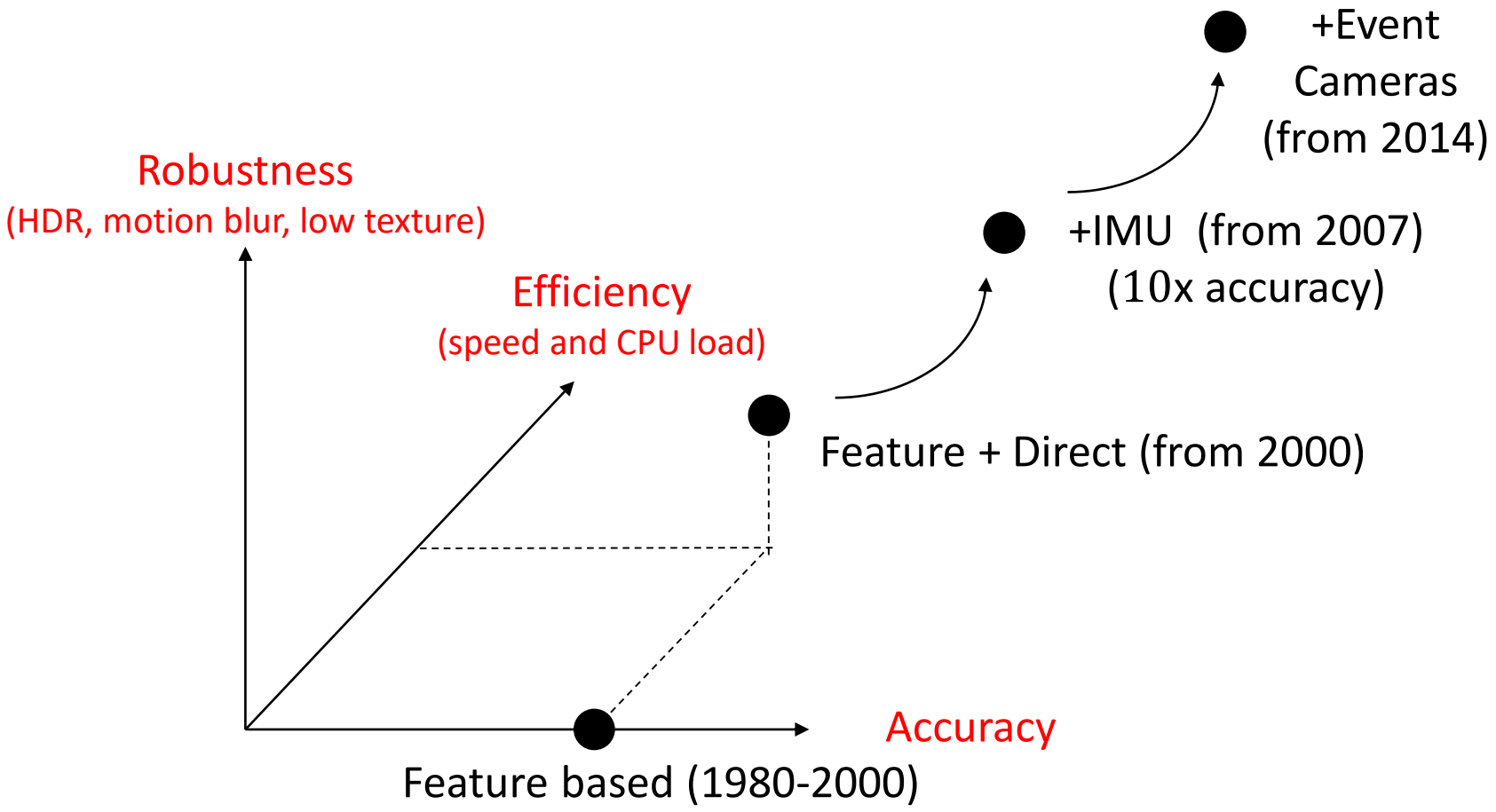
- **Lunch**: Sandwiches will be served

- **Exercise** Session: Q&A on final VO integration
  - Room **UZH AND 3.46** from **15:00 to 17:00 hrs**

Exams Questions

- The oral exam will last 30 minutes
- It will consist of one application question followed by two theoretical questions
- This document contains a "**non exhaustive**" list of possible application questions and an "**exhaustive**" list of all the topics that you should learn about the course, which will be subject of discussion in the theoretical part: http://rpg.ifi.uzh.ch/docs/teaching/2018/Exam_Questions.pdf

A Short Recap of the last 30 years of Visual Inertial SLAM



Robustness: Challenges of Vision for SLAM

- IMU alone only helpful for short motions; **drifts very quickly** without visual constraint
- Biggest challenges for vision today is robustness to:
  - **High Dynamic Range (HDR)**
    - Can be handled with Active Exposure Control or Event cameras
  - High-speed motion (i.e., **motion blur**)
    - Can be handled with event cameras
  - **Low-texture** scenes
    - Can be handled with Dense Methods, or with Depth cameras (laser projector) or by getting closer to the scene, or by using context (e.g., machine learning)
  - **Dynamic environments**
    - Can be handled with an IMU, using context (e.g., machine learning)
- Current VO algorithms and sensors have **large latencies** (50-200 ms)
  - Can we reduce this to much below a 1ms?
    - Can be handled with event cameras

Active Exposure Control for HDR Scenes

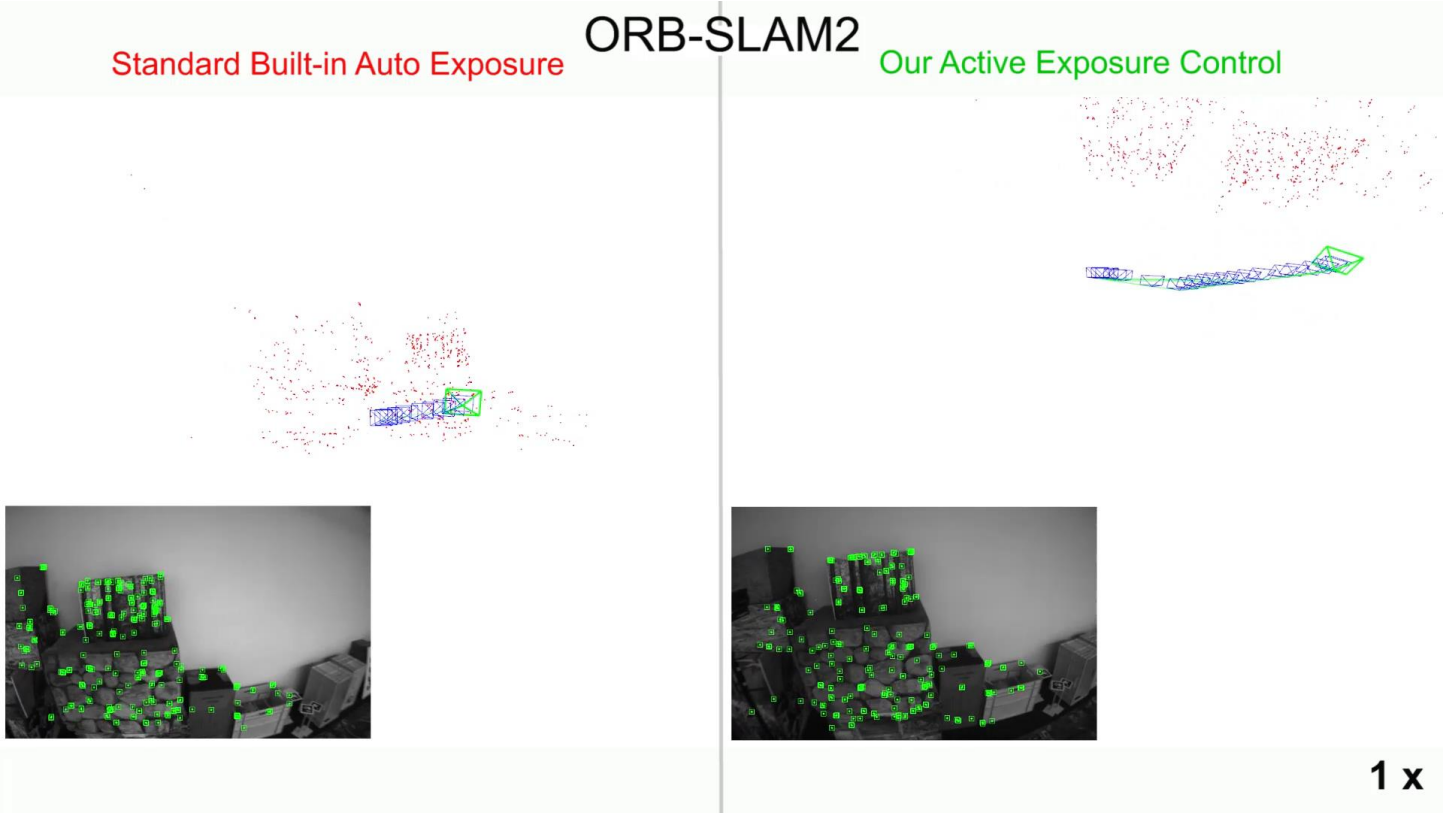
- Goal: Actively control exposure to maximize image gradient information

$$M_{\text{perc}}(p) \quad = \quad \text{percentile}(\{G(\mathbf{u}_i)\}_{\mathbf{u}_i \in \mathbf{I}}, p)$$

- Simple gradient ascent control

$$\Delta t_{\text{next}} = \Delta t + \gamma \frac{\partial M_{\text{softperc}}}{\partial \Delta t}$$

Computed from photometric response function



Zhang, Forster, Scaramuzza, Active Exposure Control for Robust Visual Odometry in HDR Environments, ICRA'17

Event-based Cameras

Outline

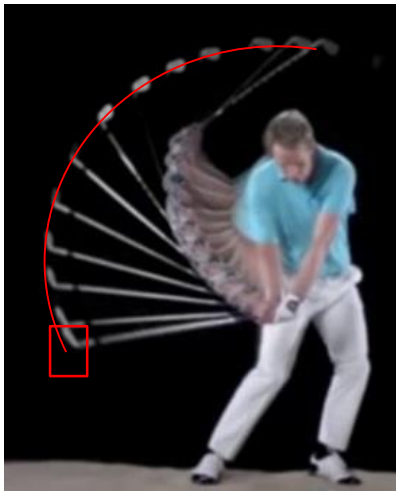
- Motivation
- DVS sensor and its working principle
- Traditional sampling vs level crossing sampling
- Current commercial applications
- Calibration patterns
- A simple optic flow algorithm
- Event-by-event vs Event-packet processing
  - Case studies
- DAVIS sensor
  - Case study

Open Challenges in Computer Vision

The past 60 years of research have been devoted to frame-based cameras …but they are not good enough!

Latency

Motion blur

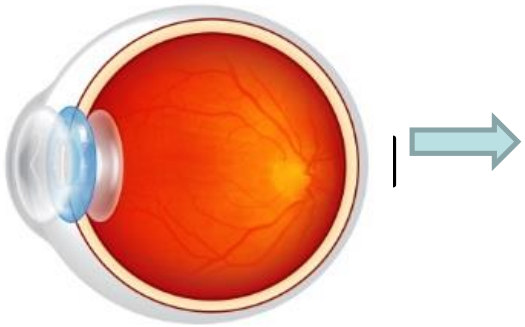


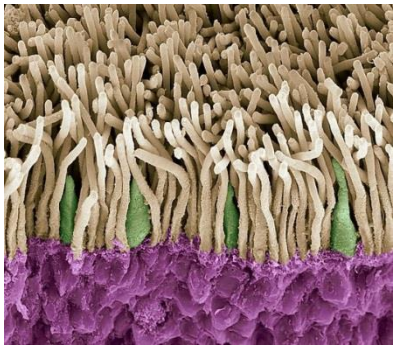
Dynamic Range

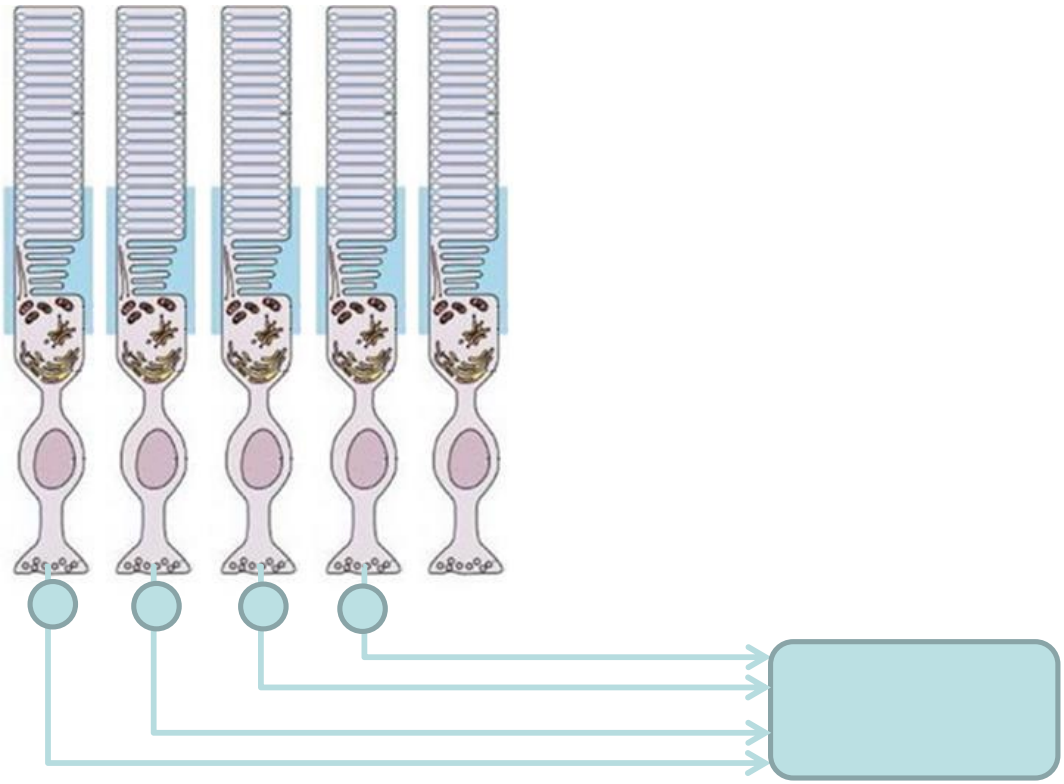
Event cameras do not suffer from these problems!

Human Vision System

- 130 million **photoreceptors**
- But only 2 million **axons**!







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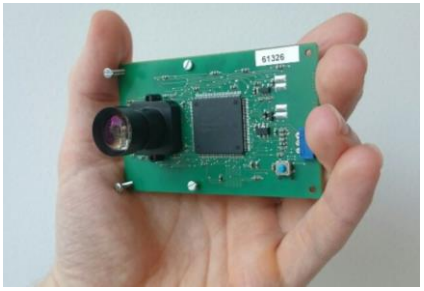
Dynamic Vision Sensor (DVS)



DVS from inilabs.com

Advantages

- **Low-latency** (~1 micro-seconds)
- **High-dynamic range (HDR)** (140 dB instead 60 dB)
- **High updated rate** (1 MHz)
- **Low power** (10mW instead 1W)

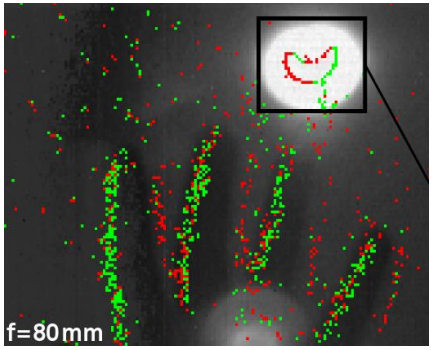
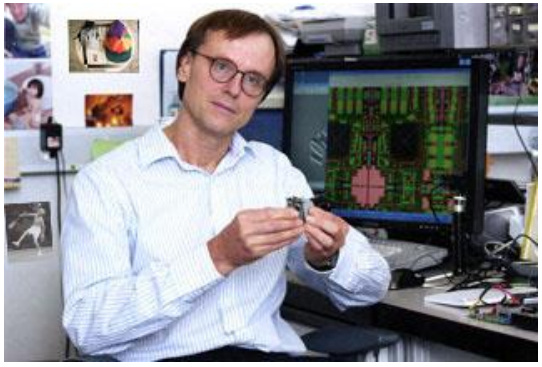


Image of solar eclipse captured by a DVS, without black filter!

