University of Zurich[UZH]

ROBOTICS & PERCEPTION GROUP

Vision Algorithms for Mobile Robotics

Lecture 14
Event-based Vision

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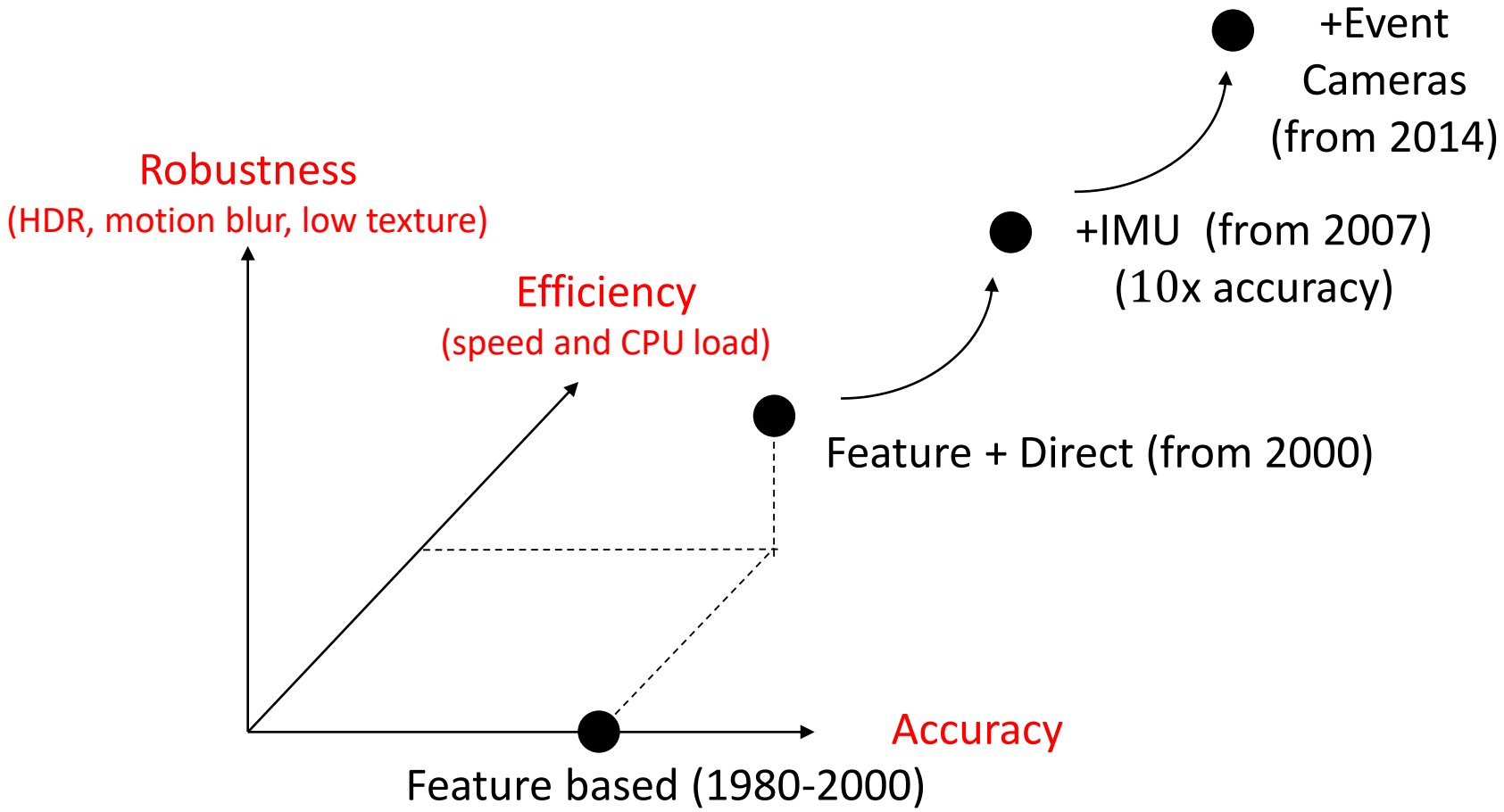
http://rpg.ifi.uzh.ch

Lab Exercise – Today

Q&A on Exams followed by final VO integration

A Short Recap of the last 30 years of VIO



References

- **Tutorial** paper:
  Gallego, Delbruck, Orchard, Bartolozzi, Taba, Censi, Leutenegger, Davison, Conradt, Daniilidis, Scaramuzza, **Event-based Vision: A Survey**, IEEE Transactions of Pattern Analysis and Machine Intelligence, 2020. PDF

- List of event camera papers, codes, datasets, companies: https://github.com/uzh-rpg/event-based_vision_resources

- Event-camera simulator: http://rpg.ifi.uzh.ch/esim.html

- More on event camera research: http://rpg.ifi.uzh.ch/research_dvs.html

Open Challenges in Computer Vision

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

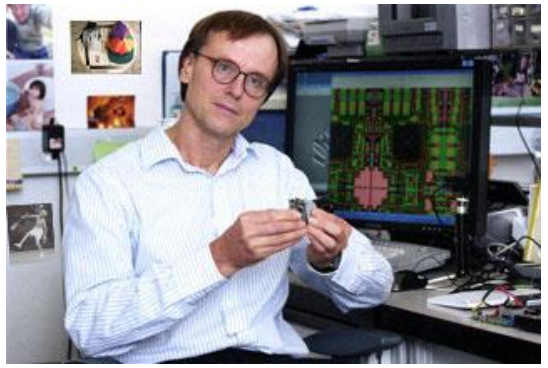
Latency & Motion blur

Dynamic Range

- **Event cameras** do not suffer from these problems

What is an Event Camera

First commercialized by Prof. T. Delbruck in 2008 at the Institute of Neuroinformatics of UZH & ETH under the name of Dynamic Vision Sensor (DVS)



Prof. Tobi Delbruck, UZH & ETH Zurich

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)

Challenges

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

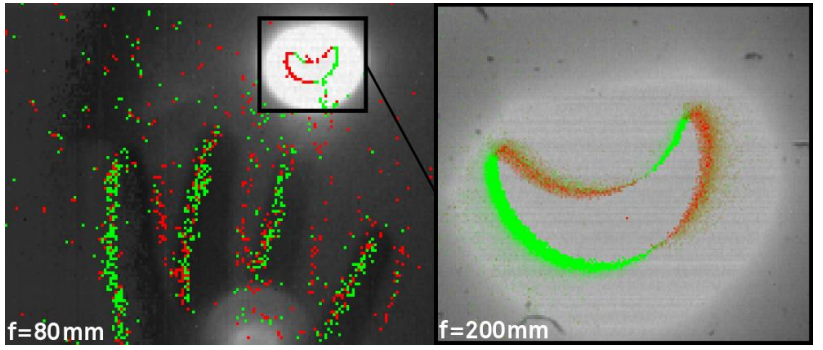
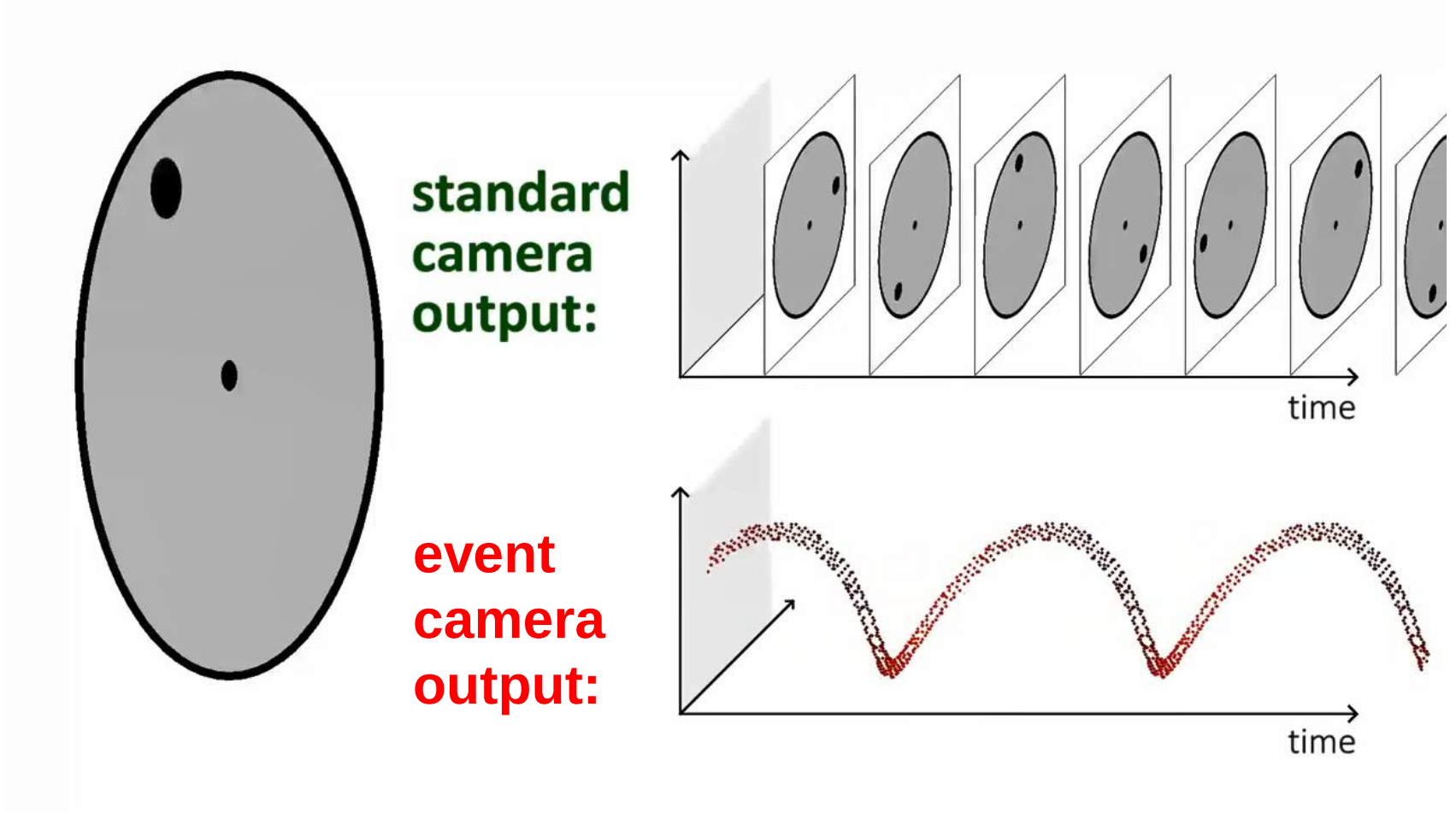


Image of solar eclipse captured by an event camera without black filter

Lichtsteiner, Posch, Delbruck, A 128x128 120 dB 15µs Latency Asynchronous Temporal Contrast Vision Sensor, IEEE Journal of Solid-State Circuits, 2008. PDF

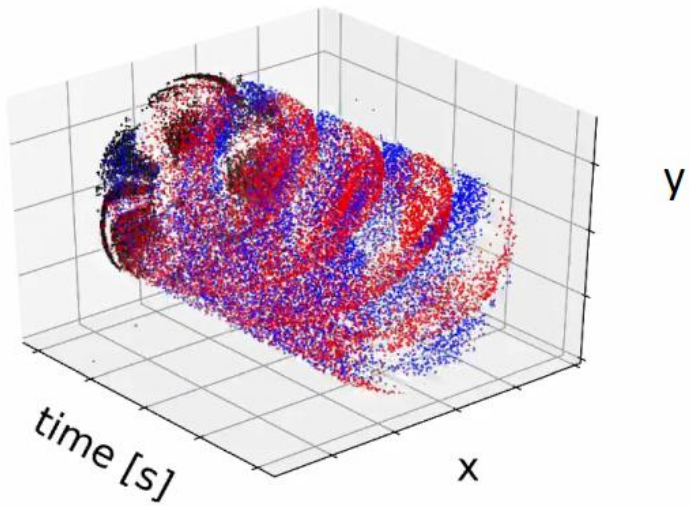
Animation of an Event Camera Output



Video from here: https://youtu.be/LauQ6LWTkxM?t=30

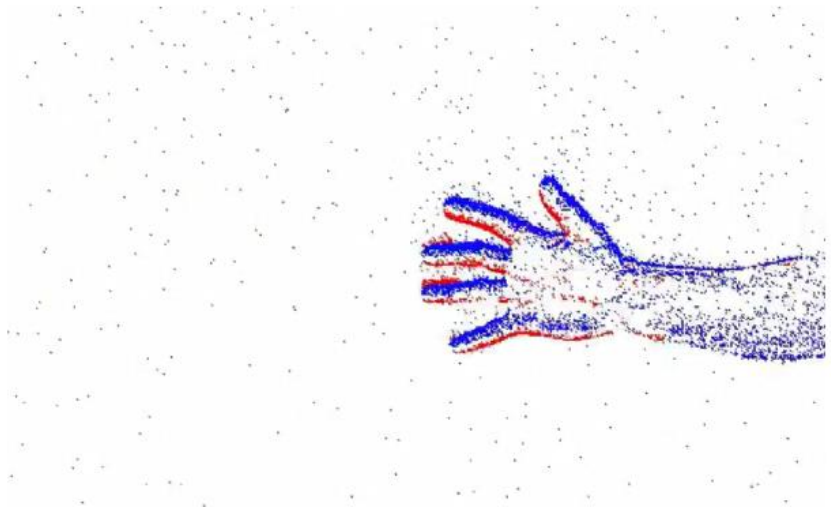
Conventional frames

Events



Events in the **space-time** domain (x, y, t)