Disadvantages

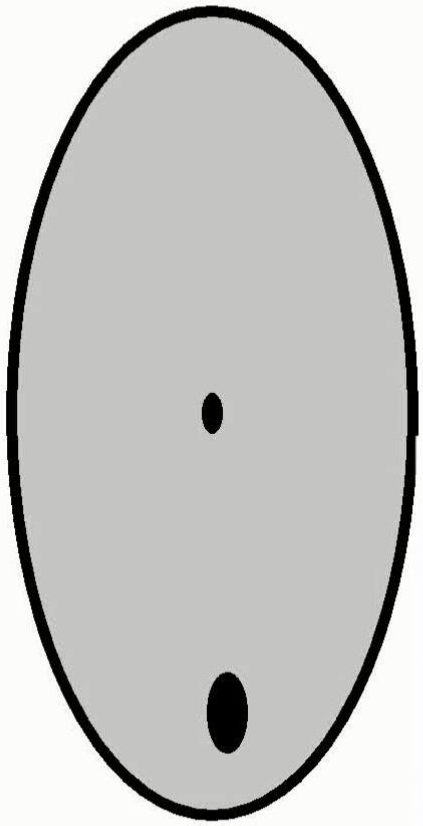
- **Paradigm shift**: Requires totally **new vision algorithms**:
  - **Asynchronous** pixels
  - **No intensity information** (only binary intensity changes)



Prof. Tobi Delbruck, UZH & ETH Zurich

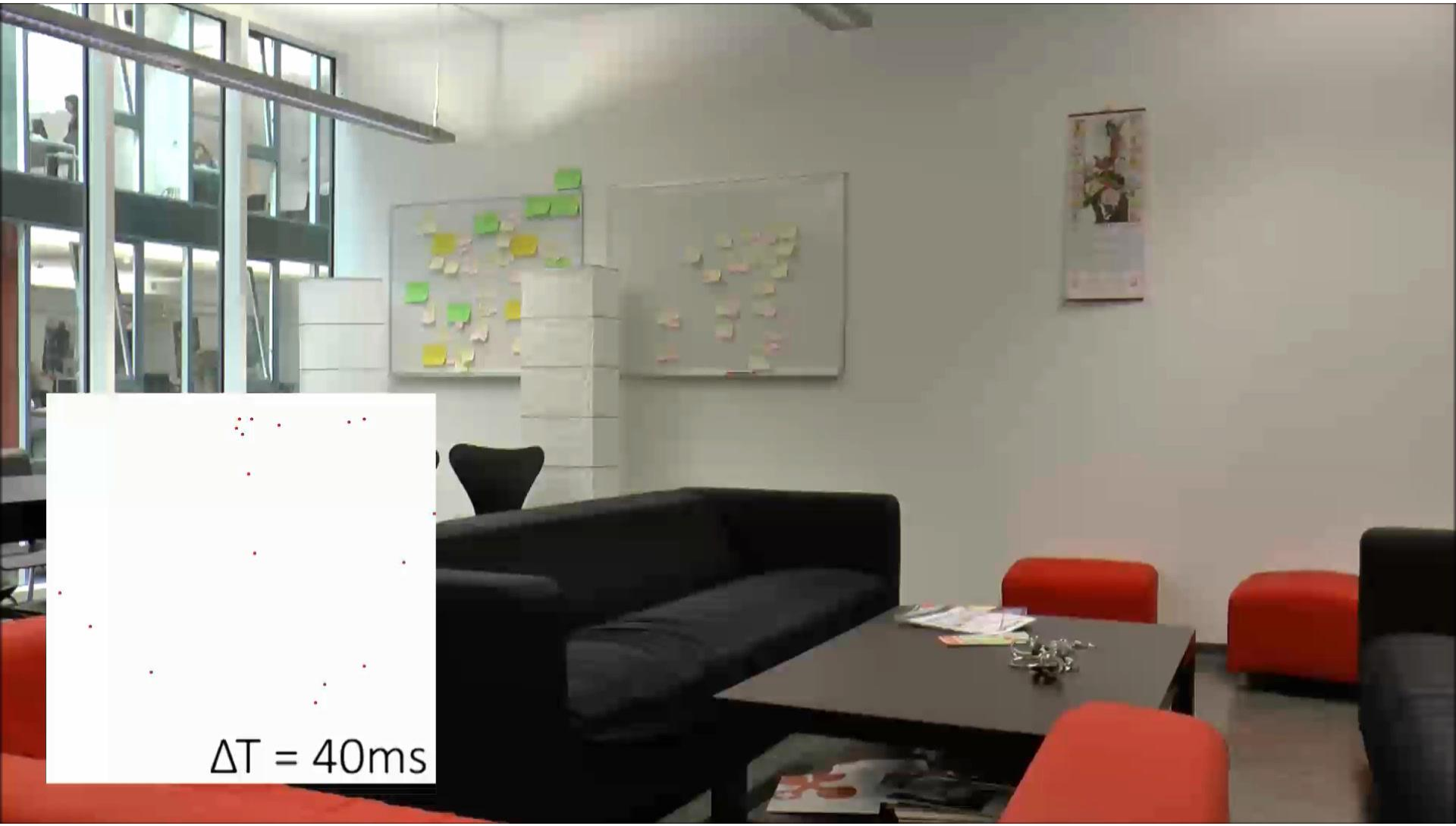
1. Lichtsteiner et al., A 128x128 120 dB 15µs Latency Asynchronous Temporal Contrast Vision Sensor, 2008
2. Brandli et al., A 240x180 130dB 3us Latency Global Shutter Spatiotemporal Vision Sensor, JSSC'14.

Camera vs Dynamic Vision Sensor



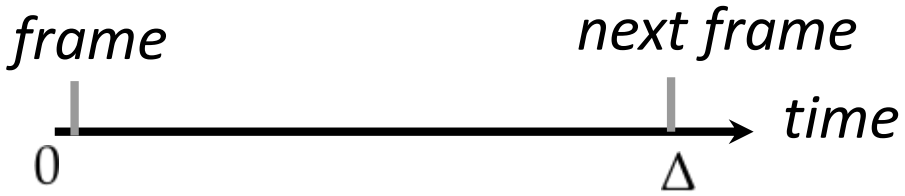
standard camera output:

Camera vs Dynamic Vision Sensor

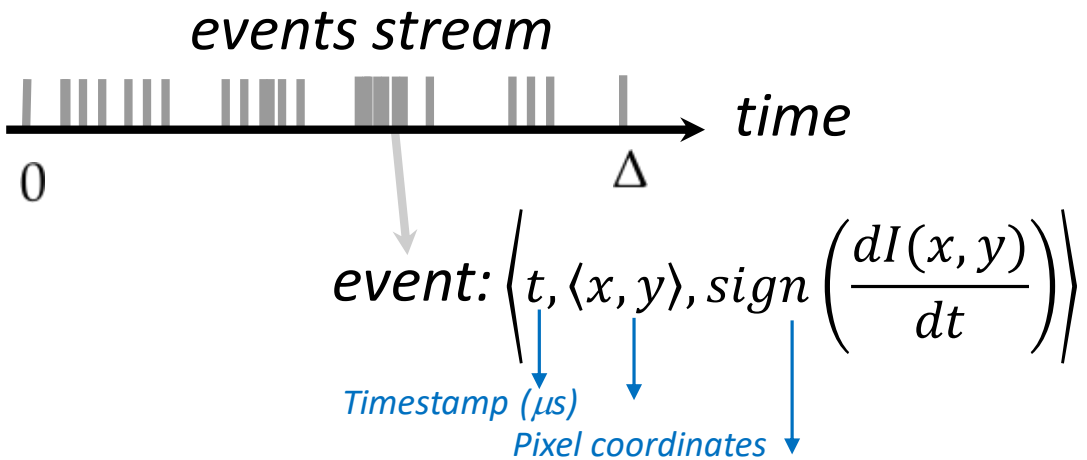


Dynamic Vision Sensor (DVS)

- 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 detects an intensity changes value



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

What is an event camera, **precisely**?

- **Asynchronous**: all pixels are *independent* from one another
- Implements ***level-crossing*** sampling rather than uniform time sampling
- Reacts to ***logarithmic*** brightness changes

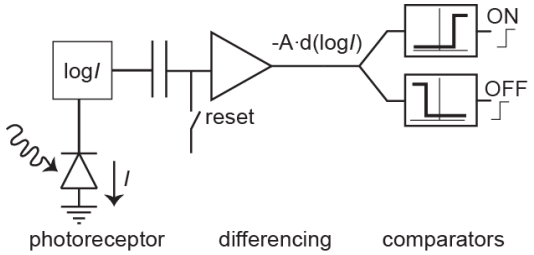
Let´s look at how this works for one pixel in detail

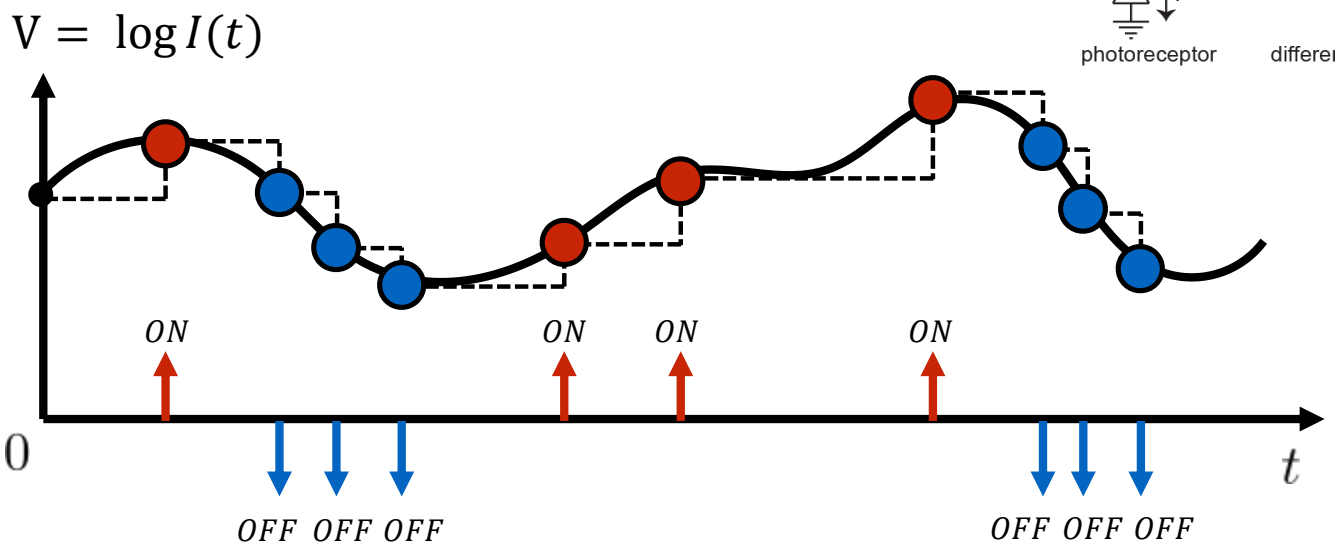
DVS Operating Principle

- A DVS detects and outputs ***asynchronous pixel-level brightness changes***
  - Each pixel is *independent* of all the other pixels
  - Events are generated any time a single pixel sees a change of the logarithm of the brightness equal to C, i.e.:

$$|\Delta \log I| \; = \; |\log I(t + \Delta t) - \log I(t)| \; = C$$

  - $C \in [0.15, 0.20]$ is called ***Contrast sensitivity*** and can be tuned by the user
  - Since brightness changes can be either positive or negative, we can have two types of events:
    - **ON event**: if $\Delta \log I = C$
    - **OFF event**: if $\Delta \log I = -C$





Outline

- Motivation
- DVS sensor and its working principle
- Uniform time sampling vs level-crossing sampling
- Current commercial applications
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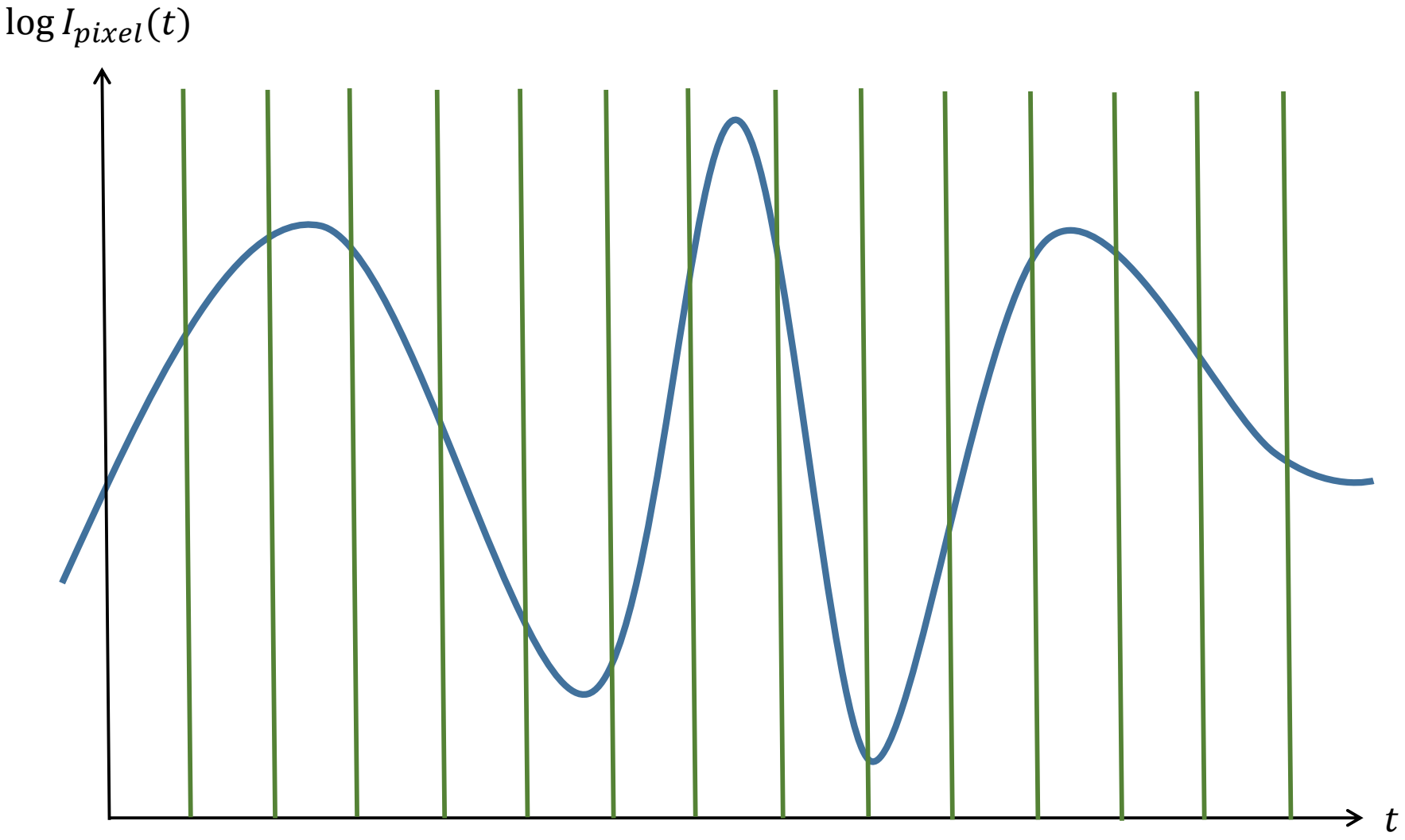
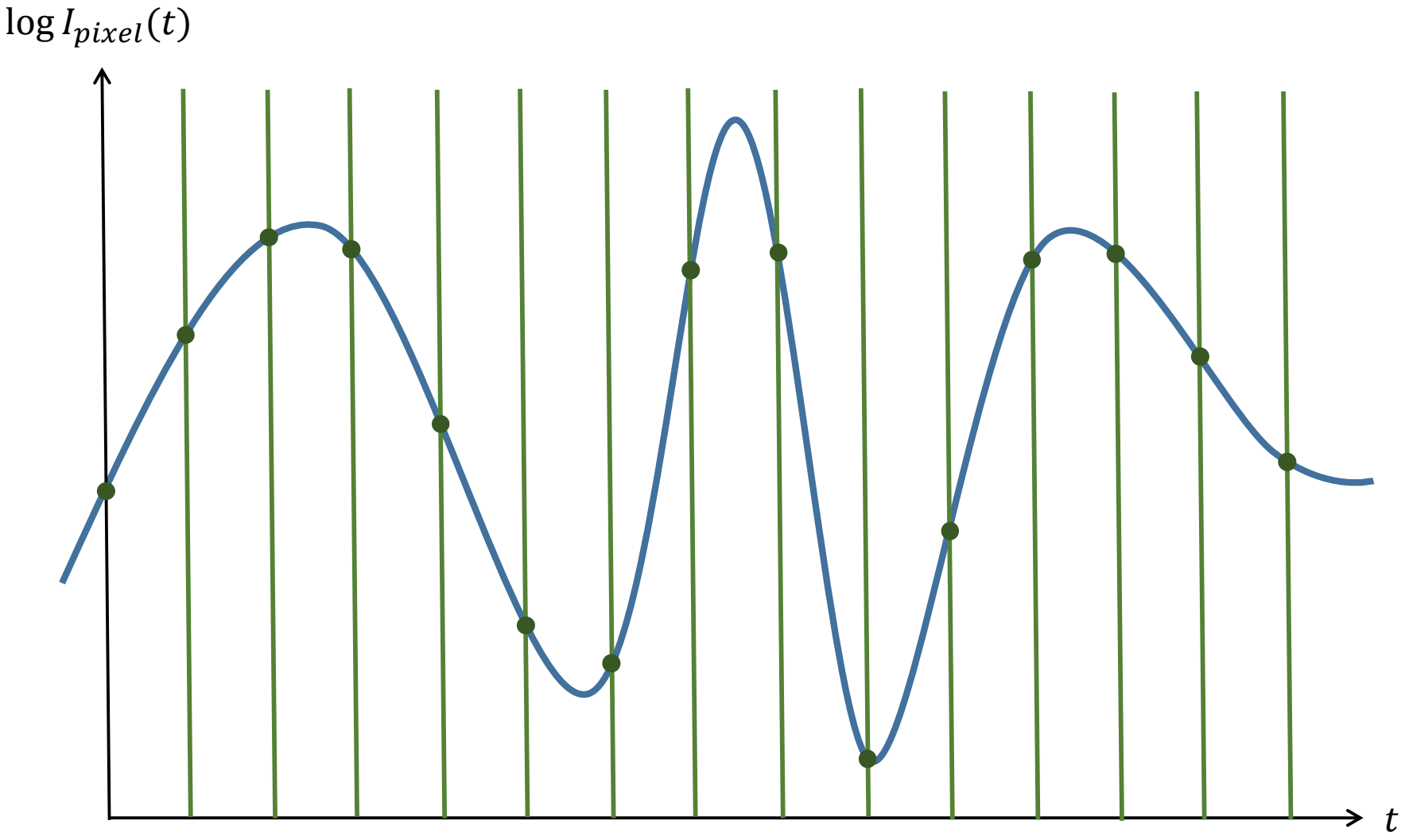
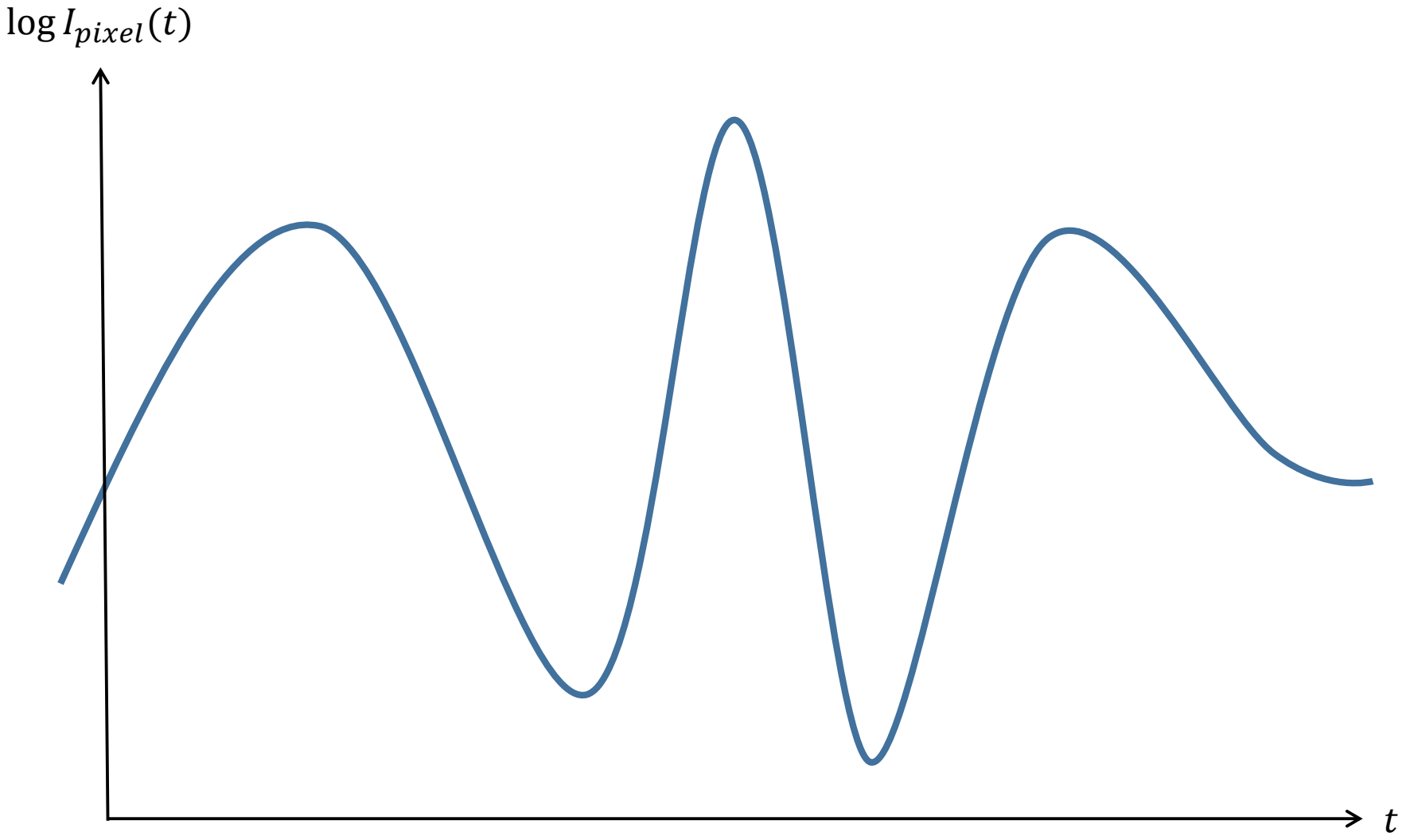
Uniform time sampling



Uniform time sampling

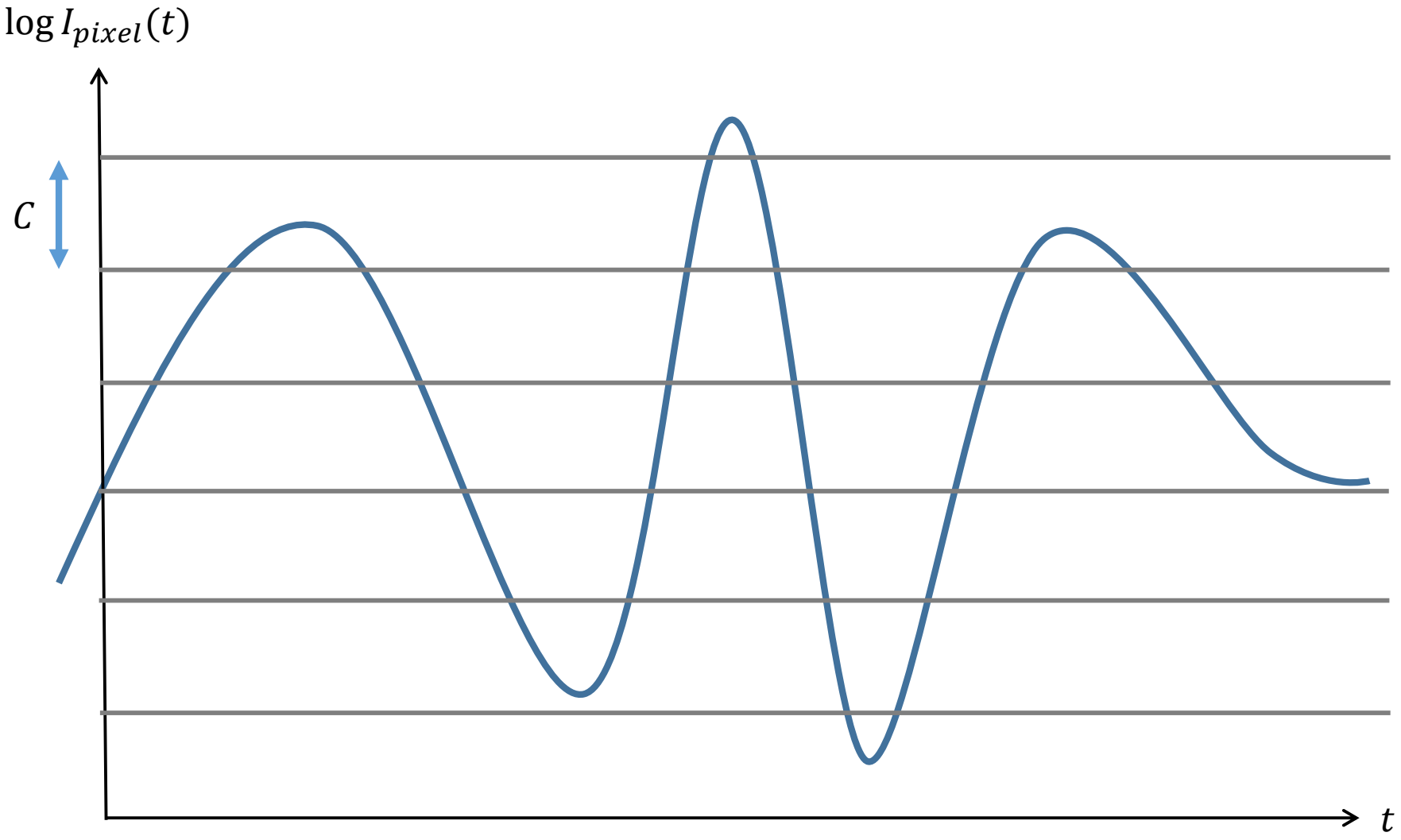


Level-crossing sampling



Level-crossing sampling

- An **event** is generated when the signal *change* equals C



Level-crossing sampling

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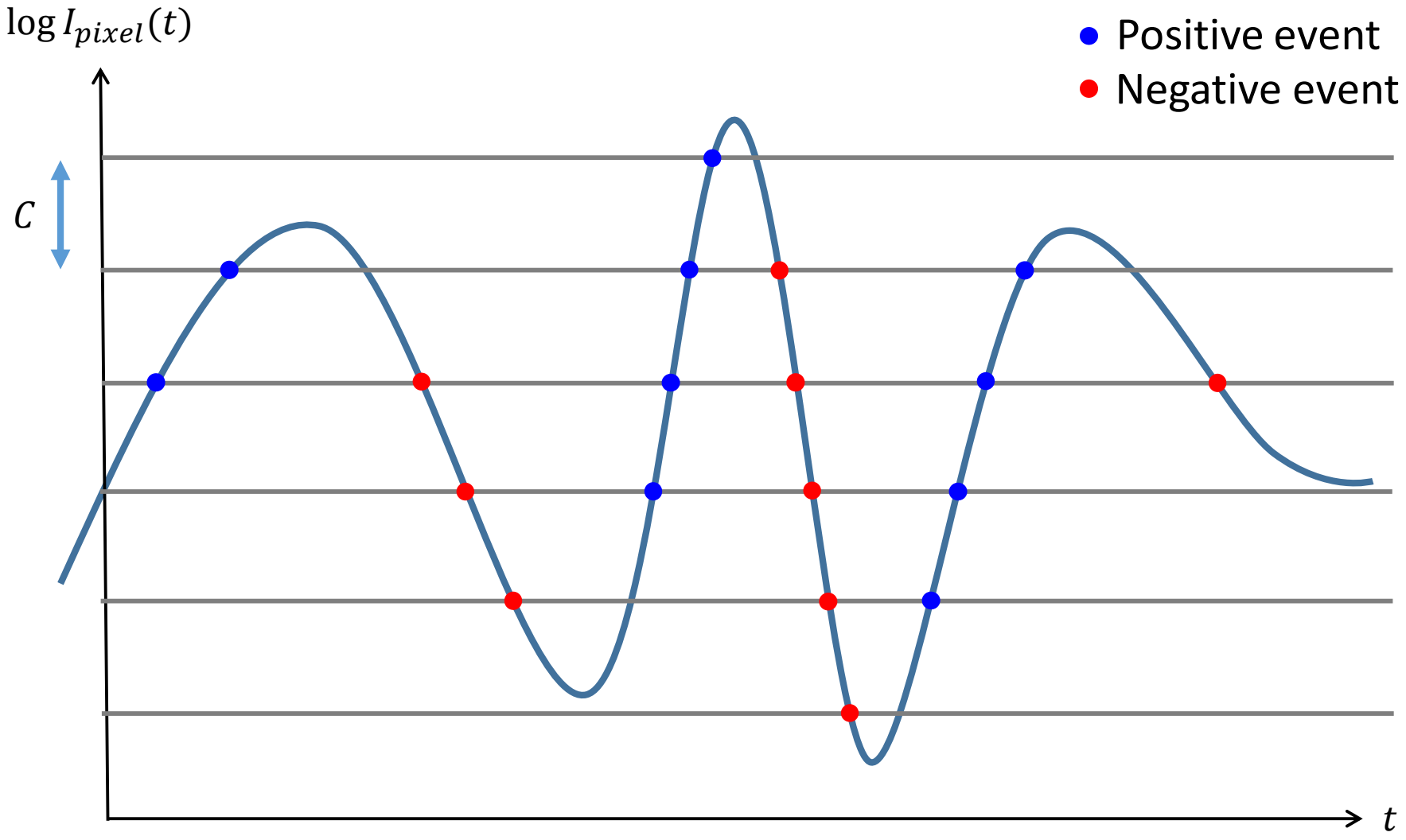

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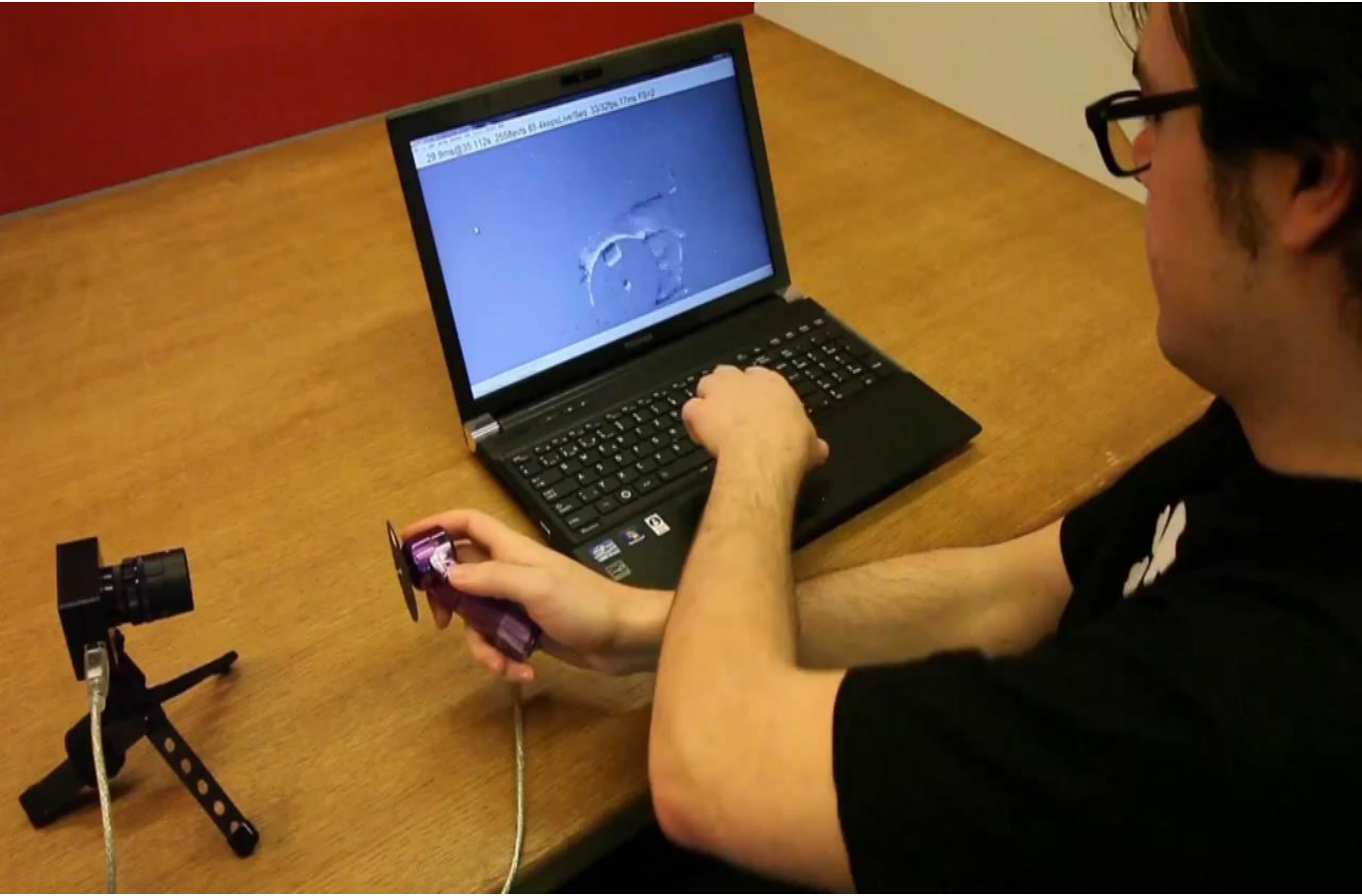
Current Applications of event cameras

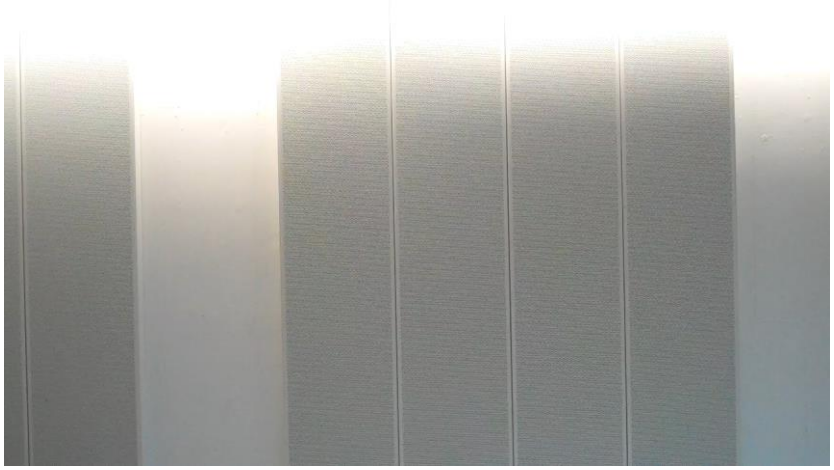
- Low-power Monitoring and Video Surveillance:
  - Traffic and moving object detection and tracking
- Fast closed-loop control
- High-dynamic range imaging
- Low-power gesture recognition (IBM TV gesture control)
- High speed flow speed estimation
- Robust visual SLAM: low-power, HDR, and high speed applications

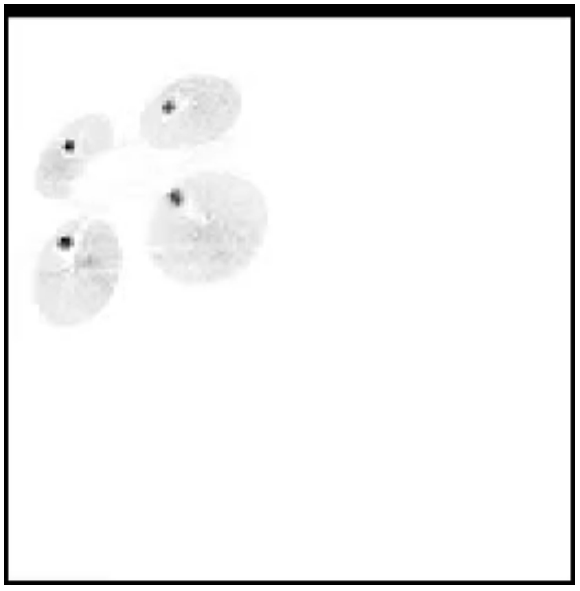
https://inivation.com/dvs/videos/

The DVS is fast



The DVS is fast





1 frame = 33 ms

1 frame = 1 ms

1 frame = 0.05 ms

Censi, Delbruck, Scaramuzza, *Low-latency localization by active led markers tracking using a dynamic vision sensor*. IROS 2013

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	**346x260 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	**~1MB/s on average**
Power consumption	150 W + llighting	1.4 W	**10 mW**
Dynamic range	n.a.	60 dB	**140 dB**

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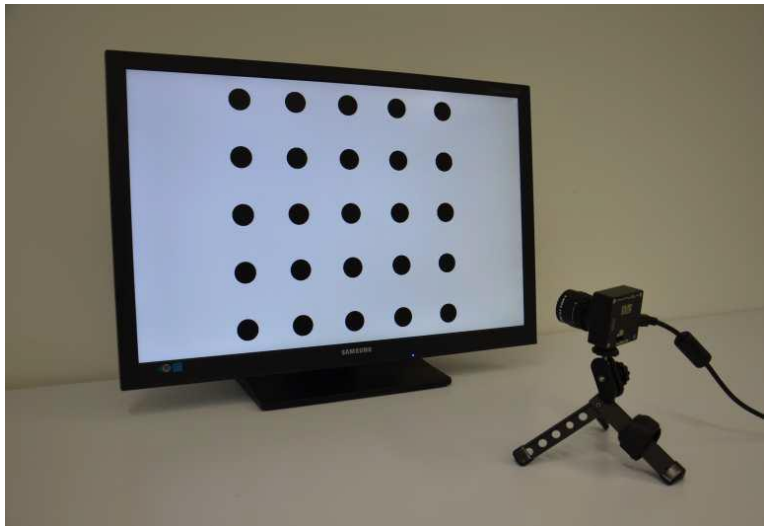
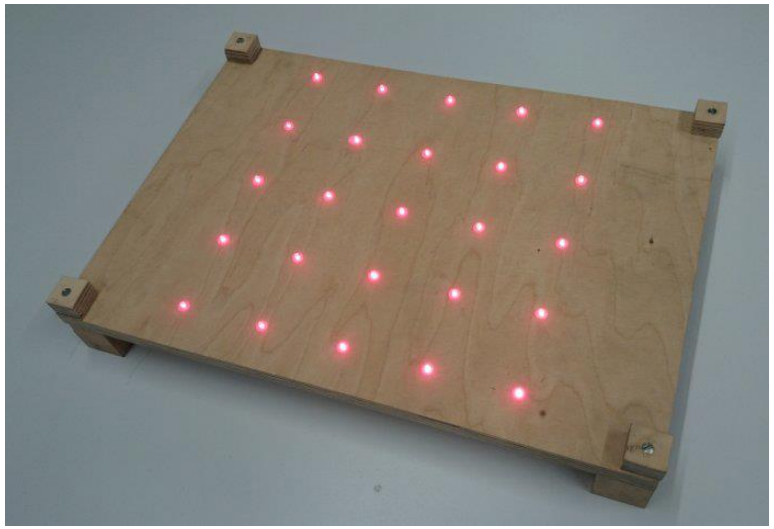
Calibration of a DVS [IROS'14]