Conventional frames

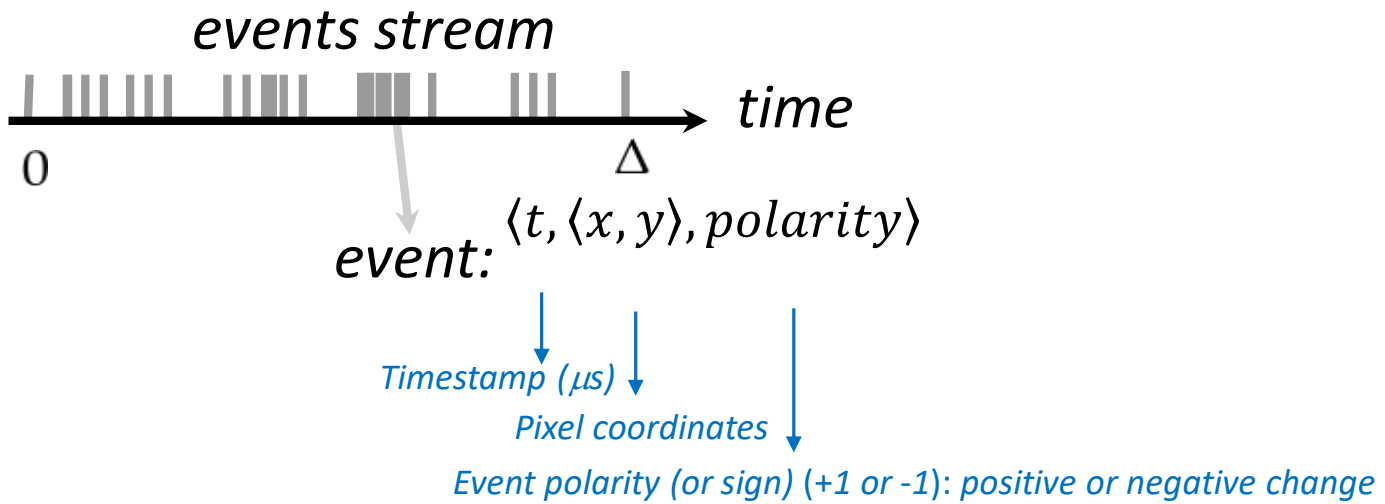


Events in the **image domain** (x, y)
Integration time but can be arbitrary: from 1 microsecond to infinity)

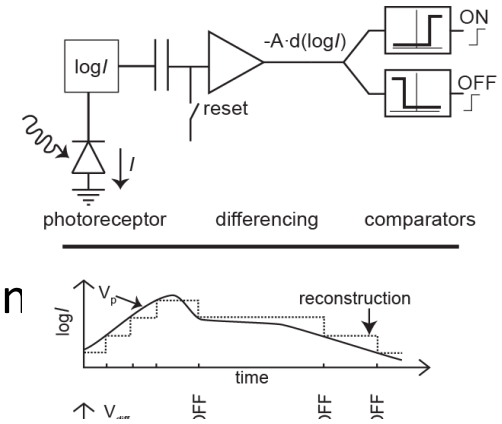
Standard Camera vs. Event Camera

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

- By contrast, an event camera outputs **asynchronous events** at **microsecond resolution**. An event is generated each time a single pixel detects a change of intensity

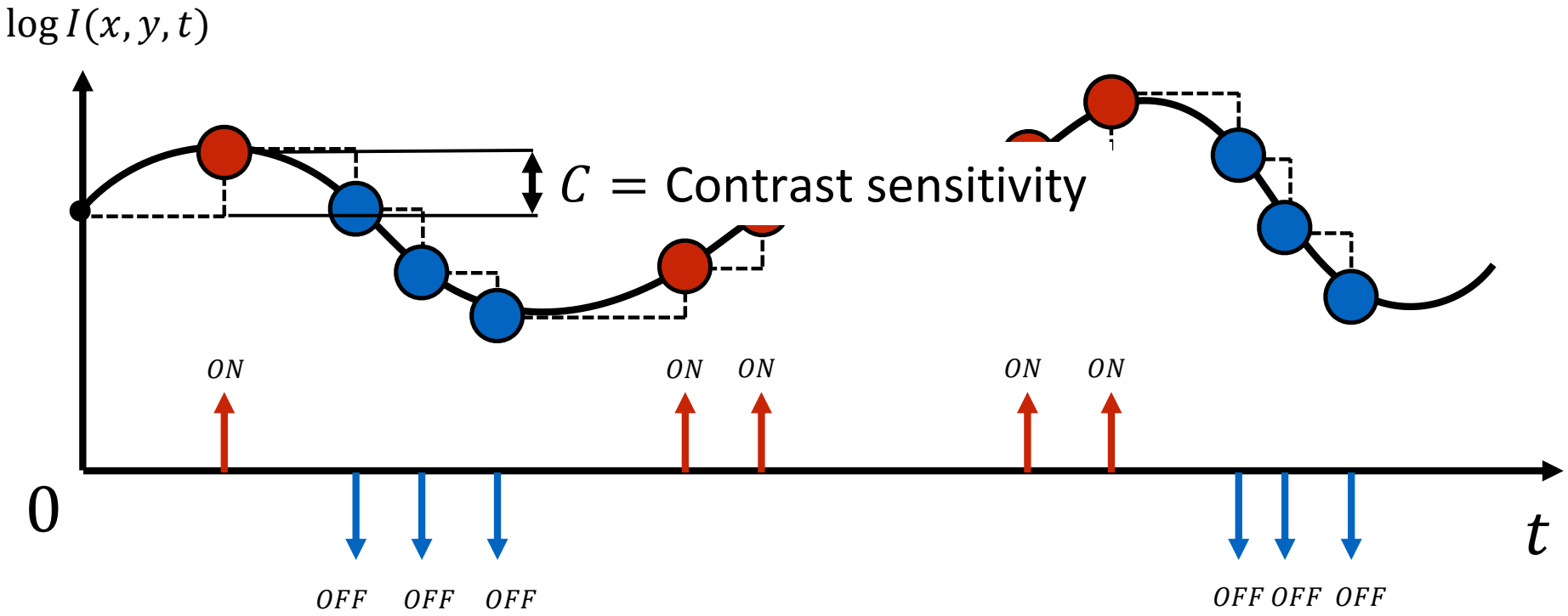


Generative Event Model



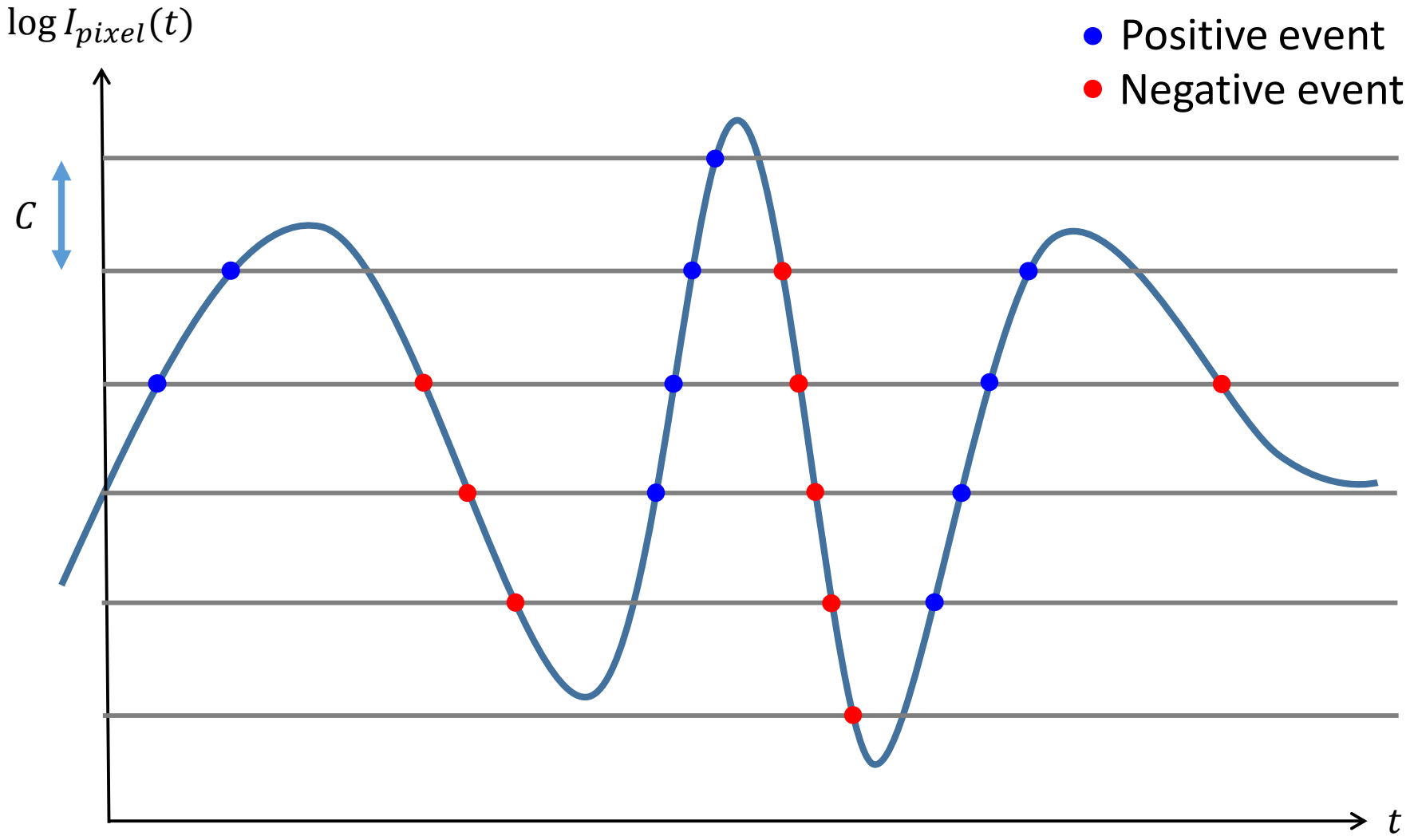
- Consider the intensity at a **single pixel** (x, y). An event is generated when the followin satisfied:

$$\log I(x, y, t + \Delta t) - \log I(x, y, t) = \pm C$$

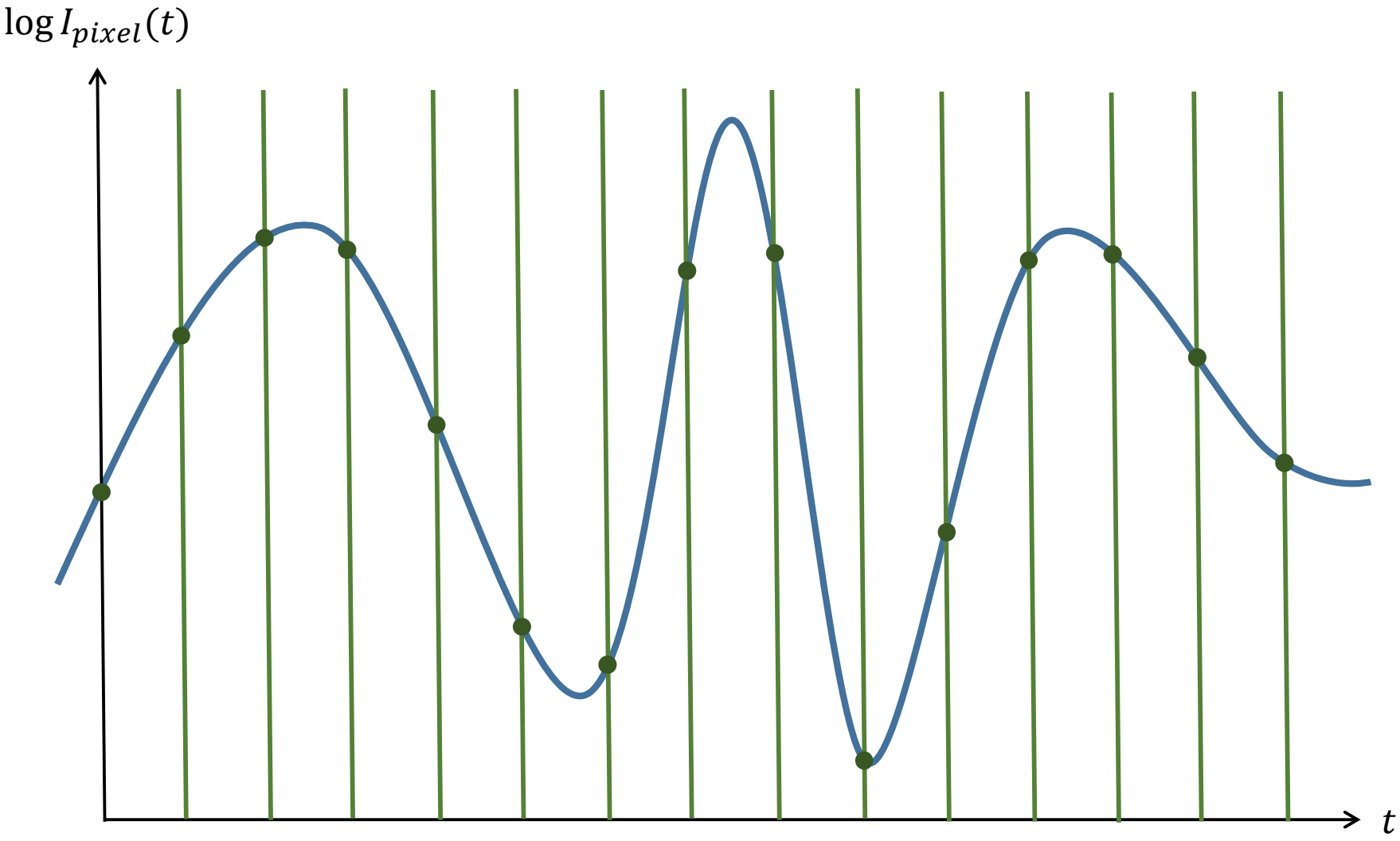


Events are triggered **asynchronously**

Event cameras sample intensity when this crosses a threshold **(Level-crossing sampling)**



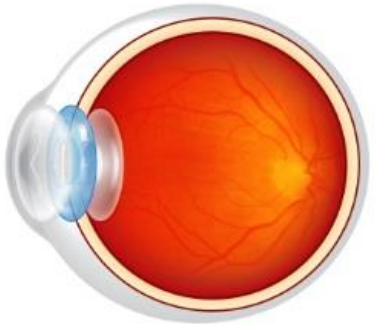
Standard cameras sample intensity at uniform time intervals **(uniform time sampling)**

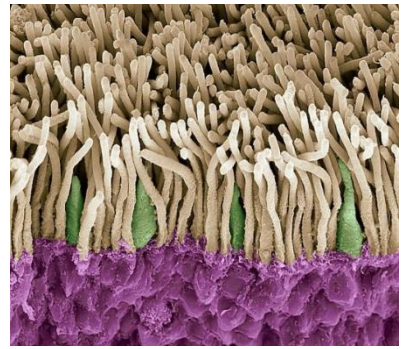


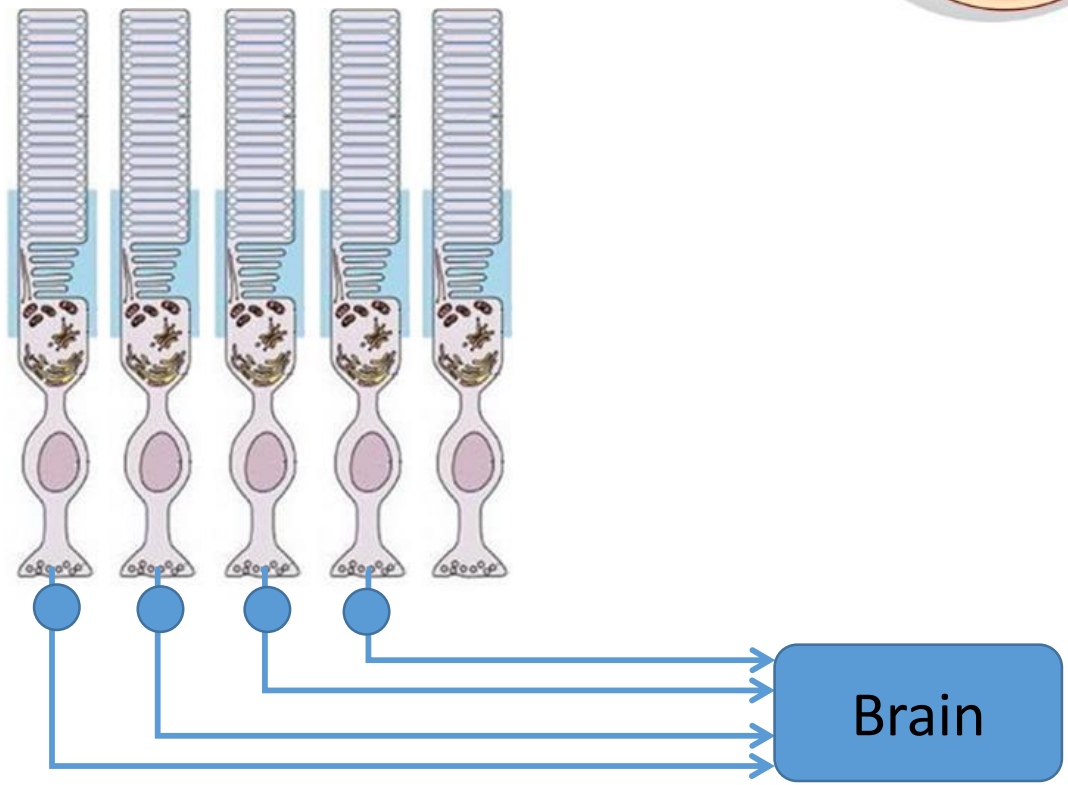
Event cameras are inspired by the Human Eye

Human retina:

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







Who sells event cameras and how much are they?

- Prophesee & SONY:
  - **ATIS sensor: events**, **IMU**, absolute intensity at the event pixel
  - Resolution: **1M pixels**
  - **Cost: ~5,000 USD**

- Inivation & Samsung
  - **DAVIS sensor**: **frames**, **events**, **IMU**.
  - Resolution**: VGA** (640x480 pixels)
  - **Cost: ~5,000 USD**

- CelePixel Technology & Omnivision:
  - **Celex One:** events, IMU, absolute intensity at the event pixel
  - Resolution: **1M pixels**
  - **Cost: ~1,000 USD**

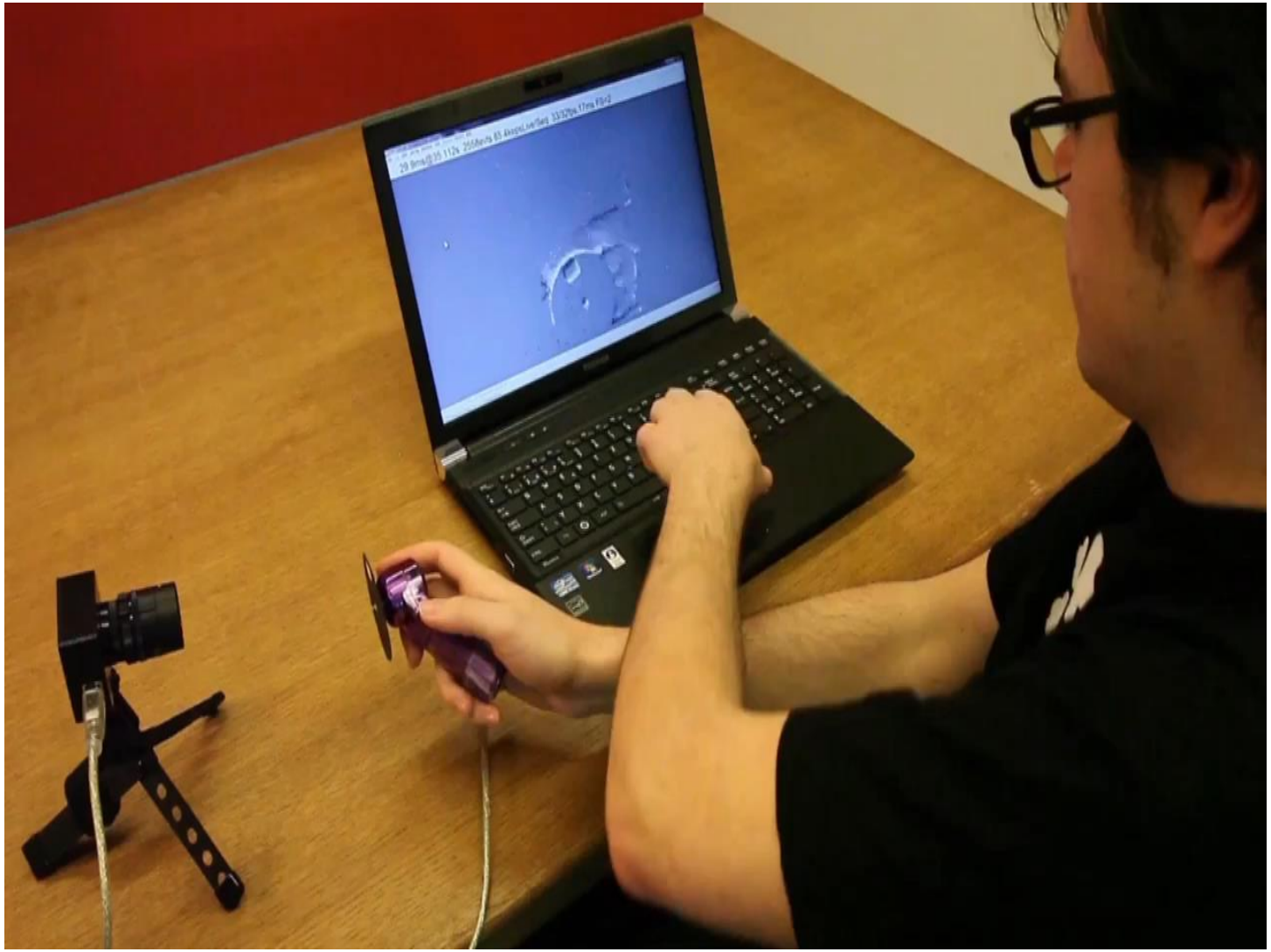
- **Cost to sink to <5$** when killer application found (recall first ToF camera (>10,000 USD) today <5 USD)