- 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





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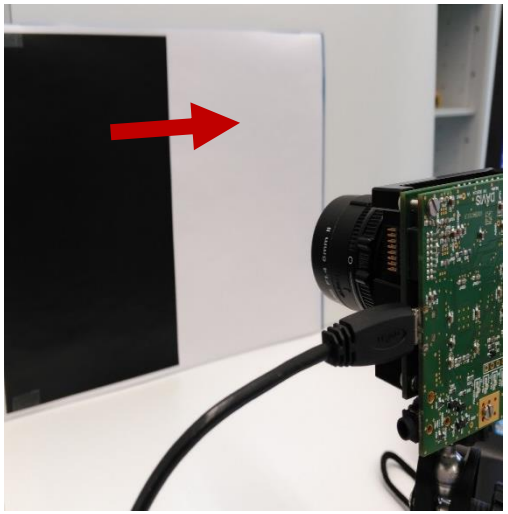
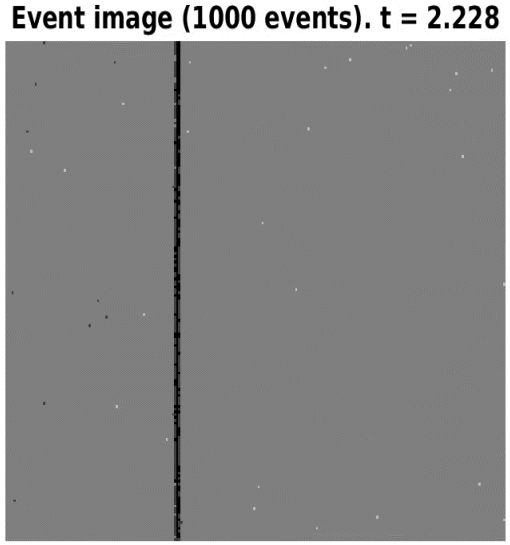
A Simple Optical Flow Algorithm

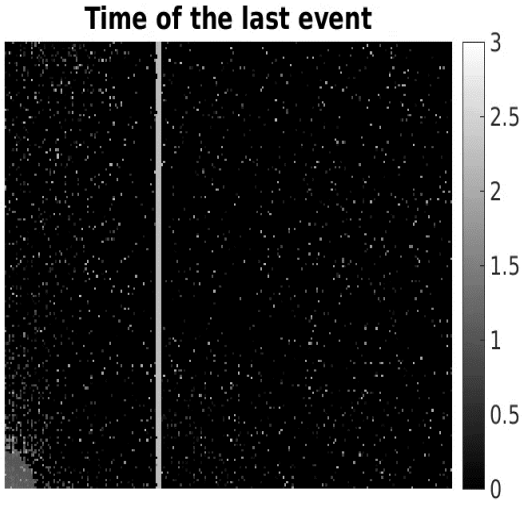
A moving edge

Horizontal motion

White pixels become black → brightness decrease → negative events (in black color)





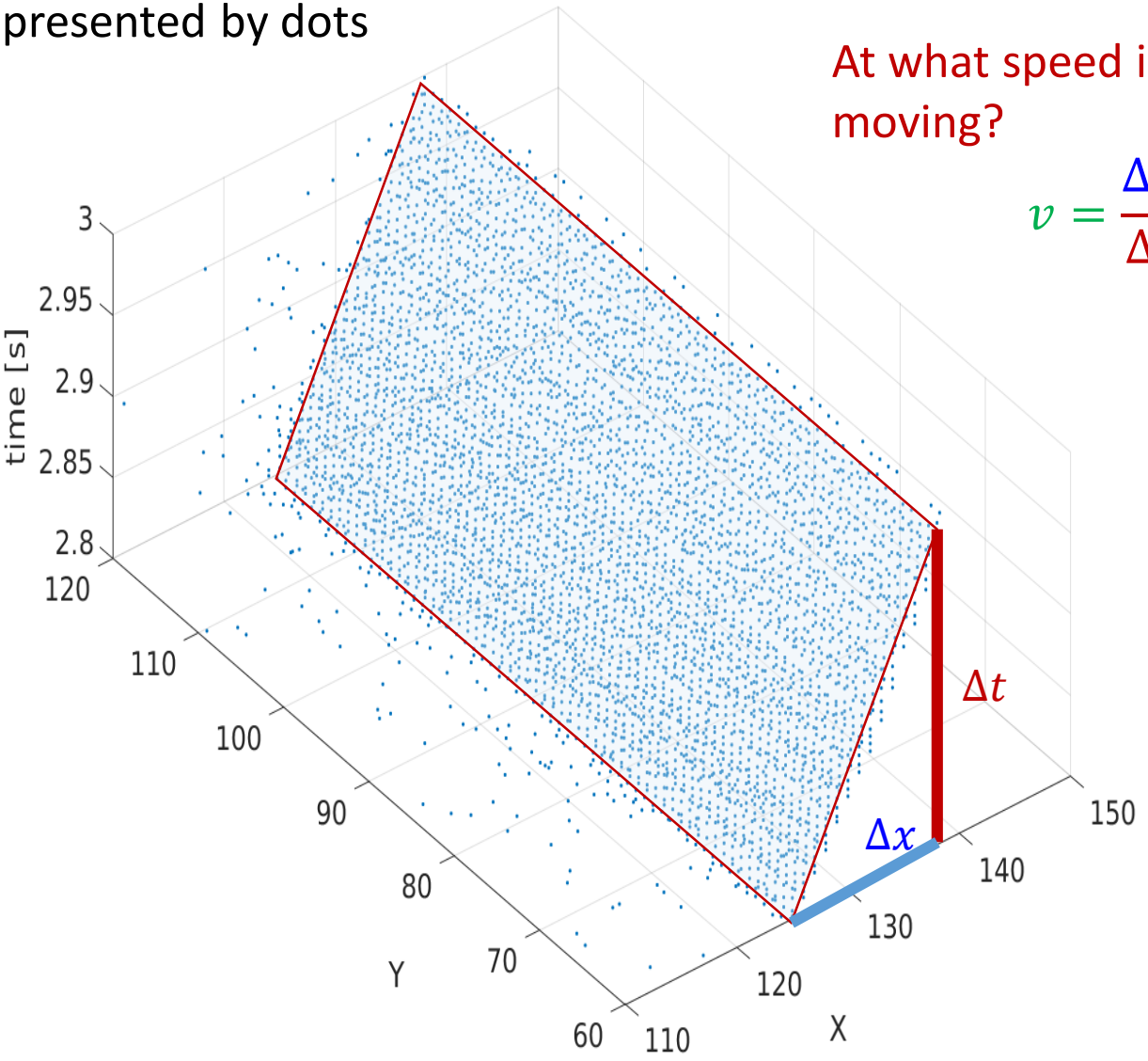


A moving edge

The same edge, visualized in space-time.
Events are represented by dots

At what speed is the edge moving?

$$v = \frac{\Delta x}{\Delta t}$$

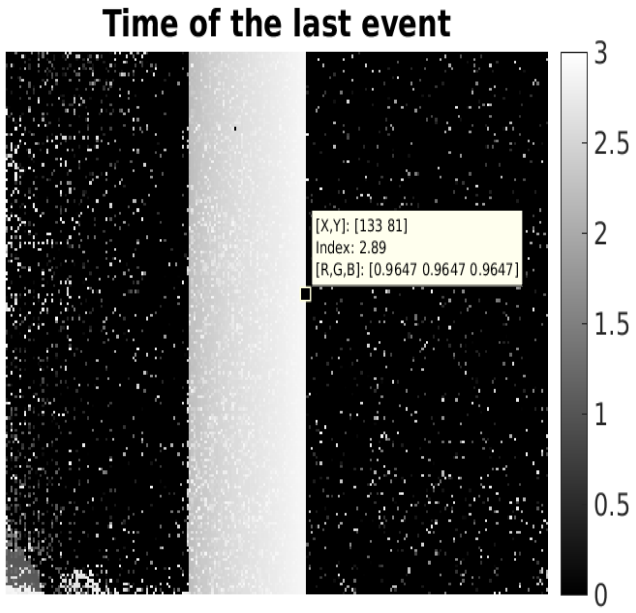


A moving edge

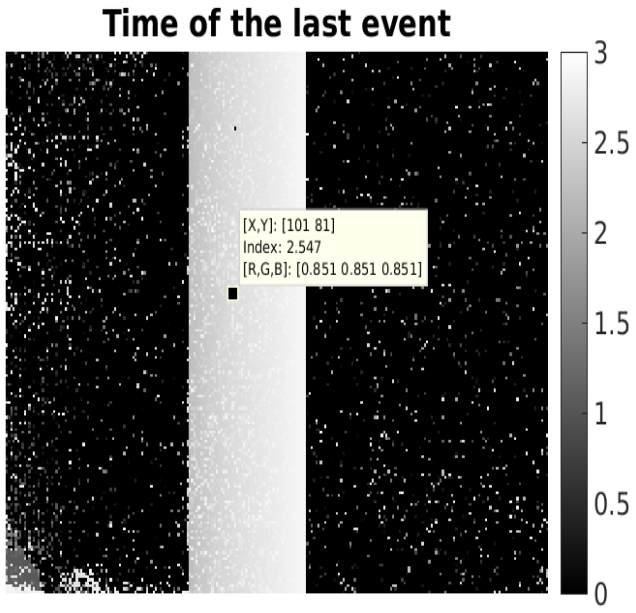
Speed of the edge:

$$v = \frac{(133 - 101)}{(2.89 - 2.547)} = 93.3\ pix/sec$$

At t = 2.89, X = 133



At t = 2.547, X = 101



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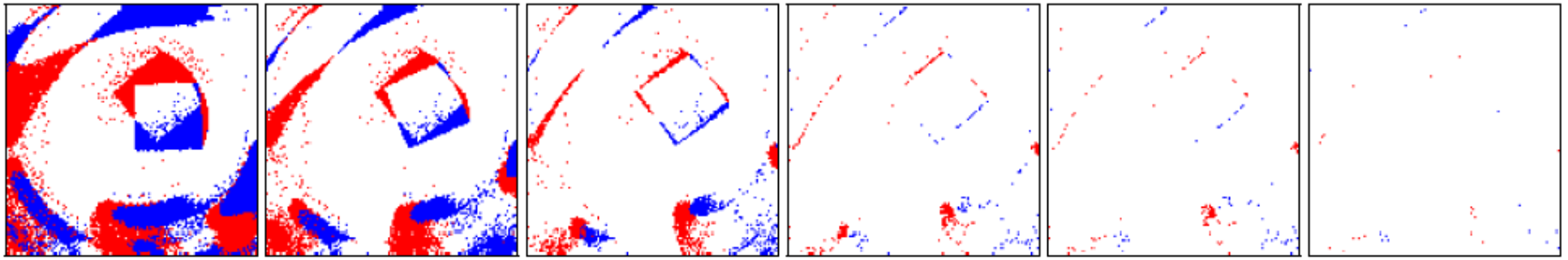
How many events should be used?



(a) $\Delta T = 33\,\text{ms}$ (b) $\Delta T = 15\,\text{ms}$ (c) $\Delta T = 5\,\text{ms}$ (d) $\Delta T = 1\,\text{ms}$ (e) $\Delta T = 0.5\,\text{ms}$ (f) $\Delta T = 0.1\,\text{ms}$

- **Event-by-event processing** (i.e., estimate the state **event by event**)
  - Pros: low latency (in the order of microseconds)
  - Cons: with high-speed motion, dozens of millions of events per seconds → GPU

- **Event-packet processing** (i.e., **process the last N events**)
  - Pros: N ca be tuned to allow real-time performance on a CPU
  - Cons: no longer microsecond resolution (when is this really necessary?)

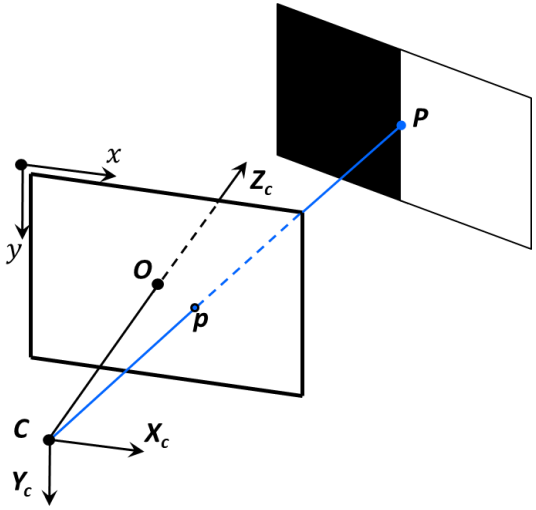
Censi, Strubel, Brandli, Delbruck, Scaramuzza, Low-latency localization by Active LED Markers tracking using a Dynamic Vision Sensor, IROS'13

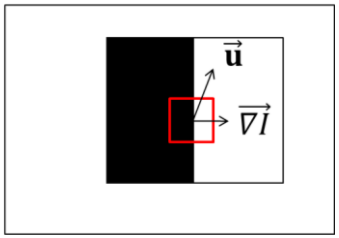
Event-by-Event based Processing

Event Generation Model

- To simplify the notation, let's assume from now on that $I(x, y, t) = Log(I(x, y, t))$
- Consider a given pixel $p(x, y)$ with gradient $\nabla I(x, y)$ undergoing the motion $\boldsymbol{u} = (u, v)$ in pixels, induced by a moving 3D point $\mathbf{P}$.
- It can be shown that an event is generated if the scalar product between the the gradient vector $\nabla I(x, y)$ and the apparent motion vector $\mathbf{u} = (u, v)$ is equal to C:

$$-\nabla I \cdot \mathbf{u} = C$$





- Censi & Scaramuzza, Low Latency, Event-based Visual Odometry, ICRA'14
- Gallego, Lund, Mueggler, Rebecq, Delbruck, Scaramuzza, Event-based, 6-DOF Camera Tracking from Photometric Depth Maps, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017.

Proof

The proof comes from the brightness constancy assumption, which says that the intensity value of p, before and after the motion, must remain unchanged (Lecture 11, slides 17 and 22):

$$I(x, y, t) = I(x + u, y + v, t + \Delta t)$$

By replacing the right-hand term by its 1st order approximation at $t + \Delta t$, we get:

$$I(x, y, t) = I(x, y, t + \Delta t) + \frac{\partial I}{\partial x} u + \frac{\partial I}{\partial y} v$$

$$\Rightarrow \; I(x, y, t + \Delta t) - I(x, y, t) = -\frac{\partial I}{\partial x} u - \frac{\partial I}{\partial y} v$$

$$\Rightarrow \; \Delta I = C = -\nabla I \cdot \mathbf{u}$$

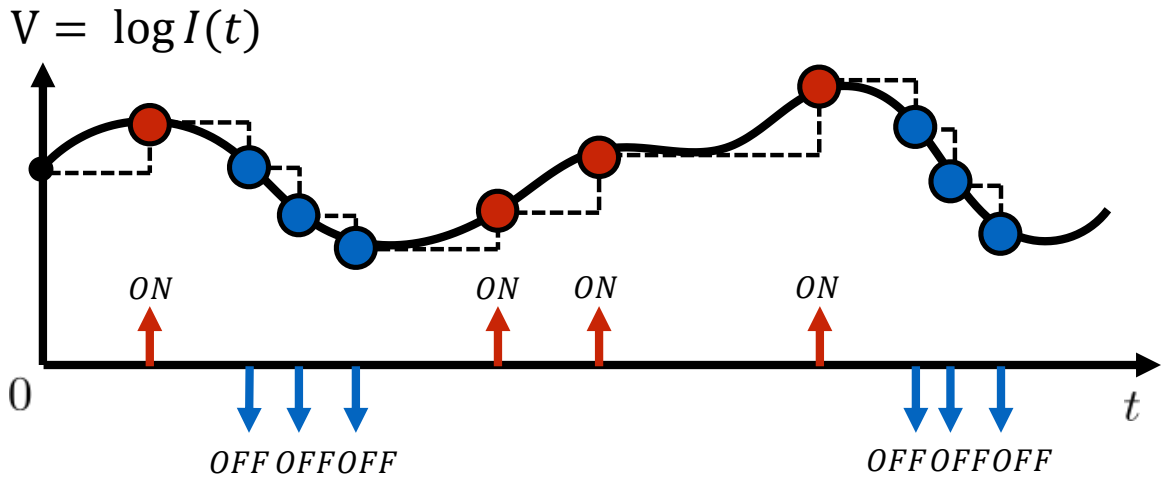
This equation describes the **linearized** event generation equation for an event generated by a gradient ∇I that moved by a motion vector $\mathbf{u}$ (optical flow) during a time interval Δt.

Case Study 1:
Image Intensity Reconstruction

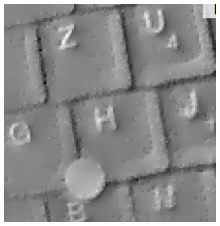
Kim, Handa, Benosman, Ieng, Davison, Simultaneous Mosaicing and Tracking with an Event Camera, BMVC'15

Image reconstruction

Recall: events are generated any time a single pixel sees a change in brightness equal to C



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



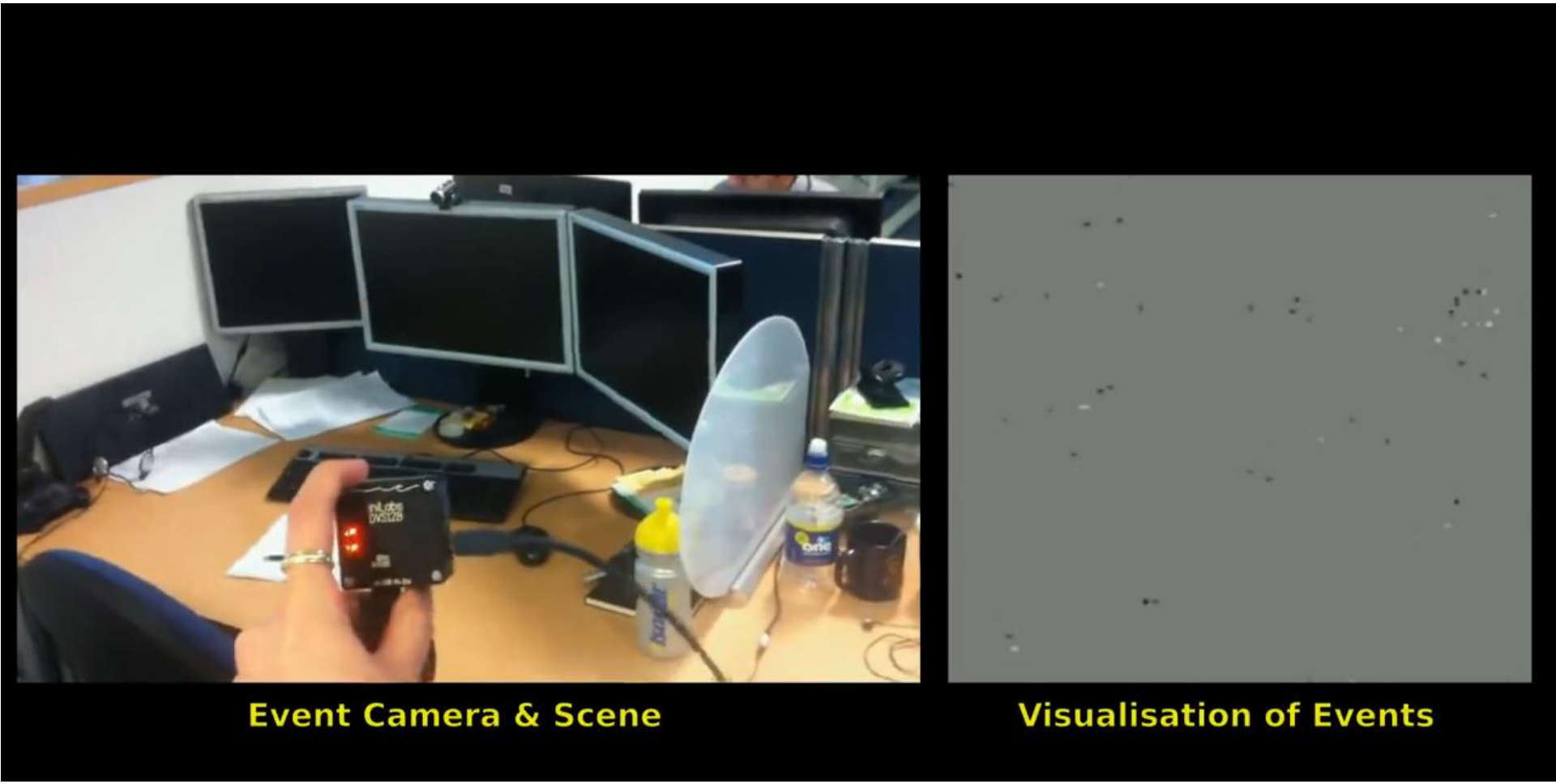
[Cook et al., IJCNN'11]

[Kim et al., BMVC'14]

- Cook, Gugelmann, Jug, Krautz, Steger, *Interacting Maps for Fast Visual Interpretation, Cook et al., IJCNN'11*
- Kim, Handa, Benosman, Ieng, Davison, Simultaneous Mosaicing and Tracking with an Event Camera, BMVC'14

Image reconstruction

Given the events and the camera motion (rotation), recover the absolute brightness.



Kim, Handa, Benosman, Ieng, Davison, Simultaneous Mosaicing and Tracking with an Event Camera, BMVC'14

Image reconstruction

- Given the events and the camera motion (rotation), recover the absolute brightness.
- How is it possible?
- Intuitive explanation: an event camera naturally responds to edges, hence, if we know the motion, we can relate the events to "world coordinates" to get an edge/gradient map. Then, just integrate the gradient map to get absolute intensity.

Steps: 1. Recover the gradient map of the scene

2. Integrate the gradient to obtain brightness

Events

Camera motion $R(t)$

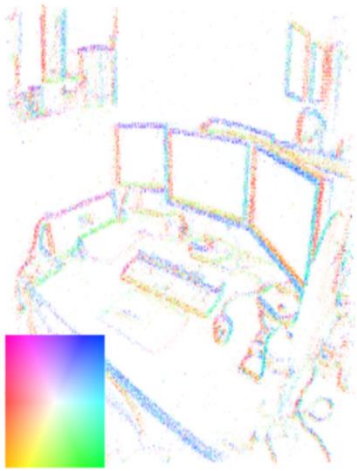


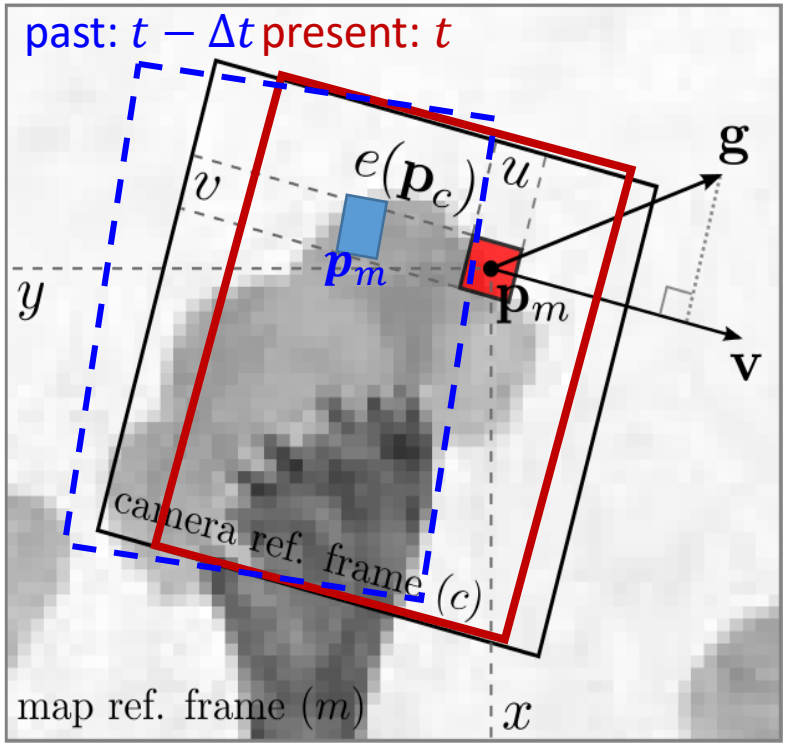
Image gradient
(magnitude and direction)

solve Poisson Eq.

[Kim et al., BMVC'14]

Image reconstruction. Step 1: compute gradient map

Brightness map M



[Kim et al., BMVC'14]

Event generated due to brightness change of size C.

Let $L = \log I$,

$$\Delta L(t) \equiv L(t) - L(t - \Delta t) = C$$

In terms of the brightness map $M(x, y)$ (panorama):

$$M(\boldsymbol{p}_m(t)) - M\big(\boldsymbol{p}_m(t - \Delta t)\big) = C$$

Using Taylor 1st order approximation:

$$M\big(\boldsymbol{p}_m(t)\big) - M\big(\boldsymbol{p}_m(t - \Delta t)\big) \approx \boldsymbol{g} \cdot \boldsymbol{v}\Delta t$$

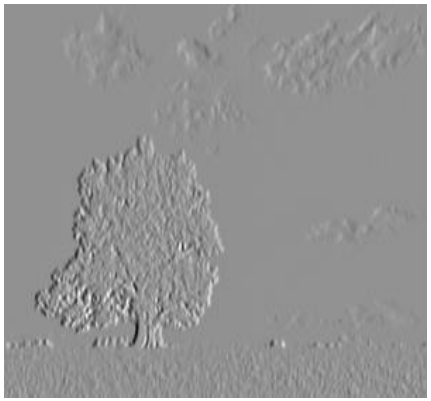
With brightness gradient $\boldsymbol{g} = \nabla M\big(\boldsymbol{p}_m(t)\big)$

Displacement: $\boldsymbol{v}\Delta t = \big(\boldsymbol{p}_m(t) - \boldsymbol{p}_m(t - \Delta t)\big)$

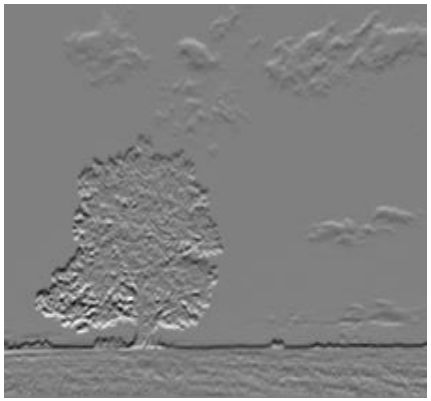
Image reconstruction. Step 2: Poisson reconstruction

Integrate gradient map $\boldsymbol{g}$ to get absolute brightness M

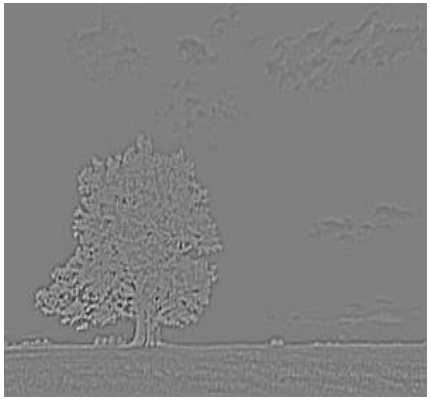
Original Image



Gradient in *x* direction $(g_x = \partial_x I)$



Gradient in *y* direction $(g_y = \partial_y I)$



Divergence $(\operatorname{div} \boldsymbol{g} = \partial_x g_x + \partial_y g_y)$

Solve Poisson eq: $(\Delta \tilde{I} = \operatorname{div} \boldsymbol{g})$ Fast using the FFT

Poisson Image Reconstruction

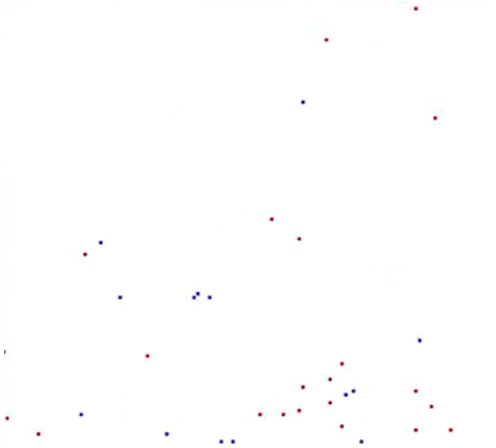
Reconstructed Image

Case Study 2:
6-DoF Pose Tracking from a Photometric Depth Map

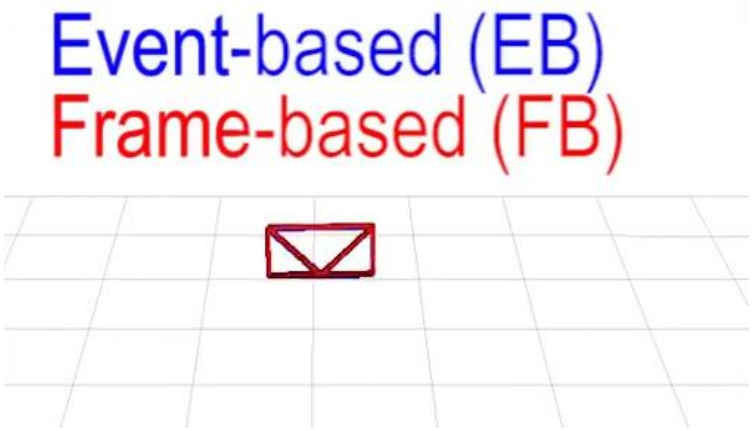
Gallego, Lund, Mueggler, Rebecq, Delbruck, Scaramuzza, Event-based, 6-DOF Camera Tracking from Photometric Depth Maps, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017.

Low-latency, High-speed 6DOF Camera Tracking

Event camera



Standard camera



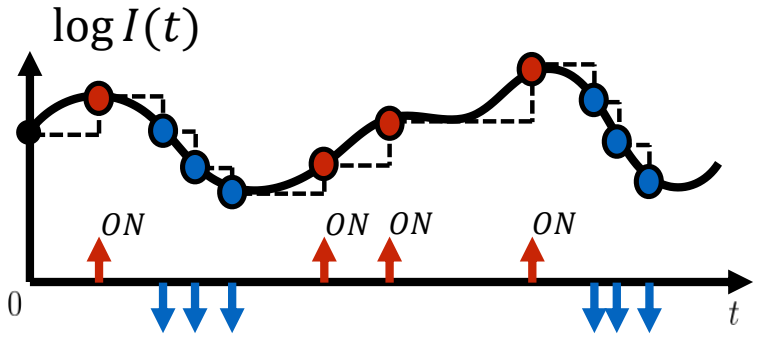
Gallego, Rebecq, Delbruck, Scaramuzza, Event-based, 6-DOF Camera, Tracking from Photometric Depth Maps, **T-PAMI**, 2018

Methodology

- **Probabilistic** approach (Bayesian filter): $p(s|e) = p(e|s)p(s)$

  Posterior Likelihood Prior

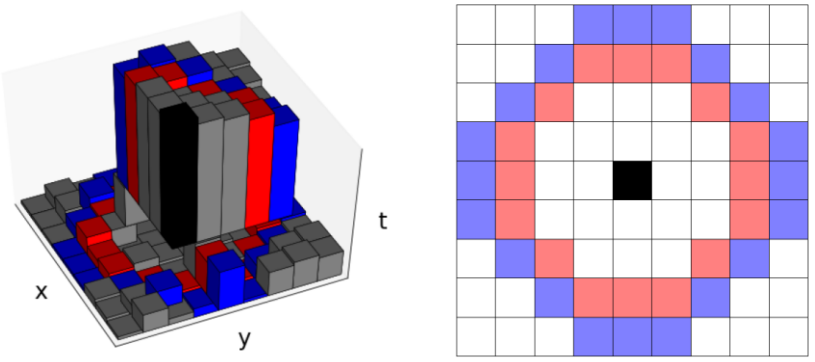
- **State vector**: $s = (R, T, C, \sigma_C, \rho)$
  - pose (R,T),
  - contrast mean value C
  - uncertainty σ_C,
  - inlier ratio ρ



- Motion model: **random walk**
- **Robust sensor model** (likelihood)
  - **Measurement function** derived from generative event model: $-\nabla I \cdot \mathbf{u} = C$

Gallego, Lund, Mueggler, Rebecq, Delbruck, Scaramuzza, Event-based, 6-DOF Camera Tracking from Photometric Depth Maps, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017.

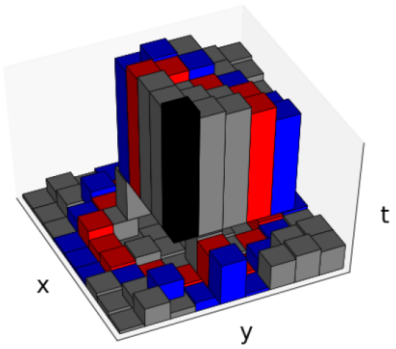
Case Study 3:
Event-based Corner Detection

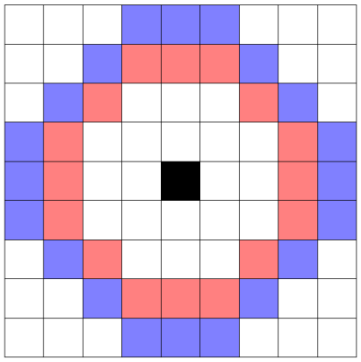


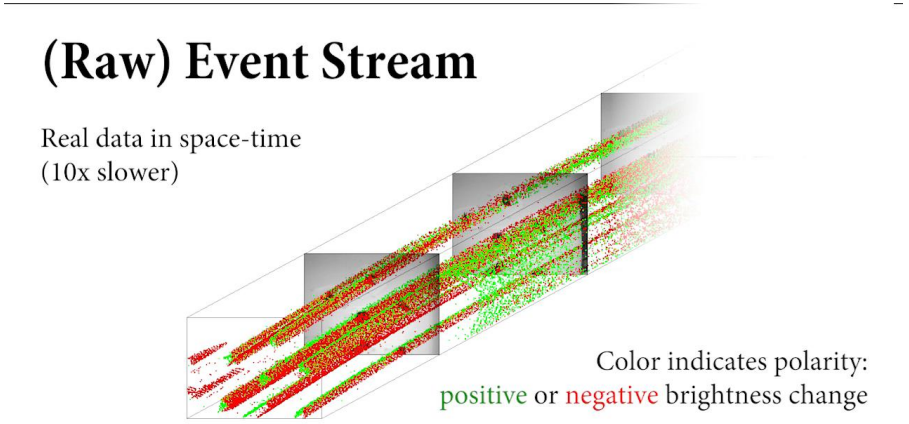
Mueggler, Bartolozzi, Scaramuzza, Fast Event-based Corner Detection, British Machine Vision Conference (BMVC), London, 2017

FAST-like Event-based Corner Detection

- Operates on Surface of Active Events





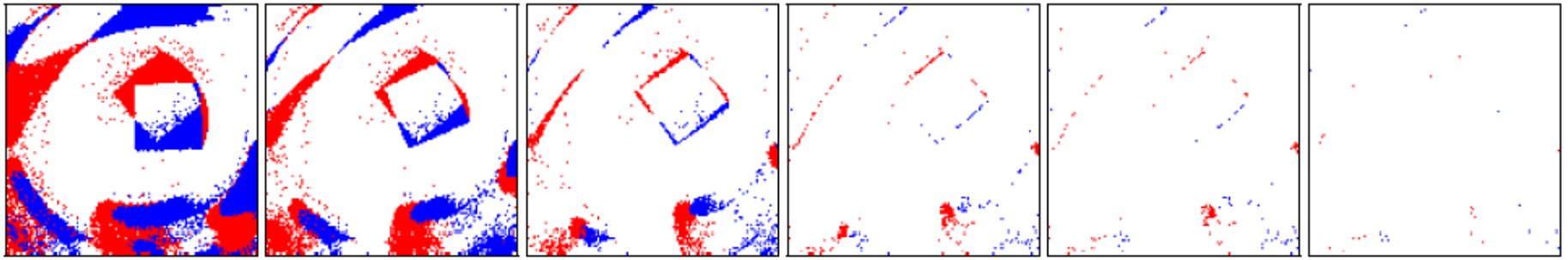


- The event is considered a corner if
  - 3-6 contiguous pixels on red ring are newer than all other pixels on the same ring and
  - 4-6 contiguous pixels on blue ring are newer than all other pixels on the same ring and

Mueggler, Bartolozzi, Scaramuzza, Fast Event-based Corner Detection, British Machine Vision Conference (BMVC), London, 2017

Event-packet based Processing

How many events should be used?