SONY

SAMSUNG

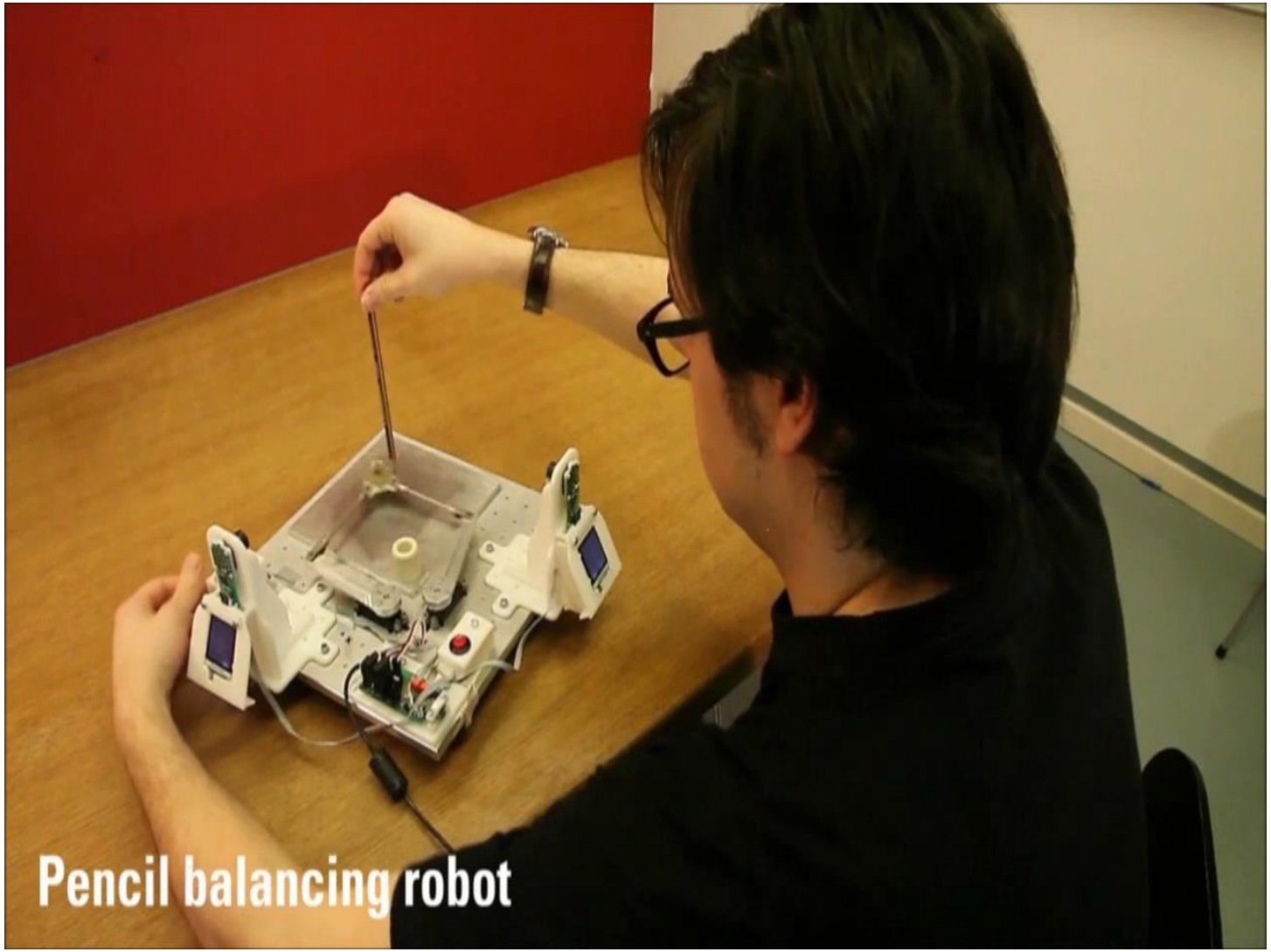
OmniVision

Event Camera Demo



https://youtu.be/QxJ-RTbpNXw

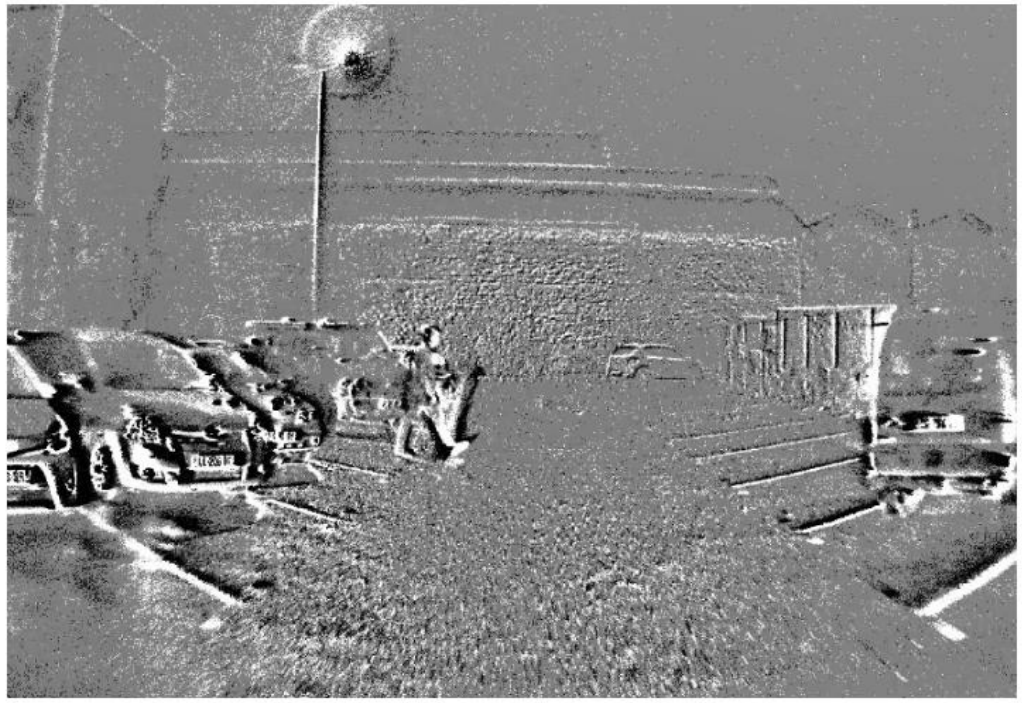
Event Camera Demo



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

Low-light Sensitivity (night drive)

GoPro Hero 6



Aggregated event image

(pixel intensity equal to the sum of positive (+1) and negative (-1) events in a given time interval)

Video courtesy of Prophesee: https://www.prophesee.ai

High-speed Camera vs. Event Camera

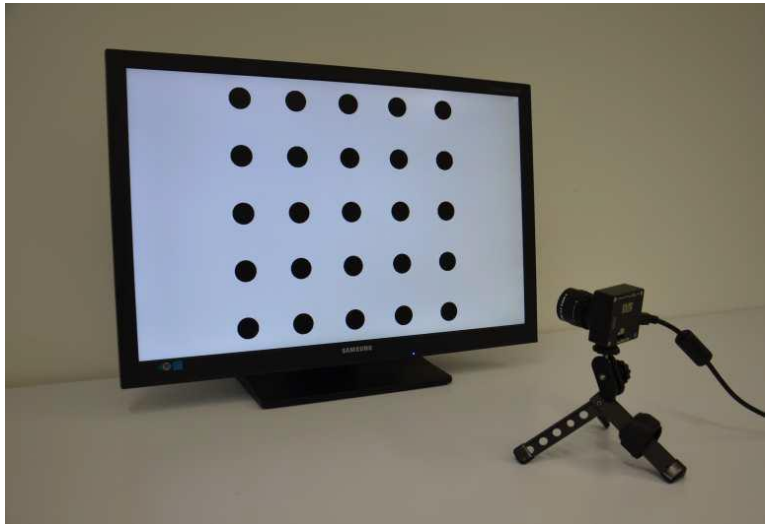
	High speed camera	Standard camera	Event Camera
Max fps or measurement rate	**Up to 1MHz**	100-1,000 fps	**1MHz**
Resolution at max fps	64x16 pixels	**>1Mpxl**	**>1Mpxl**
Bits per pixels (event)	12 bits	8-10 per pixel	**~40 bits/event** {t,(x,y),p)}
Weight	6.2 Kg	**30 g**	**30 g**
Active cooling	yes	**No cooling**	**No cooling**
Data rate	1.5 GB/s	32MB/s	**~1MB/s on average (depends on dynamics & contrast threshold)**
Mean power consumption	150 W + external light	1 W	**1 mW**
Dynamic range	not specified	60 dB	**140 dB**

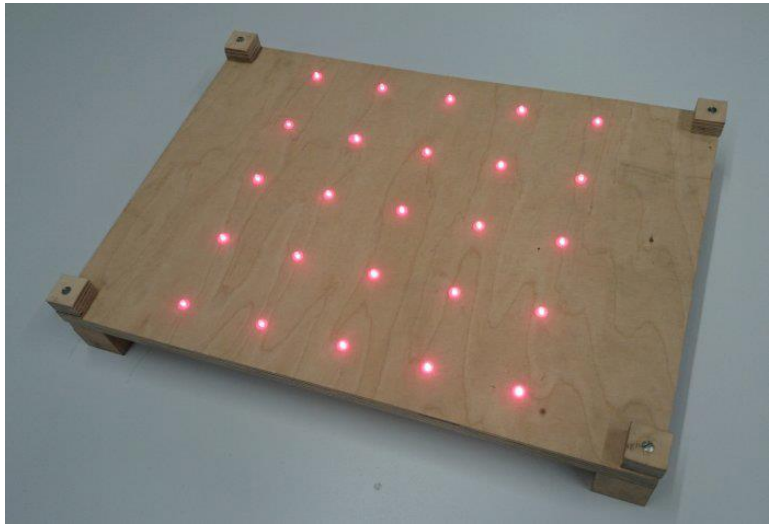
Current commercial applications

- **Monitoring and surveillance**
  - Action and gesture recognition in HDR scenes
- **Industrial automation**
  - Fast object counting
- **Computational photography**
  - Deblurring, super resolution, HDR, slow-motion video
- **Automotive**:
  - low-latency detection, object classification, low-power and low-memory storage

Calibration of an Event Camera

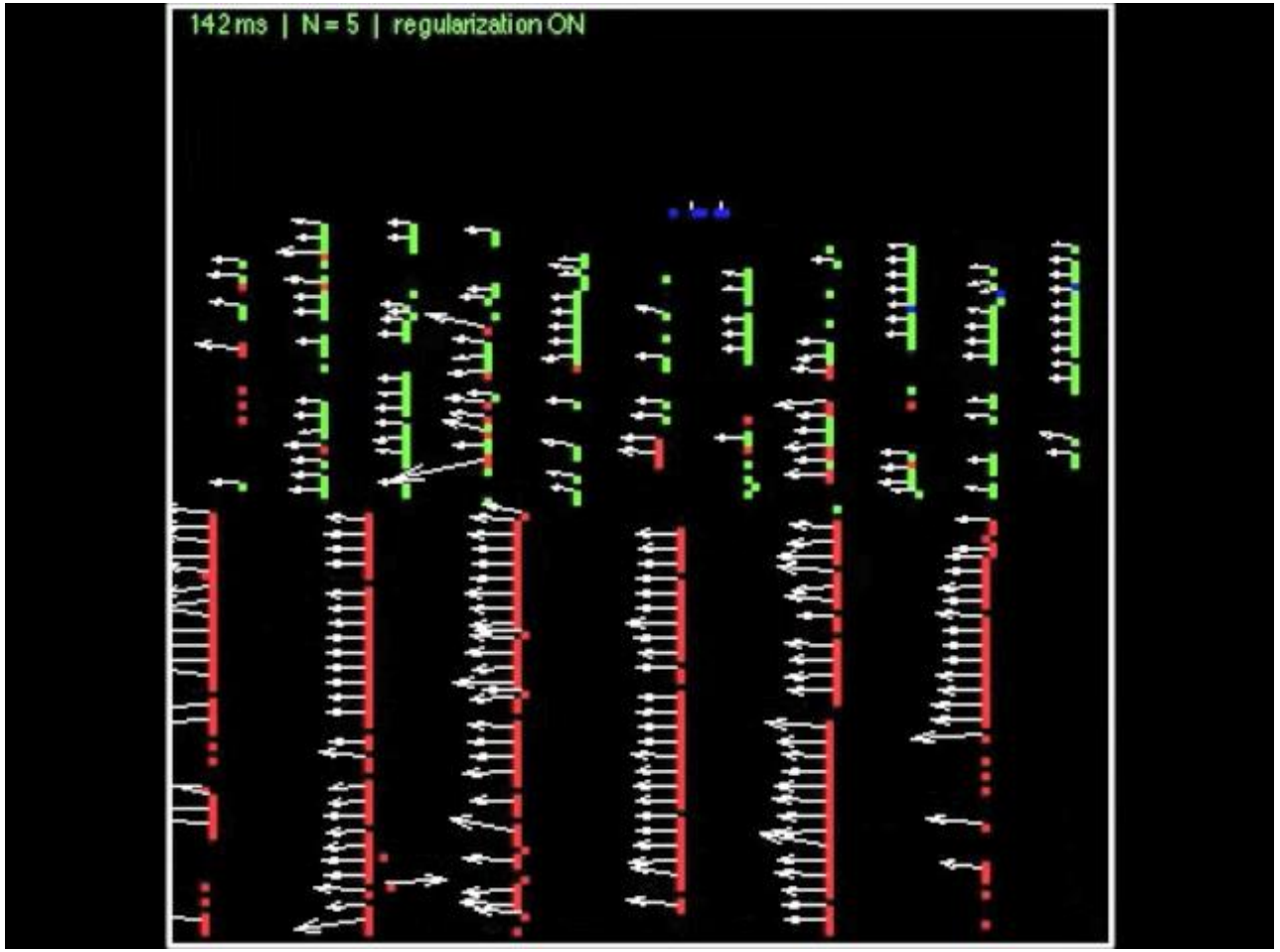
- Standard **pinhole camera model** still valid (same optics)
- Standard passive calibration patterns **cannot be used**
  - need to move the camera → inaccurate corner detection
- **Blinking patterns** (computer screen, LEDs)
- ROS DVS driver + intrinsic and extrinsic mono & stereo calibration: https://github.com/uzh-rpg/rpg_dvs_ros





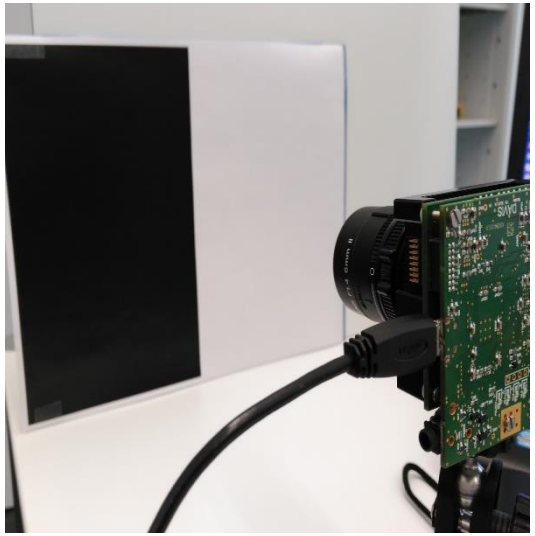
Mueggler, Huber, Scaramuzza, *Event-based 6-DOF Pose Tracking for High-Speed Maneuvers*, IEEE/RSJ International Conference on Robotics and Intelligent Systems (IROS), 2014. PDF.

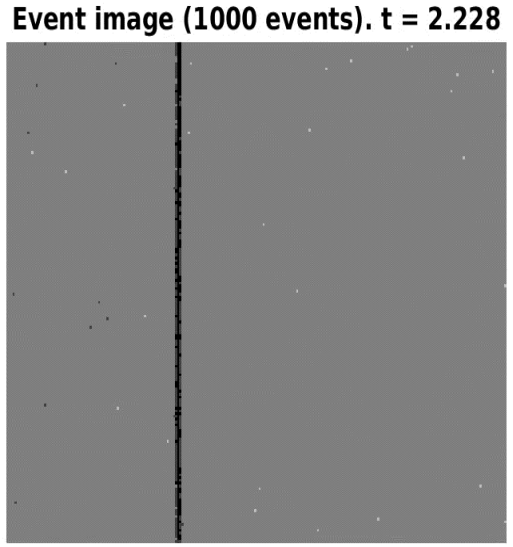
A Simple Optical Flow Algorithm

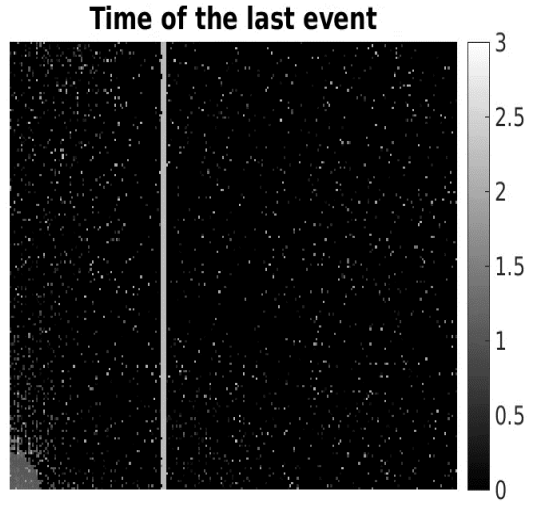


A Simple Optical Flow Algorithm

- Let’s assume pure horizontal motion
- White pixels become black → brightness decrease → negative events (in black color)

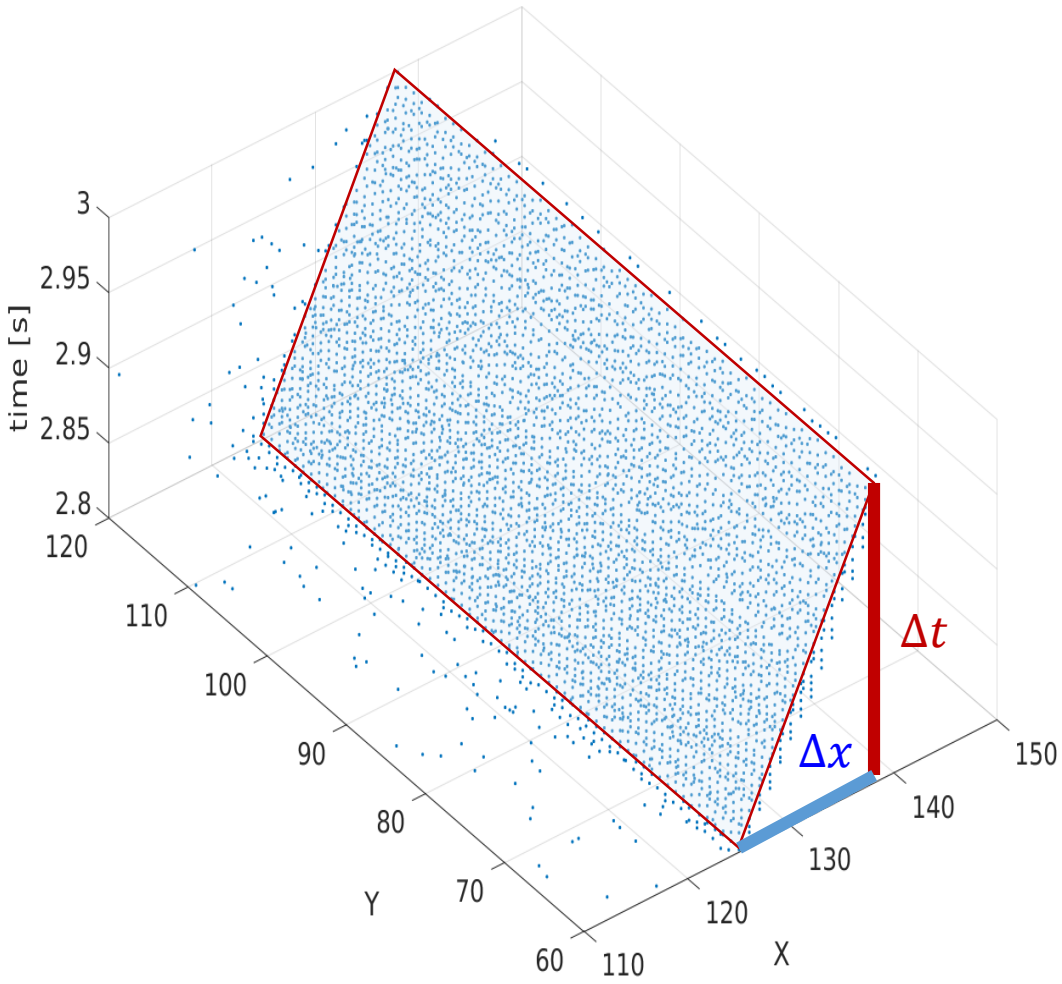






A Simple Optical Flow Algorithm

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



The edge is moving at a speed of:

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

How do we unlock the outstanding potential of event cameras?

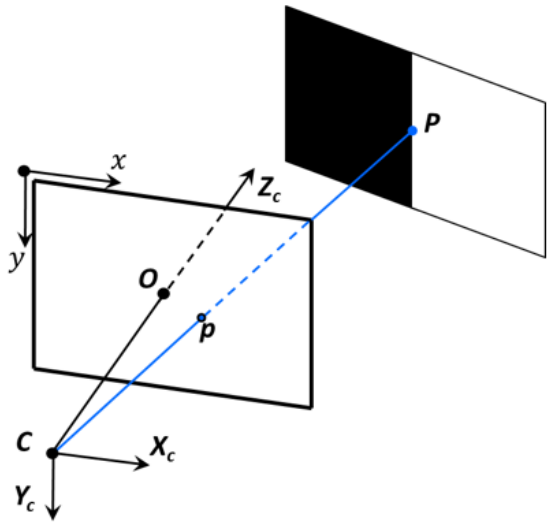
- Low latency
- High dynamic range
- No motion blur

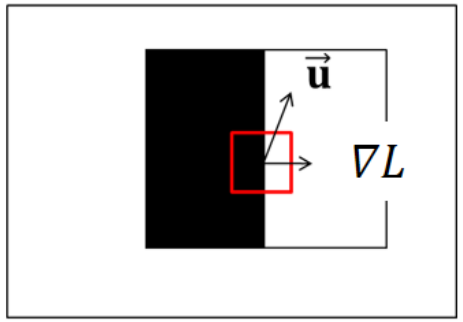
1st order approximation of the Generative Event Model

- An event is generated when the following condition is satisfied:

$$\log I(x, y, t + \Delta t) - \log I(x, y, t) = \pm C$$

- For many applications, it is convenient to derive a 1st order approximation
- Let us define $L(x, y, t) = Log(I(x, y, t))$
- Consider a given pixel $p(x, y)$ with gradient $\nabla L(x, y)$ undergoing the motion $\boldsymbol{u} = (u, v)$ in pixels, induced by a moving 3D point $\boldsymbol{P}$

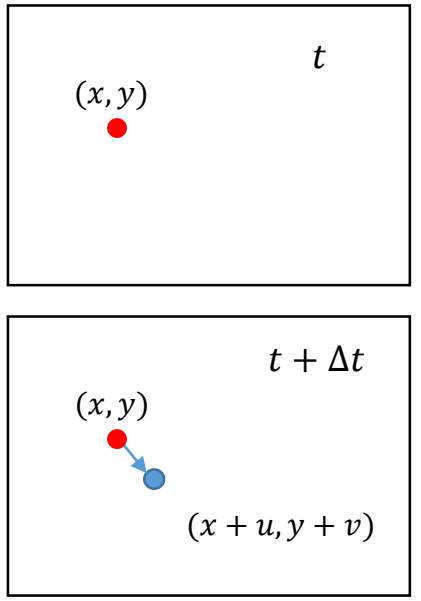




1st order approximation of the Generative Event Model

- Let's apply the **brightness constancy assumption**, which says that the intensity value of p before and after the motion must remain unchanged:

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



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

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

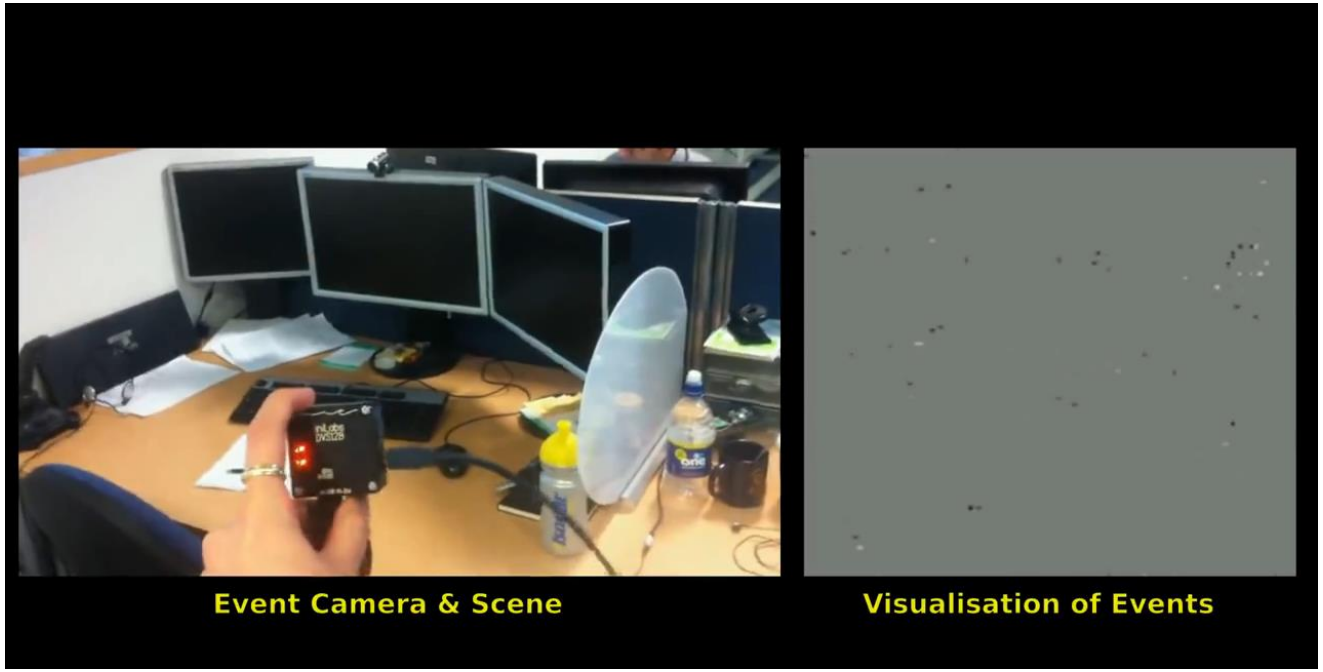
$$\Rightarrow \; L(x, y, t + \Delta t) - L(x, y, t) = -\frac{\partial L}{\partial x} u - \frac{\partial L}{\partial y} v$$

$$\Rightarrow \boxed{\pm C = -\nabla L \cdot \boldsymbol{u}}$$

- This formula shows that **maximum generation of events** (i.e., higher event rate) occurs when the **relative motion of the camera is perpendicular to the edge** and is **minimum when parallel** to the edge.