(a) $\Delta T = 33\,\text{ms}$ (b) $\Delta T = 15\,\text{ms}$ (c) $\Delta T = 5\,\text{ms}$ (d) $\Delta T = 1\,\text{ms}$ (e) $\Delta T = 0.5\,\text{ms}$ (f) $\Delta T = 0.1\,\text{ms}$

- **Event-by-event processing** (i.e., estimate the state **event by event**)
  - Pros: low latency (in principle down to microseconds)
  - Cons: with high-speed motion -> dozens of millions of events per seconds → GPU

- **Event-packet processing** (i.e., **process the last N events**)
  - Pros: N ca be tuned to allow real-time performance on a CPU
  - Cons: no longer microsecond resolution (when is this really necessary?)

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

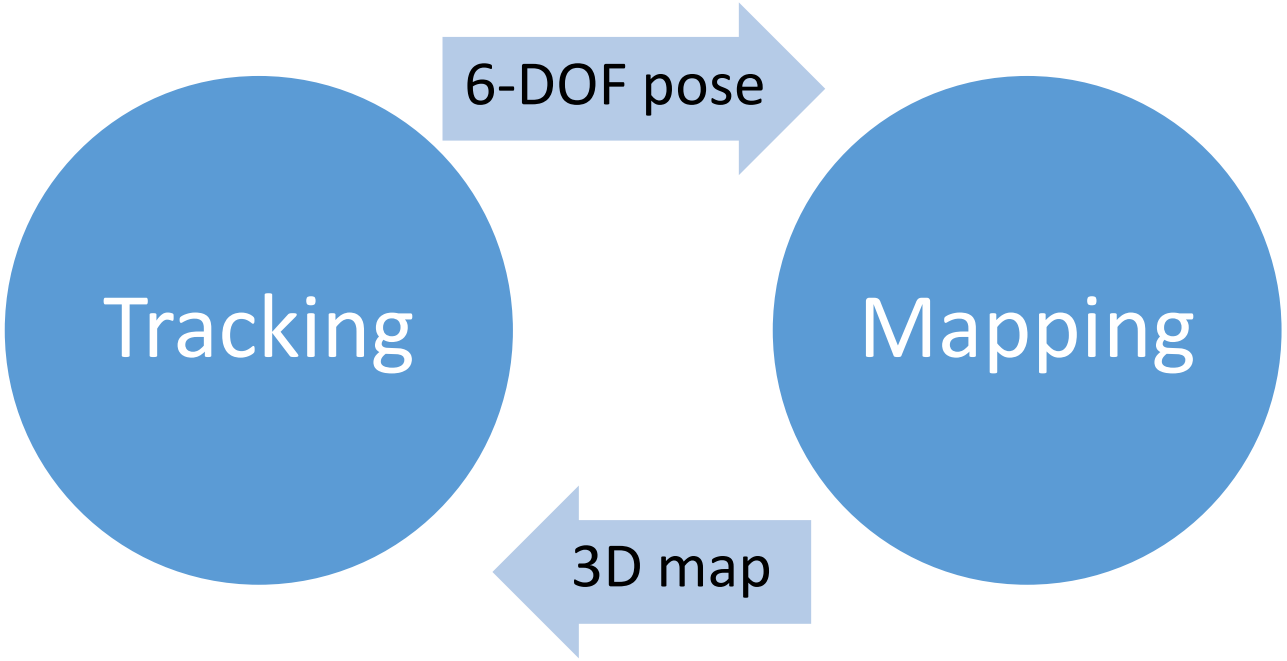
EVO:
A Geometric Approach to Event-based 6-DOF Parallel Tracking and Mapping in Real-time

Rebecq, Horstschäfer, Gallego, Scaramuzza

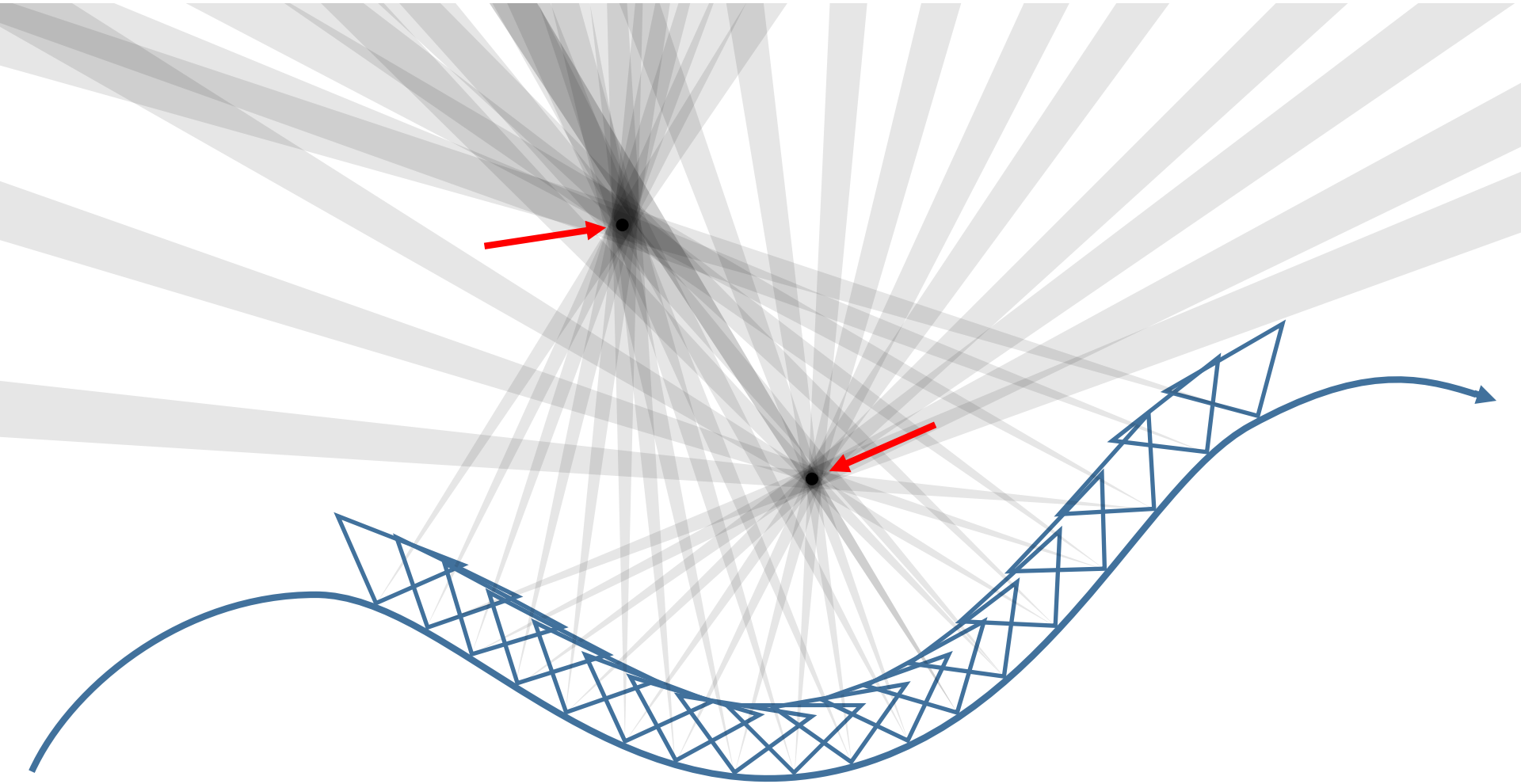
IEEE Robotics & Automation Letters, 01/2017 (presented at ICRA'17)

EU Patent 2017

Parallel Tracking and Mapping



How the 3D mapping works

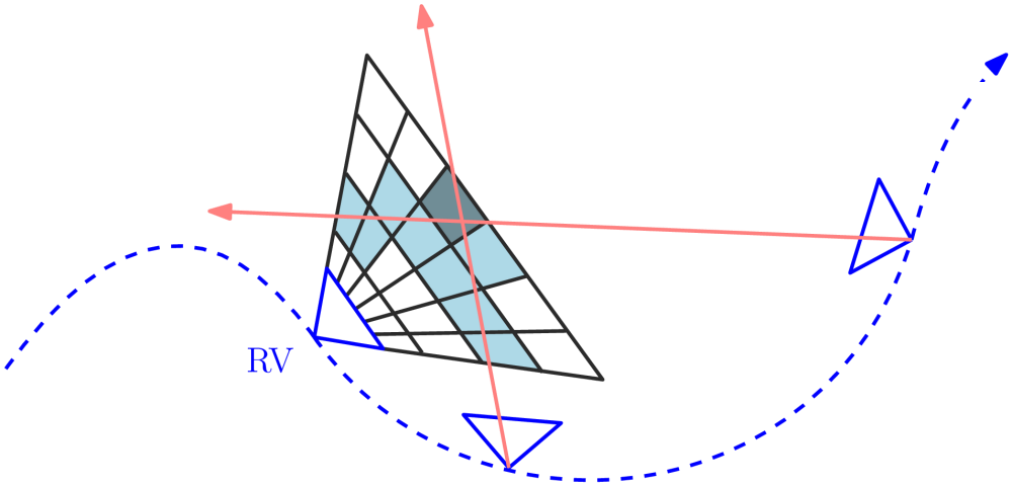


An event camera reacts to strong gradients in the scene

Areas of high ray-density likely indicate the presence of 3D structures

How the 3D mapping works

- Ray-density: Disparity Space Image (DSI)
- Projective sampling grid (DSI)
  + adaptive thresholding

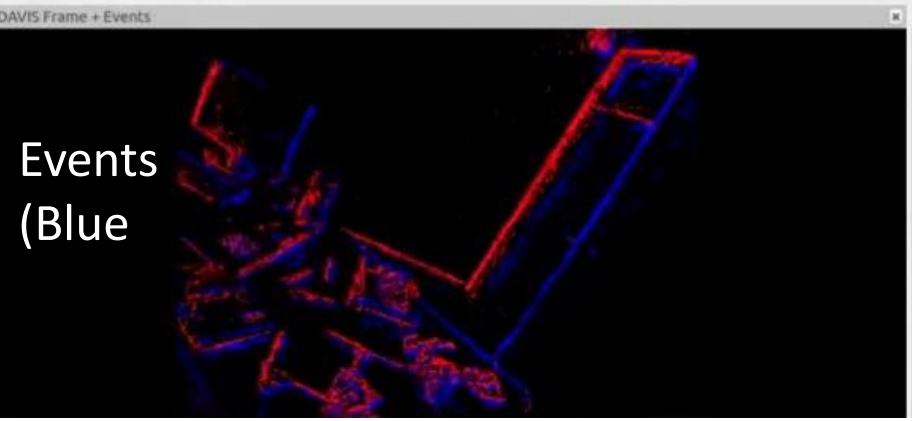


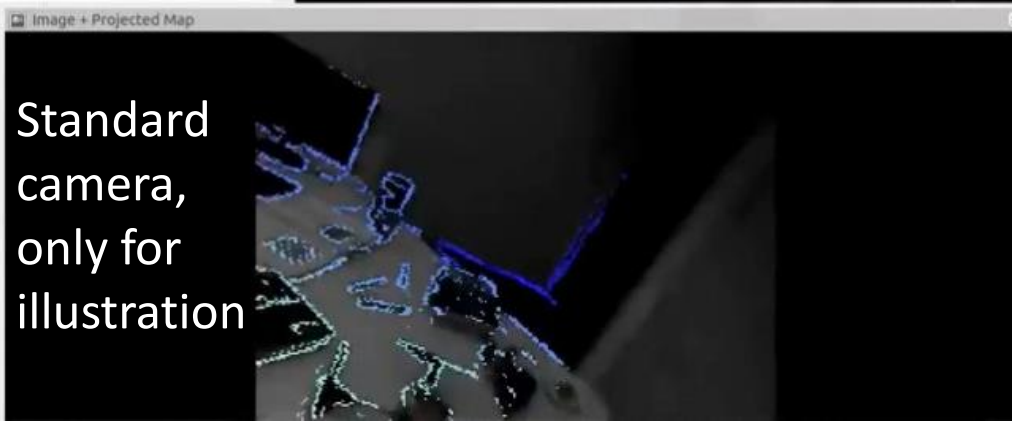
Non-uniform, projective grid,
centered on a reference viewpoint

240 x 180 x 100 voxels

Rebecq, Gallego, Scaramuzza, EMVS: Event-based Multi-View Stereo, IJCV'17, Code

EVO: semi-dense event-SLAM





Rebecq, Horstschaefer, Gallego, Scaramuzza, EVO: A Geometric Approach to Event-based 6-DOF Parallel Tracking and Mapping in Real-time, IEEE Robotics and Automation Letters (RA-L), 2017

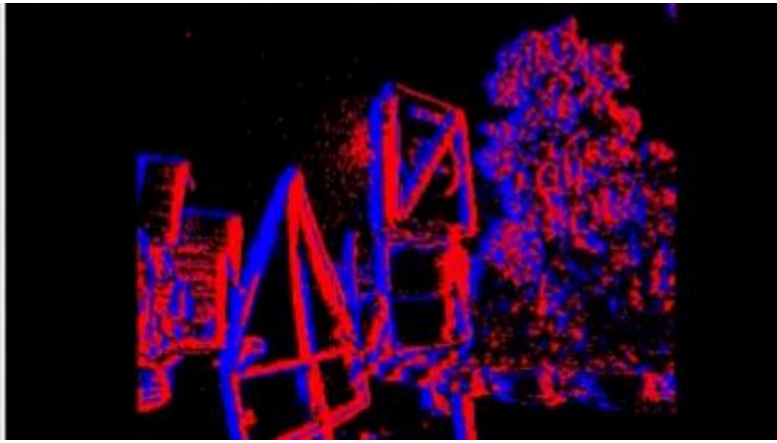
EVO: semi-dense event-SLAM
Robustness to HDR Scenes

iPhone camera

Frame of a standard camera

Intensity reconstruction from events

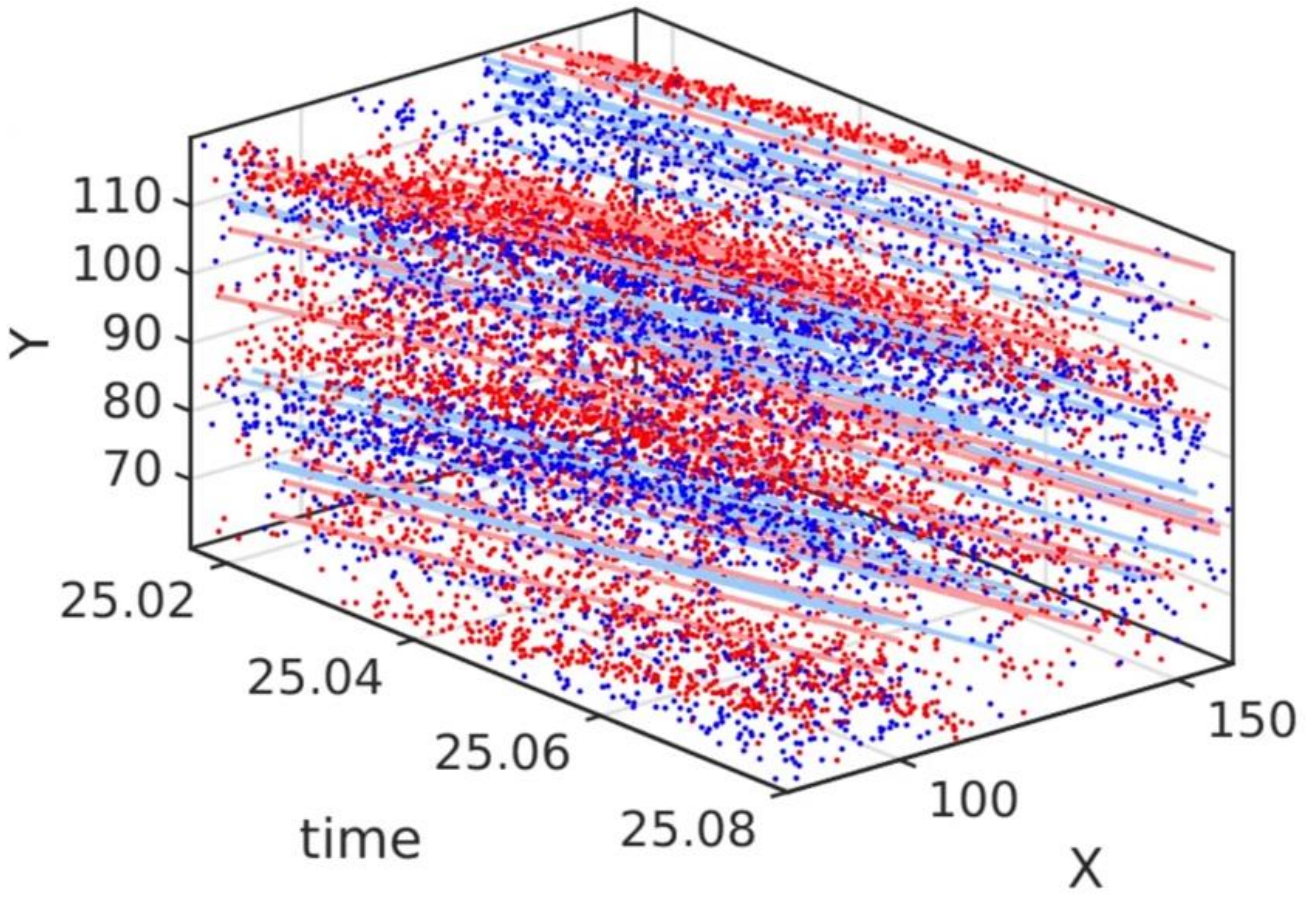
Events only



Rebecq, Horstschaefer, Gallego, Scaramuzza, EVO: A Geometric Approach to Event-based 6-DOF Parallel Tracking and Mapping in Real-time, IEEE Robotics and Automation Letters (RA-L), 2017