Application 1: Image Reconstruction from events

- Probabilistic **simultaneous gradient reconstruction and rotation estimation** from $\pm C = -\nabla L \cdot \boldsymbol{u}$
- Obtain **image intensity from gradient** via Poisson reconstruction
- The reconstructed image has **super-resolution and High Dynamic Range** (HDR)
- Can run in **real time on a GPU**



Kim, Handa, Benosman, Ieng, Davison, *Simultaneous Mosaicing and Tracking with an Event Camera*, British Machine Vision Conference (BMVC), 2014. PDF.

Application 2: 6DoF Tracking from Photometric Map

- Probabilistic **6DoF motion estimation** from $\pm C = -\nabla L \cdot \boldsymbol{u}$
- Assumes **photometric map** (x, y, z, grayscale Intensity) is **given**
- Useful for **VR/AR applications** (low-latency, HDR, no motion blur)
- Can run in **real time on a GPU**

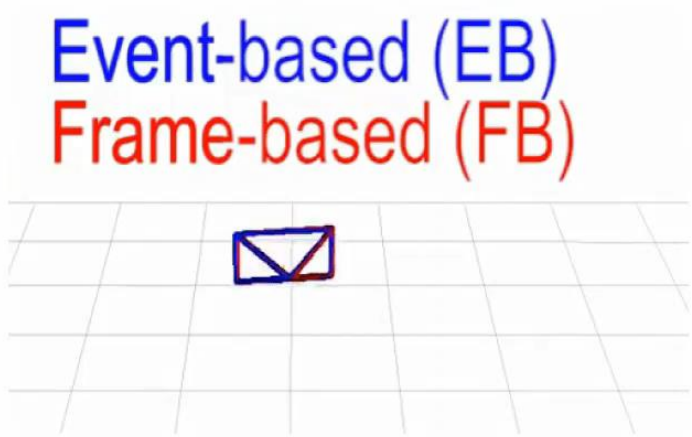
Gallego, Lund, Mueggler, Rebecq, Delbruck, Scaramuzza, *Event-based 6-DOF Camera Tracking from Photometric Depth Maps*, IEEE Transactions on Pattern Analysis and Machine Intelligence (T-PAMI), 2018. PDF. Video.

Application 2: 6DoF Tracking from Photometric Map

Event camera

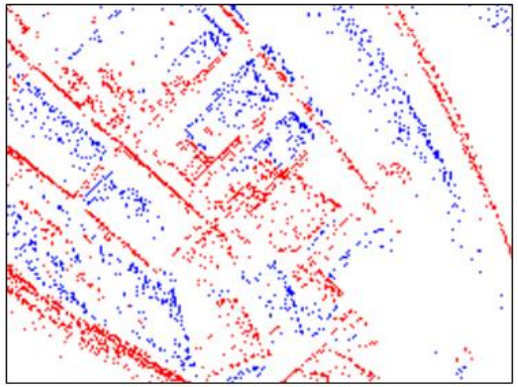
Standard camera

Motion estimation



Gallego et al., Event-based 6-DOF Camera Tracking from Photometric Depth Maps, **T-PAMI**'18. PDF Video

Combining Standard Cameras with Event Cameras



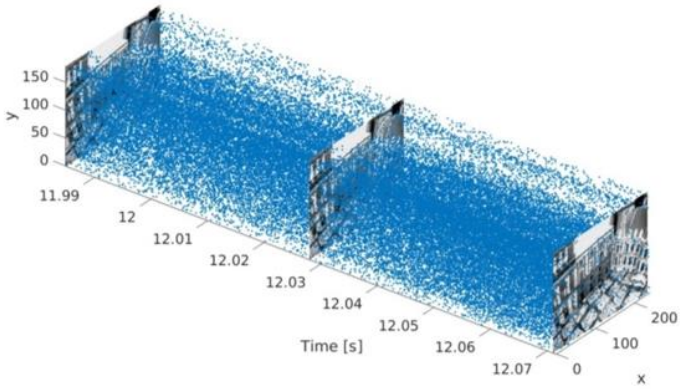
Event Camera

Standard Camera

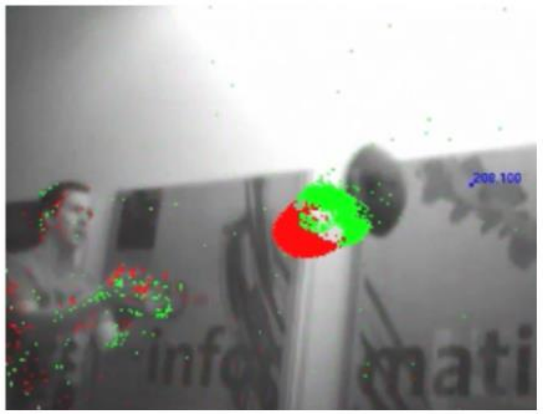
Update rate	High (asynchronous): 1 MHz	Low (synchronous)
Dynamic Range	High (140 dB)	Low (60 dB)
Motion Blur	No	Yes
Static motion	No (event camera is a high pass filter)	Yes
Absolute intensity	No (but reconstructable up to a constant)	Yes
Maturity	< 10 years of research	> 60 years of research!

DAVIS sensor: Events + Images + IMU

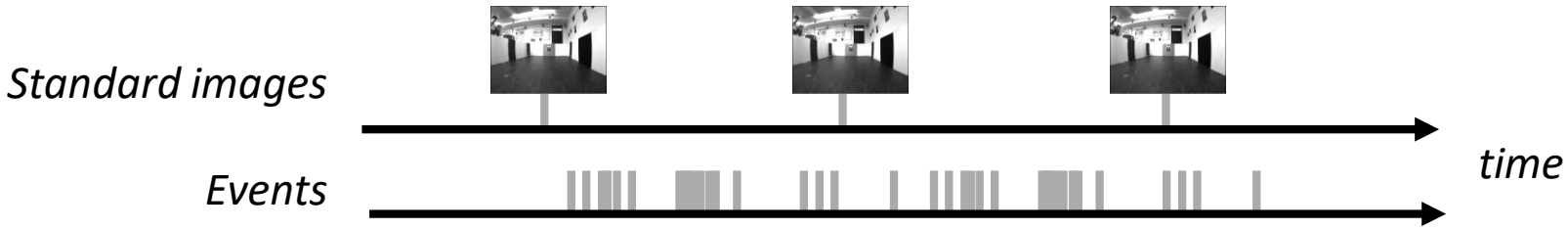
- Combines an **event and a standard camera** in the **same pixel array** (→ the same pixel can both trigger events and integrate light intensity).
- It also has an **IMU**



Spatio-temporal visualization
of the output of a DAVIS sensor



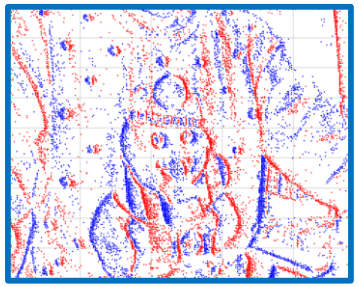
Temporal aggregation of events
overlaid on a DAVIS frame



Brandli, Berner, Yang, Liu, Delbruck, *A 240x180 130dB 3us latency global shutter spatiotemporal vision sensor*. IEEE Journal on Solid State Circuits, 2014. PDF.

Application 1: Deblurring a blurry video

- **Idea**: A **blurry image** can be regarded as the **integral of a sequence of latent images** during the exposure time, while the **events** indicate the **changes between the latent images**
- **Solution**: sharp image obtained by subtracting the double integral of event from input image

$$\log \quad \text{  } \quad - \iint \quad \text{  } \quad = \quad \log \quad \text{  }$$

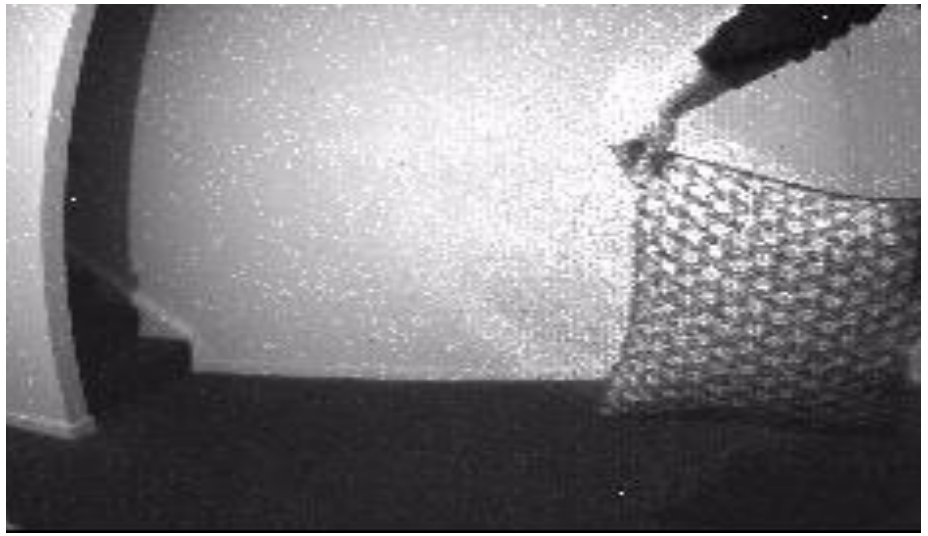
Input blur image **Input events** **Output sharp image**

Pan et al., Bringing a Blurry Frame Alive at High Frame-Rate with an Event Camera, International Conference on Computer Vision and Pattern Recognition, (CVPR), 2019. PDF.

Application 1: Deblurring a blurry video

- **Idea**: A **blurry image** can be regarded as the **integral of a sequence of latent images** during the exposure time, while the **events** indicate the **changes between the latent images**
- **Solution**: sharp image obtained by subtracting the double integral of event from input image

Input blur image

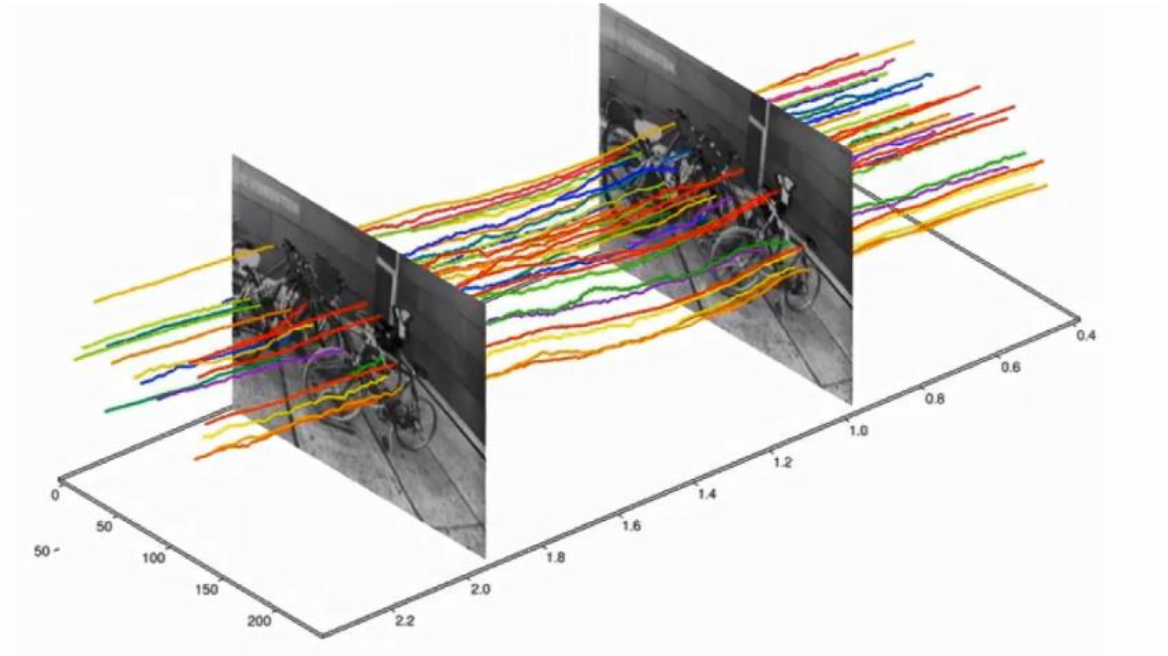


Output sharp video

Pan et al., Bringing a Blurry Frame Alive at High Frame-Rate with an Event Camera, International Conference on Computer Vision and Pattern Recognition, (CVPR), 2019. PDF.