Motion-Estimation by Contrast Maximization

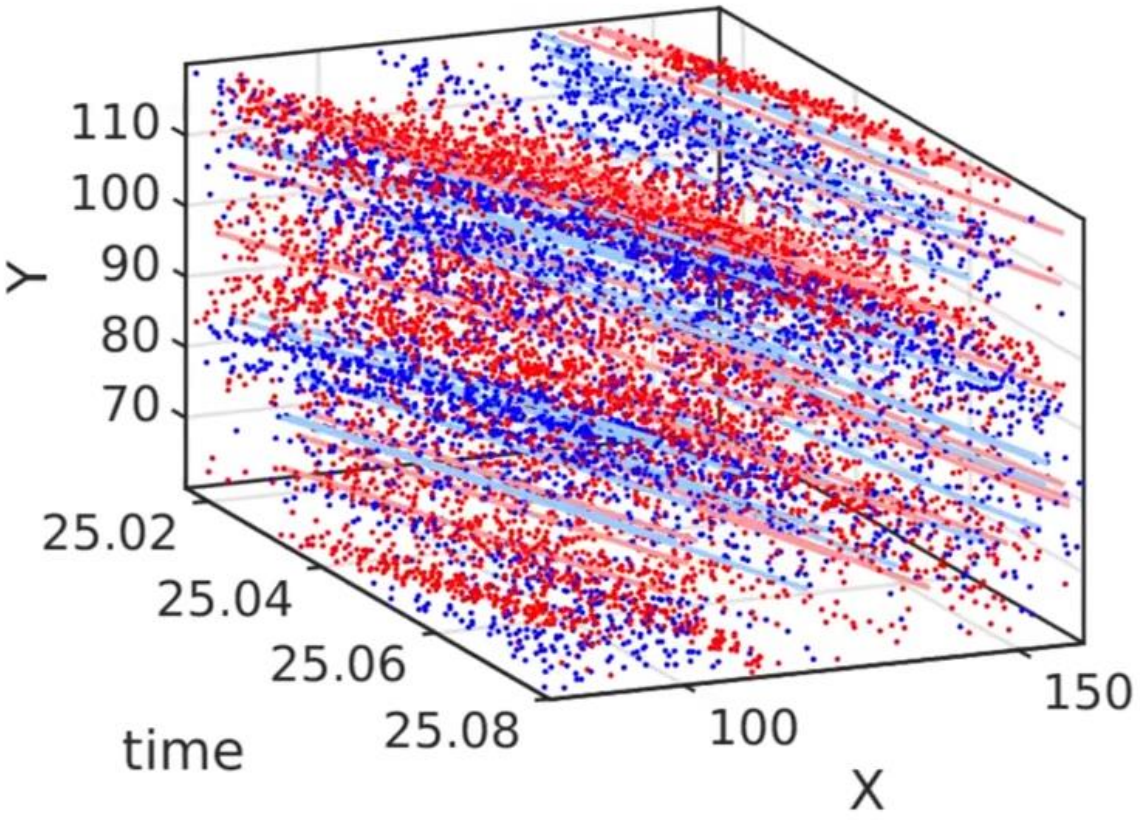
- Directly estimate the motion curves that align the events



Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE RAL'17

Motion-Estimation by Contrast Maximization

- Directly estimate the motion curves that align the events



Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE RAL'17

Motion-Estimation by Contrast Maximization

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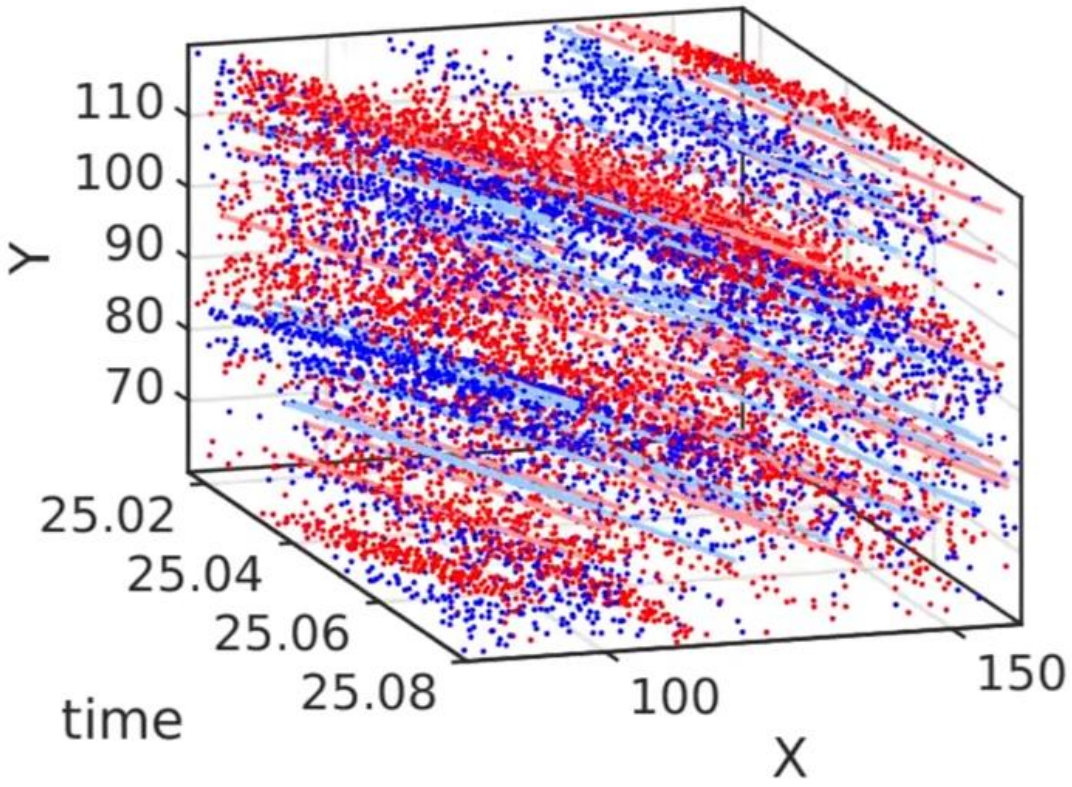
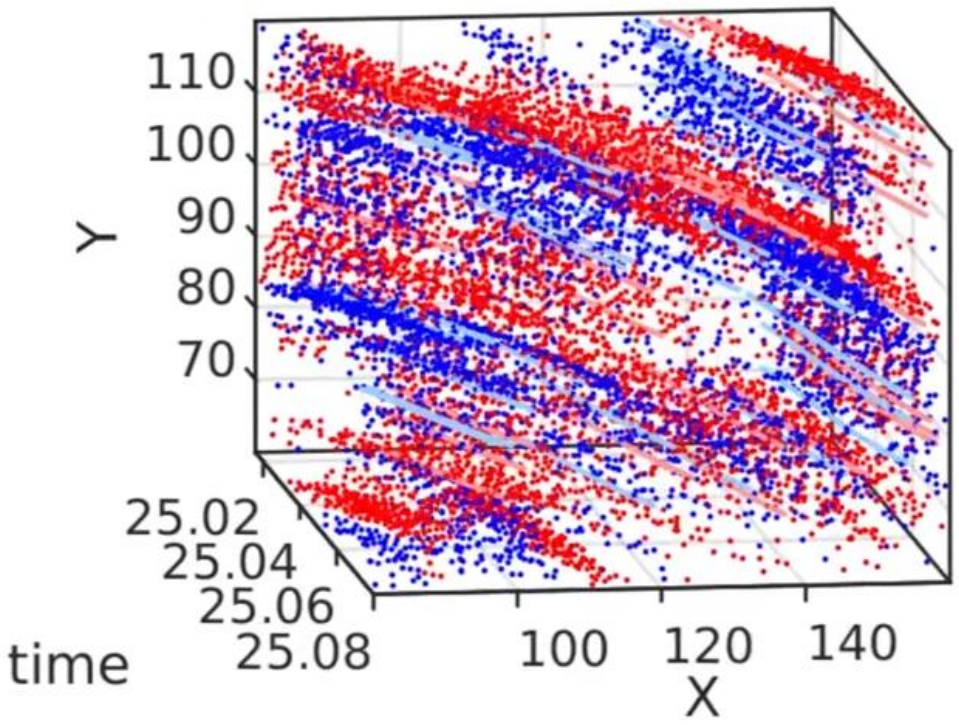


Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE RAL'17

Motion-Estimation by Contrast Maximization

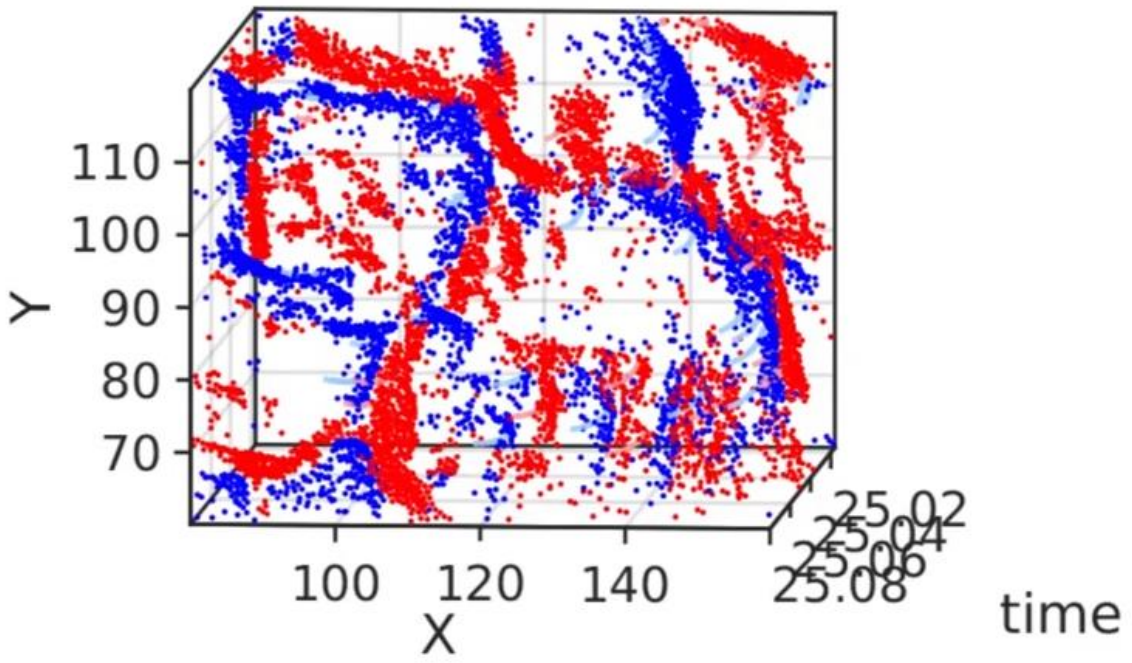
- Directly estimate the motion curves that align the events



Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE RAL'17

Motion-Estimation by Contrast Maximization

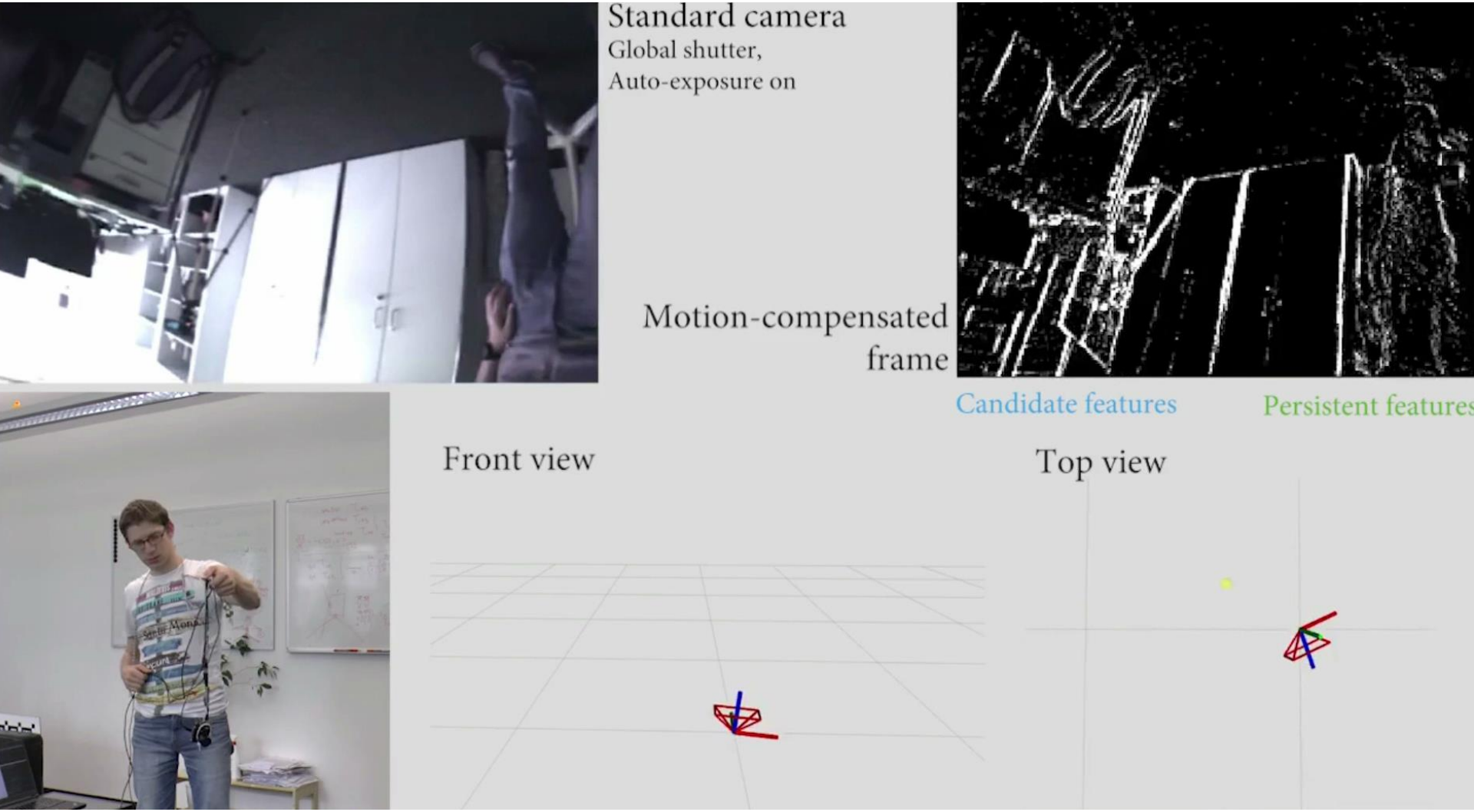
- Directly estimate the motion curves that align the events



Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE RAL'17

Events + IMU based SLAM

Impact: visual SLAM works even when spinning and event camera attached to a leash



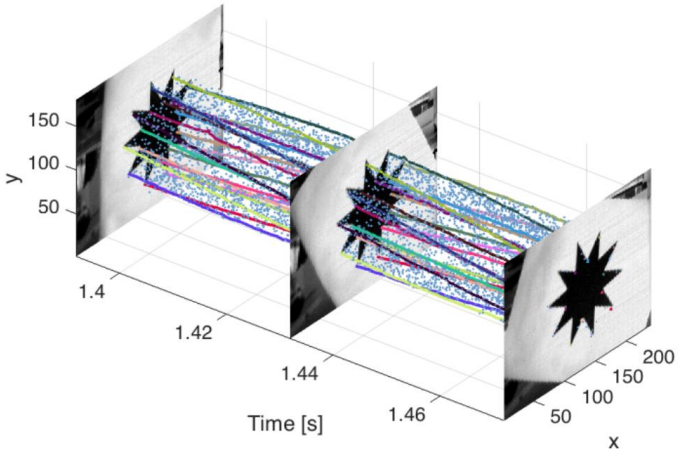
Rebecq, Horstschaefer, Scaramuzza, Real-time Visual-Inertial Odometry for Event Cameras using Keyframe-based Nonlinear Optimization, British Machine Vision Conference (BMVC), London, 2017

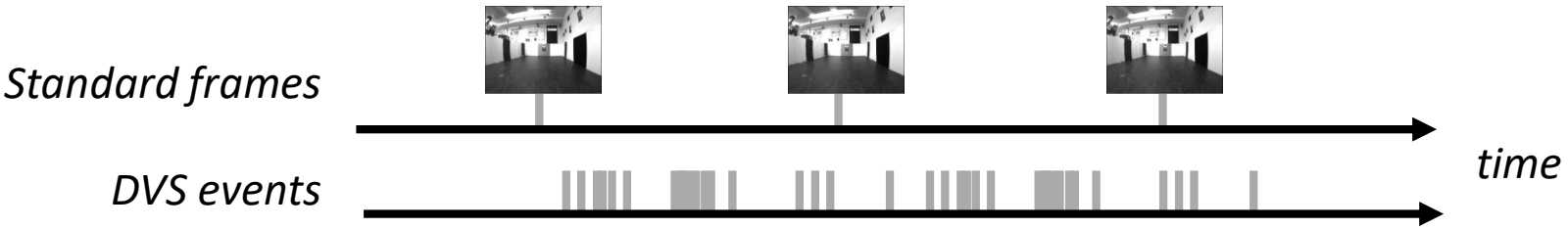
Outline

- Motivation
- DVS sensor and its working principle
- Traditional sampling vs level-crossing sampling
- Current commercial applications
- Calibration patterns
- A simple optic flow algorithm
- Event-by-event vs Event-packet processing
  - Case studies
- DAVIS sensor
  - Case study

DAVIS sensor: Dynamic and Active-pixel Vision Sensor

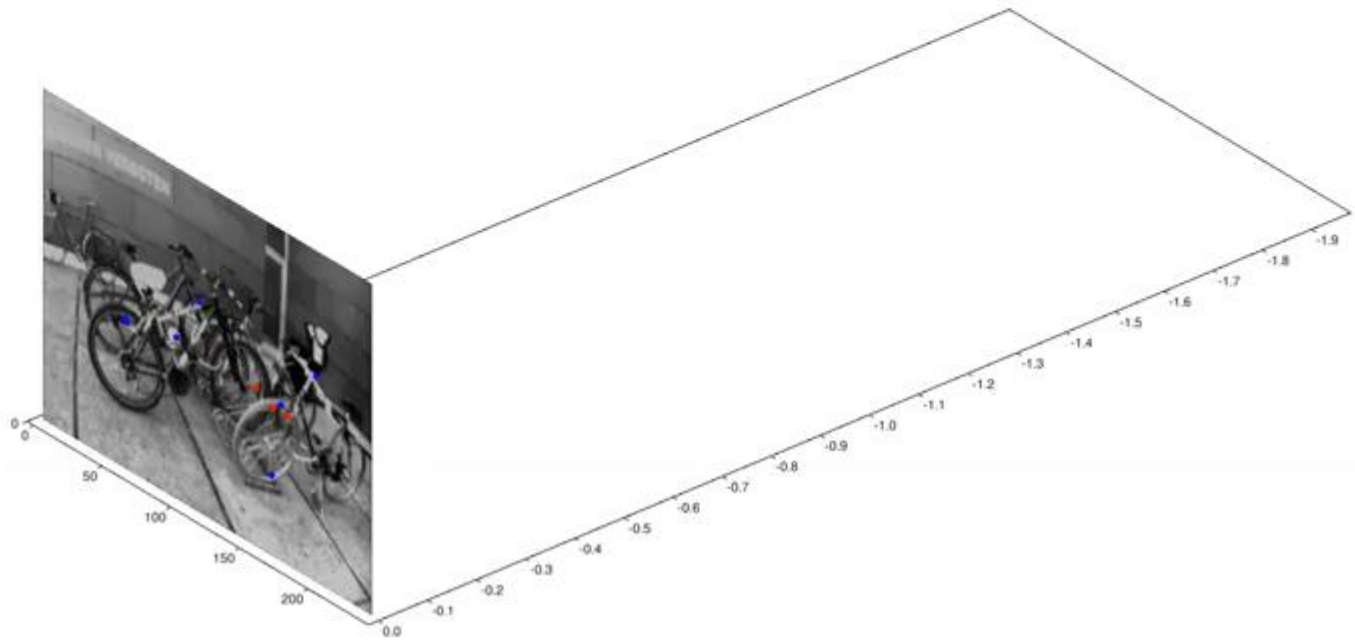
- Combines an **event** sensor (DVS) and a **standard** camera in the same pixel array
- **Output**: frames (at 30 Hz) and events (asynchronous)