Application 3: Event-based KLT Tracking

- **Goal**: Extract **features from standard frames** and track them using only **events** in the **blind time between two frames**
- Uses the event generation model via joint estimation of patch warping and optic flow



Source code: https://github.com/uzh-rpg/rpg_eklt

Gehrig, Rebecq, Gallego, Scaramuzza, *EKLT: Asynchronous, Photometric Feature Tracking using Events and Frames*, International Journal of Computer Vision (IJCV), 2019. PDF. Video. Code

Recap

- All the approaches seen so far use the **generative event model**

$$\log I(x, y, t + \Delta t) - \log I(x, y, t) = \pm C$$

- or its 1st order approximation

$$\pm C = -\nabla L \cdot \mathbf{u}$$

which **requires knowledge of the contrast sensitivity** C

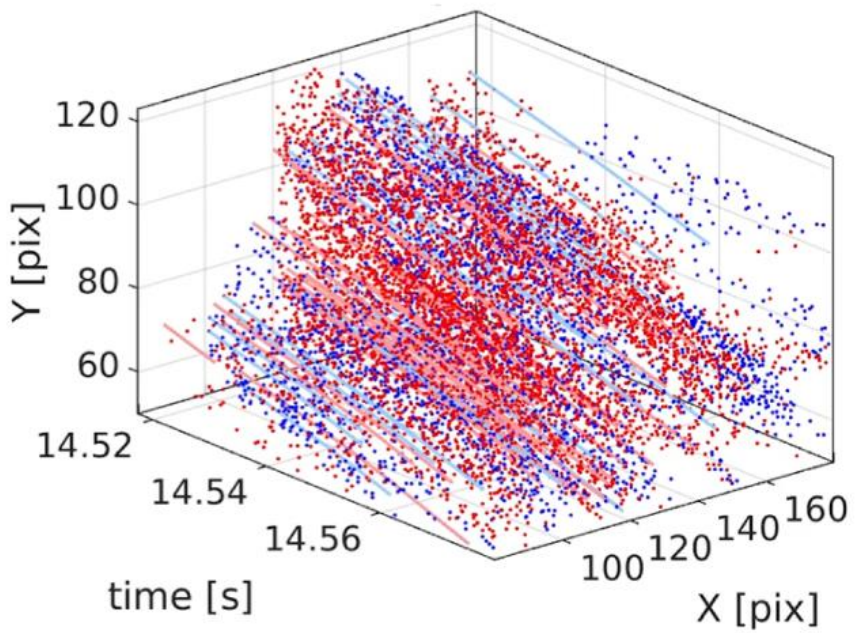
- Unfortunately, $\boldsymbol{C}$ **is scene dependent** and might **differ from pixel to pixel**
- **Alternative approach: Contrast maximization framework**

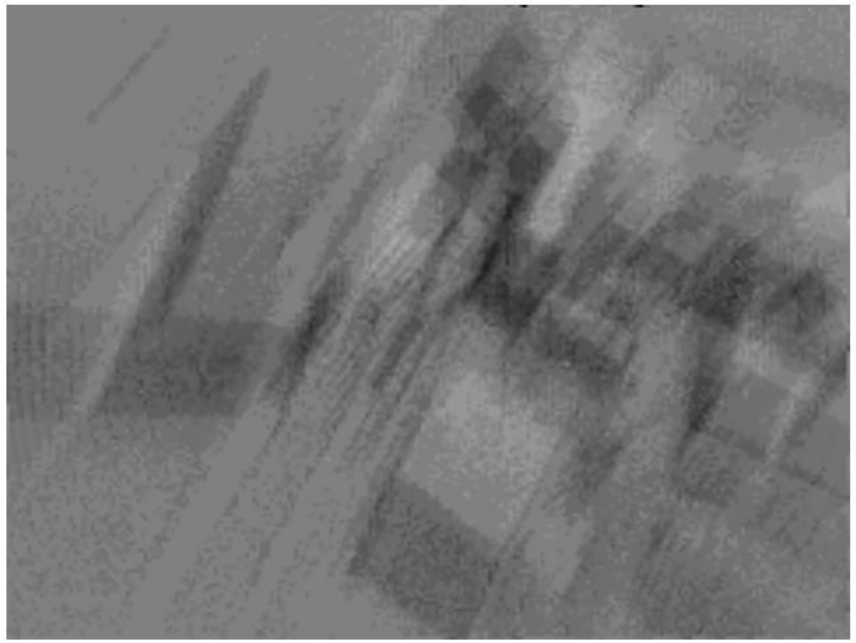
Contrast Maximization Framework

- Motion estimation
- 3D reconstruction
- SLAM
- Optical flow estimation
- Feature tracking
- Motion segmentation
- Unsupervised learning

Contrast Maximization Framework

Idea: Warp spatio-temporal volume of events to **maximize contrast** (e.g., sharpness) of the resulting image



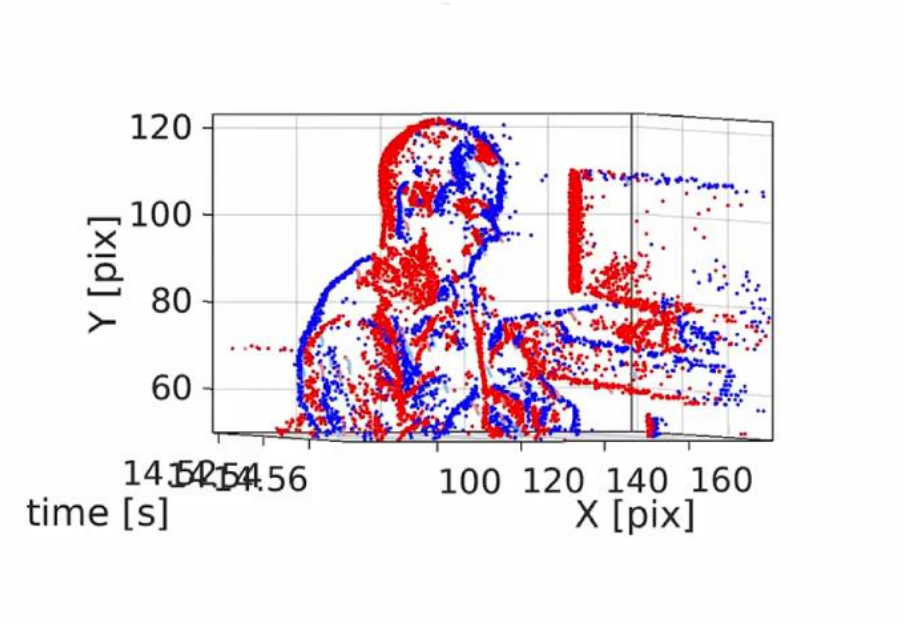


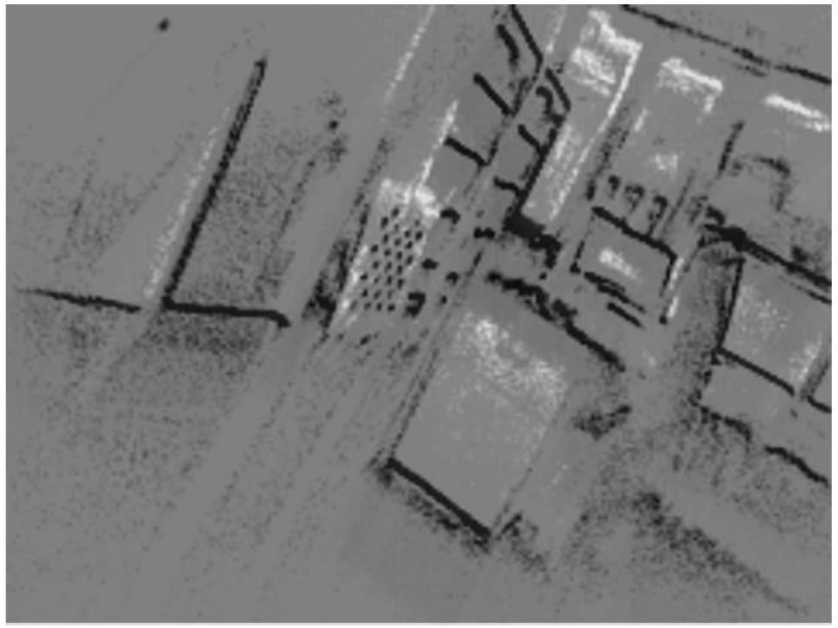
Aggregated image
without motion correction

Gallego, Rebecq, Scaramuzza, *A Unifying Contrast Maximization Framework for Event Cameras*, CVPR18, PDF, Video
Gallego, Gehrig, Scaramuzza, *Focus Is All You Need: Loss Functions for Event-based Vision*, CVPR19, PDF.

Contrast Maximization Framework

Idea: Warp spatio-temporal volume of events to **maximize contrast** (e.g., sharpness) of the resulting image

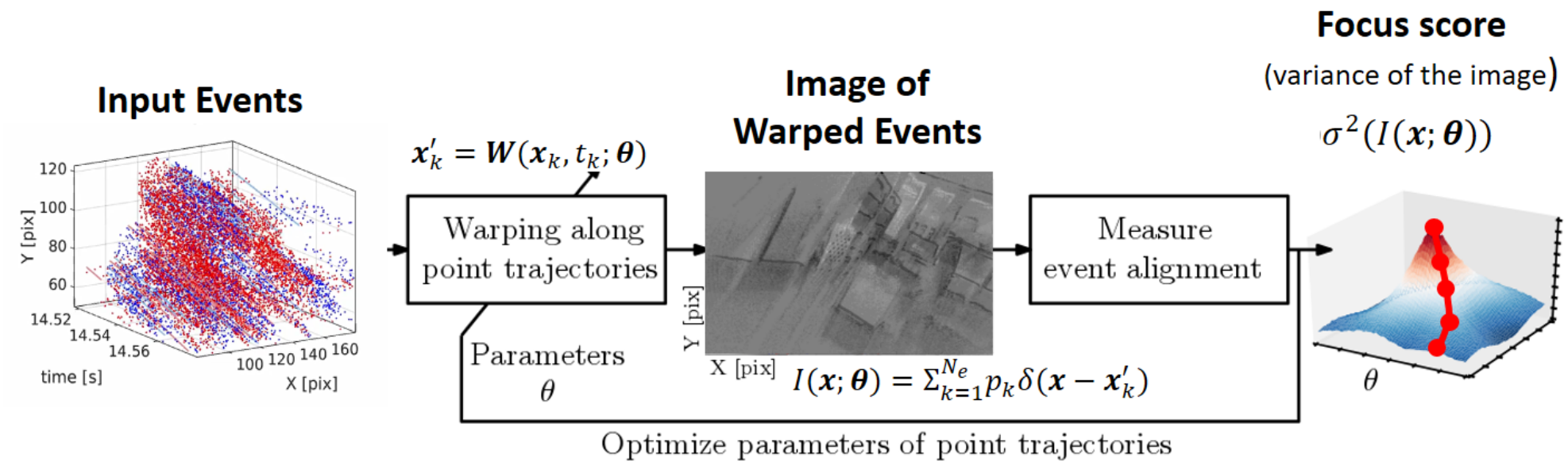




Aggregated image
with motion correction

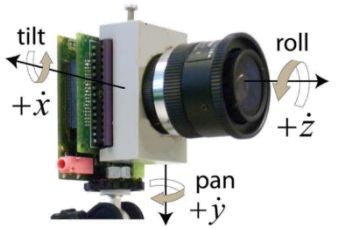
Gallego, Rebecq, Scaramuzza, *A Unifying Contrast Maximization Framework for Event Cameras*, CVPR18, PDF, Video
Gallego, Gehrig, Scaramuzza, *Focus Is All You Need: Loss Functions for Event-based Vision*, CVPR19, PDF.