Brandli et al. *A 240x180 130dB 3us latency global shutter spatiotemporal vision sensor*. IEEE JSSC, 2014

Low-latency Feature Tracking in the Blind Time between Frames

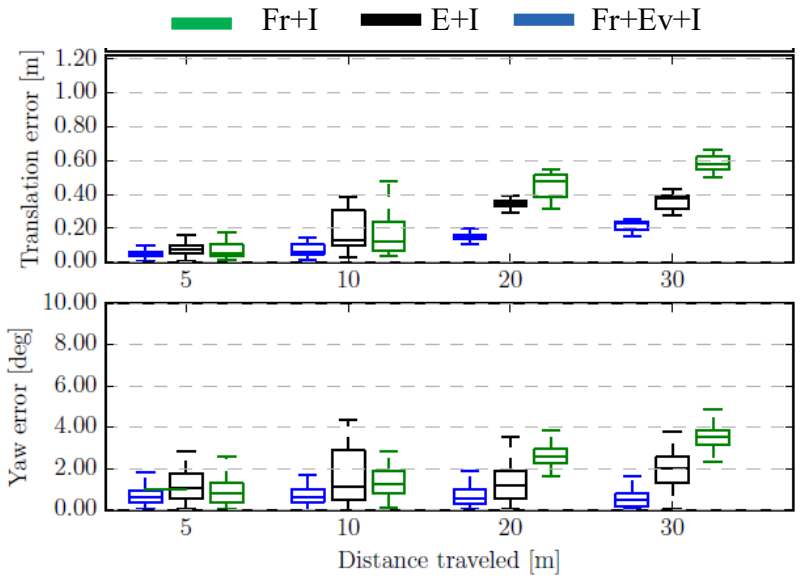


Gehrig et al., Asynchronous, Photometric Feature Tracking using Events and Frames, **ECCV'18, Oral Talk**

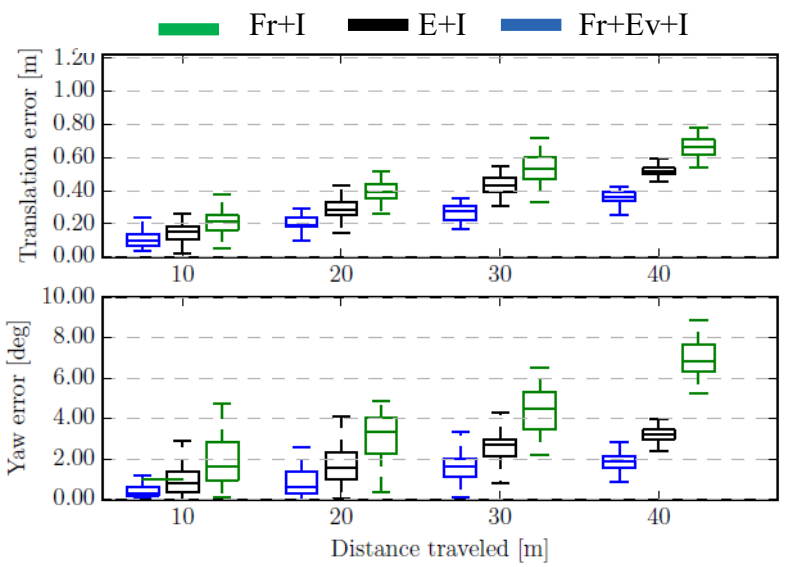
UltimateSLAM: combines Frames + Events + IMU

Adding standard frames increases the accuracy further

High-speed sequence



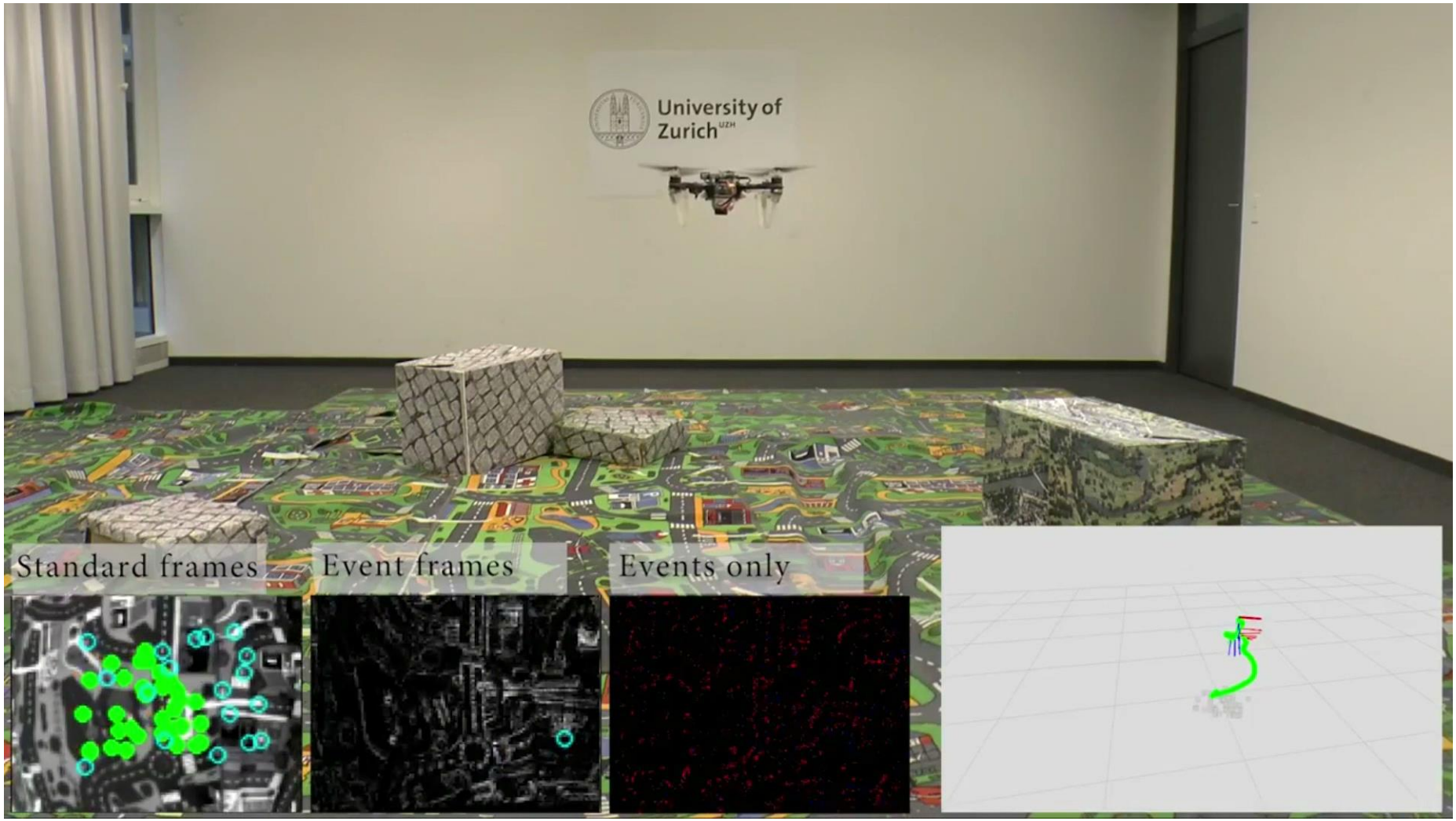
HDR sequence



Vidal, Rebecq, Horstschaefer, Scaramuzza, Ultimate SLAM? Combining Events, Images, and IMU for Robust Visual SLAM in HDR and High Speed Scenarios

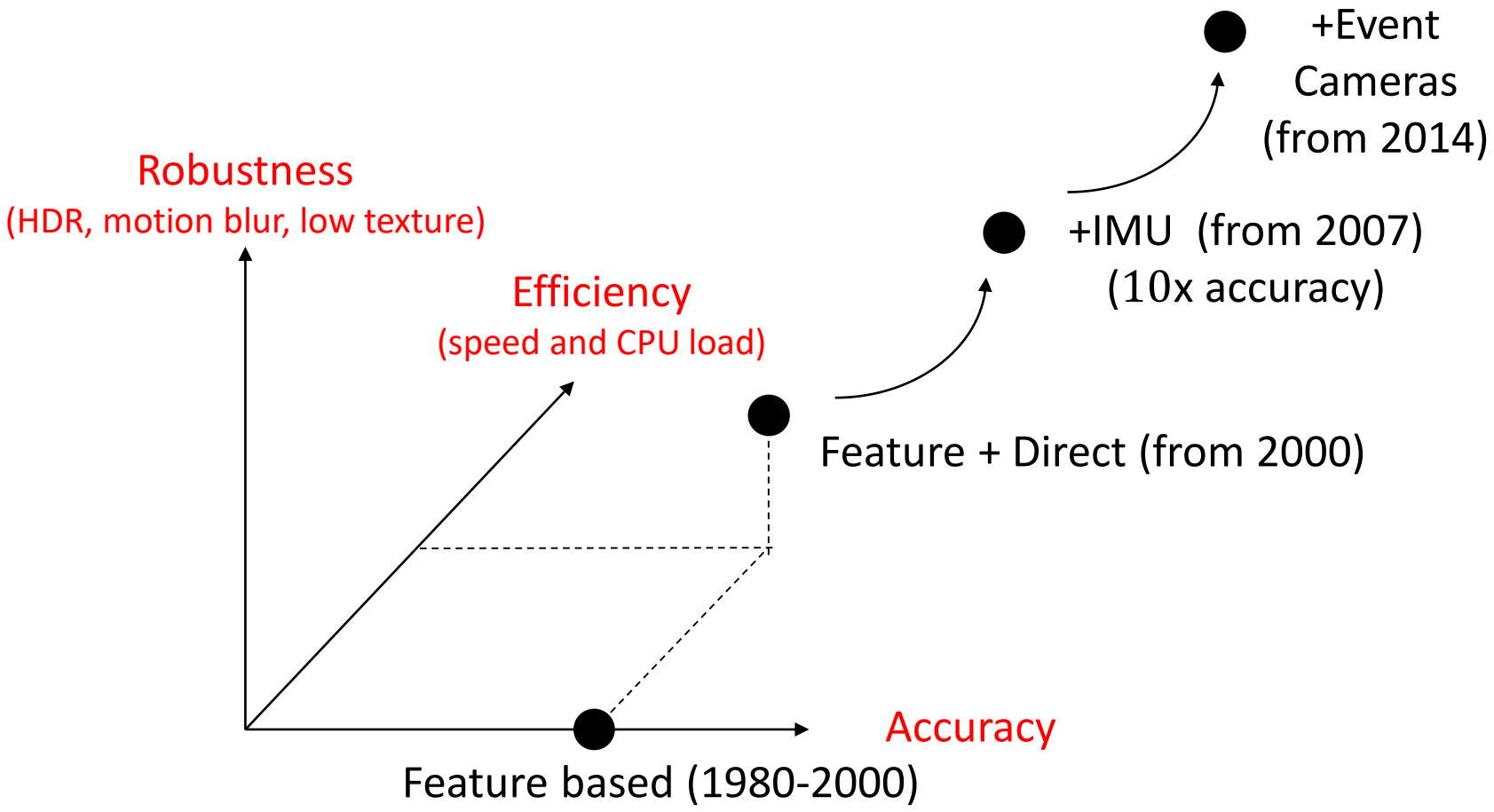
Autonomous Navigation with an Event Camera

UltimateSLAM running fully onboard (Odroid XU4)



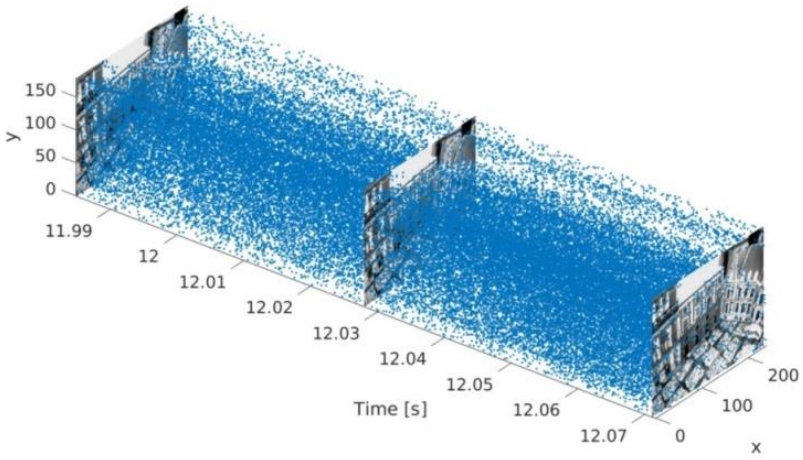
Vidal, Rebecq, Horstschaefer, Scaramuzza, Ultimate SLAM? Combining Events, Images, and IMU for Robust Visual SLAM in HDR and High Speed Scenarios

A Short Recap of the last 30 years of Visual Inertial SLAM



Event Camera Datasets [IJRR'17]

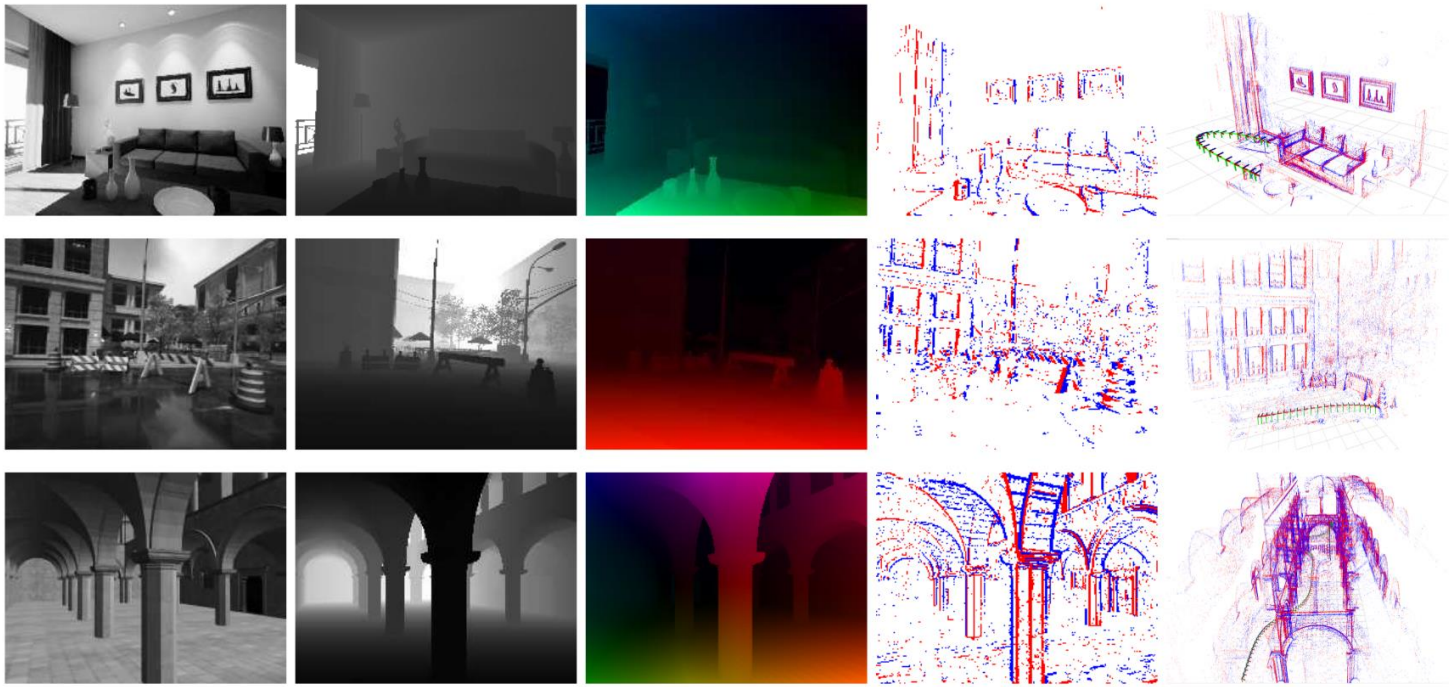
- **Publicly available**: http://rpg.ifi.uzh.ch/davis_data.html
- **First event camera dataset** specifically made **for VO and SLAM**
- **Many diverse scenes:** HDR, Indoors, Outdoors, High-speed
- **Blender simulator of event cameras**
- Includes
  - **IMU**
  - **Frames**
  - **Events**
  - **Ground truth** from a motion capture system



Mueggler, Rebecq, Gallego, Delbruck, Scaramuzza, *The Event Camera Dataset,* IJRR, 2017. PDF

ESIM: Event Camera Simulator [IJRR'17]

- **Publicly available**: http://rpg.ifi.uzh.ch/esim.html



H. Rebecq, D. Gehrig, D. Scaramuzza, **ESIM: an Open Event Camera Simulator,** CORL'18.
PDF YouTube Project page

Conclusions

- Visual Inertial SLAM **theory** is **well established**

- Biggest challenges today are **reliability and robustness** to**:**
  - High-dynamic-range scenes
  - High-speed motion
  - Low-texture scenes
  - Dynamic environments
  - Active sensor parameter control (on-the-fly tuning)

- **Event cameras** are revolutionary and provide:
  - Very **low latency** (1 μs) and **robustness** to **high speed motion** and **high-dynamic-range scenes**
  - Standard cameras studied for 50 years
    - event cameras offer have plenty of room for research
  - **Open problems on event cameras**: noise modeling, asynchronous feature and object detection and tracking, sensor fusion, asynchronous learning & recognition, low latency estimation and control, low power computation

Understanding Check

Are you able to answer the following questions?

- What is a DVS and how does it work?
- What are its pros and cons vs. standard cameras?
- Can we apply standard camera calibration techniques?
- How can we compute optical flow with a DVS?
- Could you intuitively explain why we can reconstruct the intensity?
- What is the generative model of a DVS?
- What is a DAVIS sensor?
- Can you write the equation of the event generation model and its proof?