Contrast Maximization Framework

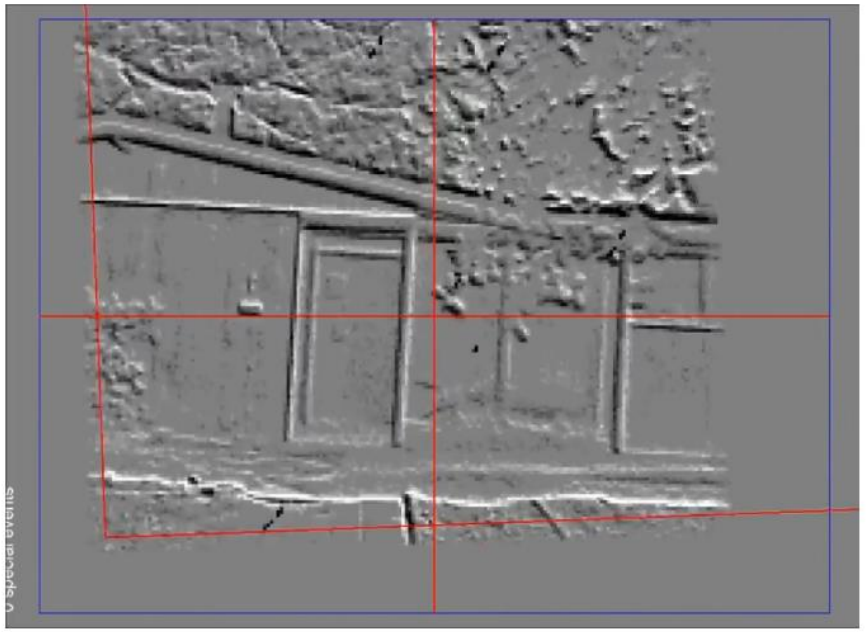


- $x'_k = W(x_k, t_k; \theta)$: This warps the (x, y) pixels coordinates of each event, not their time. Possible warps: roto-translation, affine, homography.
- $I(x;\theta) = \Sigma_{k=1}^{N_e} p_k \delta(x - x'_k)$: This builds a grayscale image, where the intensity of each pixel at the warped location (x', y') is equal to the summation of the polarity p (i.e., positive and negative events $(+1, -1)$)
- $\sigma^2(I(x;\theta))$: The assumption here is that if an image contains **high variance** then there is a wide **spread of responses, both edge-like and non-edge like**, representative of a normal, in-focus image. But if there is **very low variance**, then there is a tiny spread of responses, indicating there are very little edges in the image. As we know, the more an image is blurred, the less edges there are.

Application 1: Image Stabilization

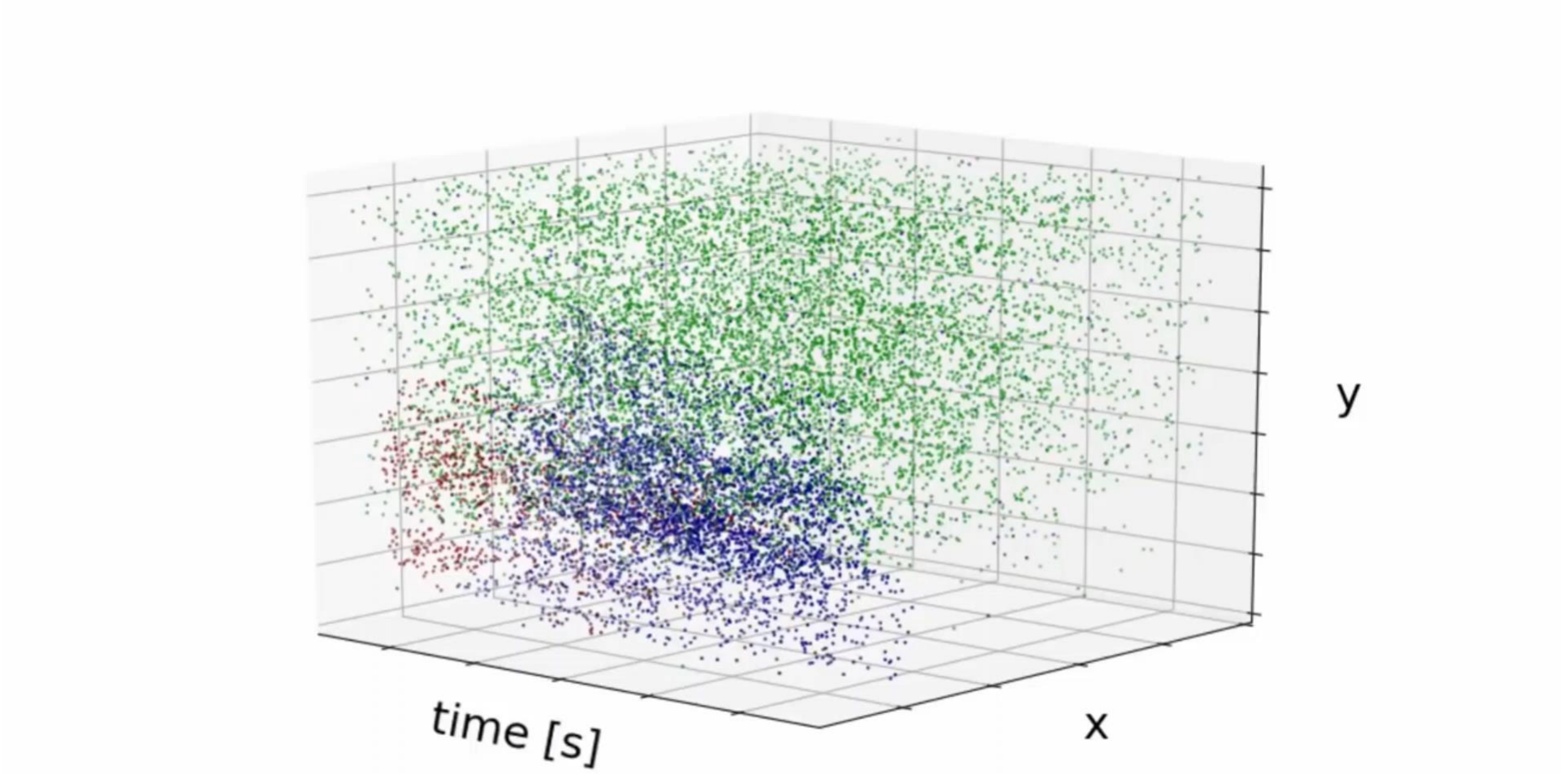


- Goal: **Estimate rotational motion (3DoF)** of an event camera
- Can process millions of events per second in real time on a smartphone PC (e.g., OdroidXU4)
- Works up to over ~1,000 deg/s



Gallego, Scaramuzza, Accurate Angular Velocity Estimation with an Event Camera, IEEE Robotics and Automation Letters (RA-L), 2016. PDF. Video.

Application 2: Motion Segmentation



Stoffregen, Gallego, Drummond, Kleeman, Scaramuzza, *Motion Segmentation by Motion Compensation,* International Conference on Computer Vision (ICCV), 2019. PDF. Video.

Application 3: Dynamic Obstacle Avoidance

- Works with relative speeds of up to **10 m/s**
- Perception **latency: 3.5 ms**

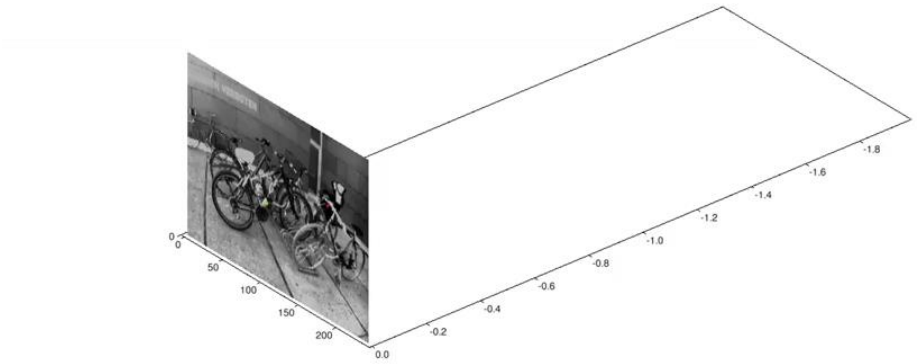
Falanga et al., *Dynamic Obstacle Avoidance for Quadrotors with Event Cameras*, Science Robotics, 2020. PDF. Video

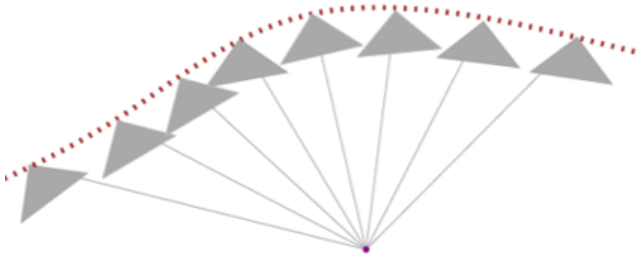
Application 4: “Ultimate SLAM”

Goal: combining **events**, **images**, and **IMU** for robust visual SLAM in HDR and high speed scenarios

Front End:
Feature tracking from Events and Frames

Back-End
State-of-the-art
Non-linear-optimization-based VIO

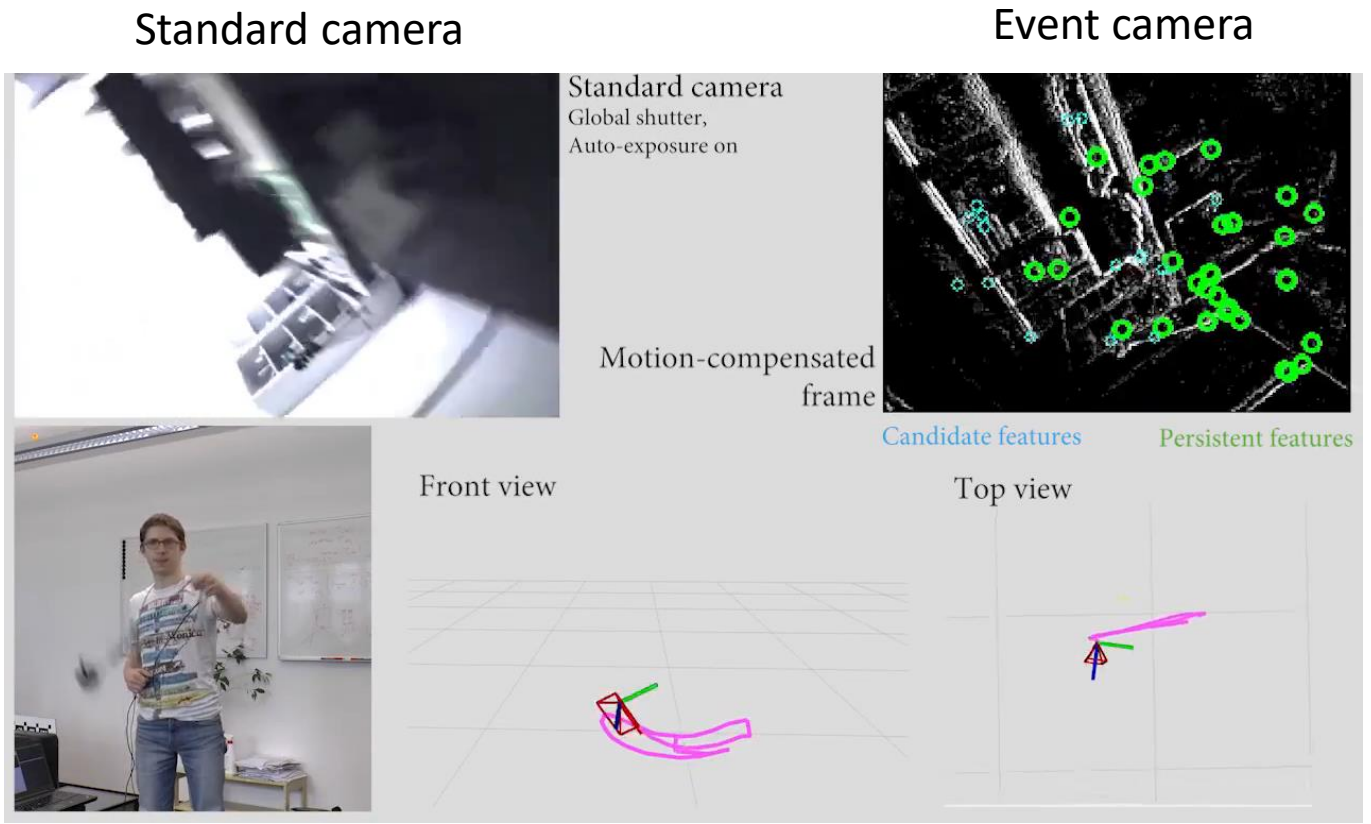




Rosinol-Vidal, Rebecq, Horstschaefer, Scaramuzza, *Ultimate SLAM? Combining Events, Images, and IMU for Robust Visual SLAM in HDR and High Speed Scenarios*, IEEE Robotics and Automation Letters (RAL), 2018 – PDF. Video. Best Paper Award Honorable Mention

Application 4: “Ultimate SLAM”

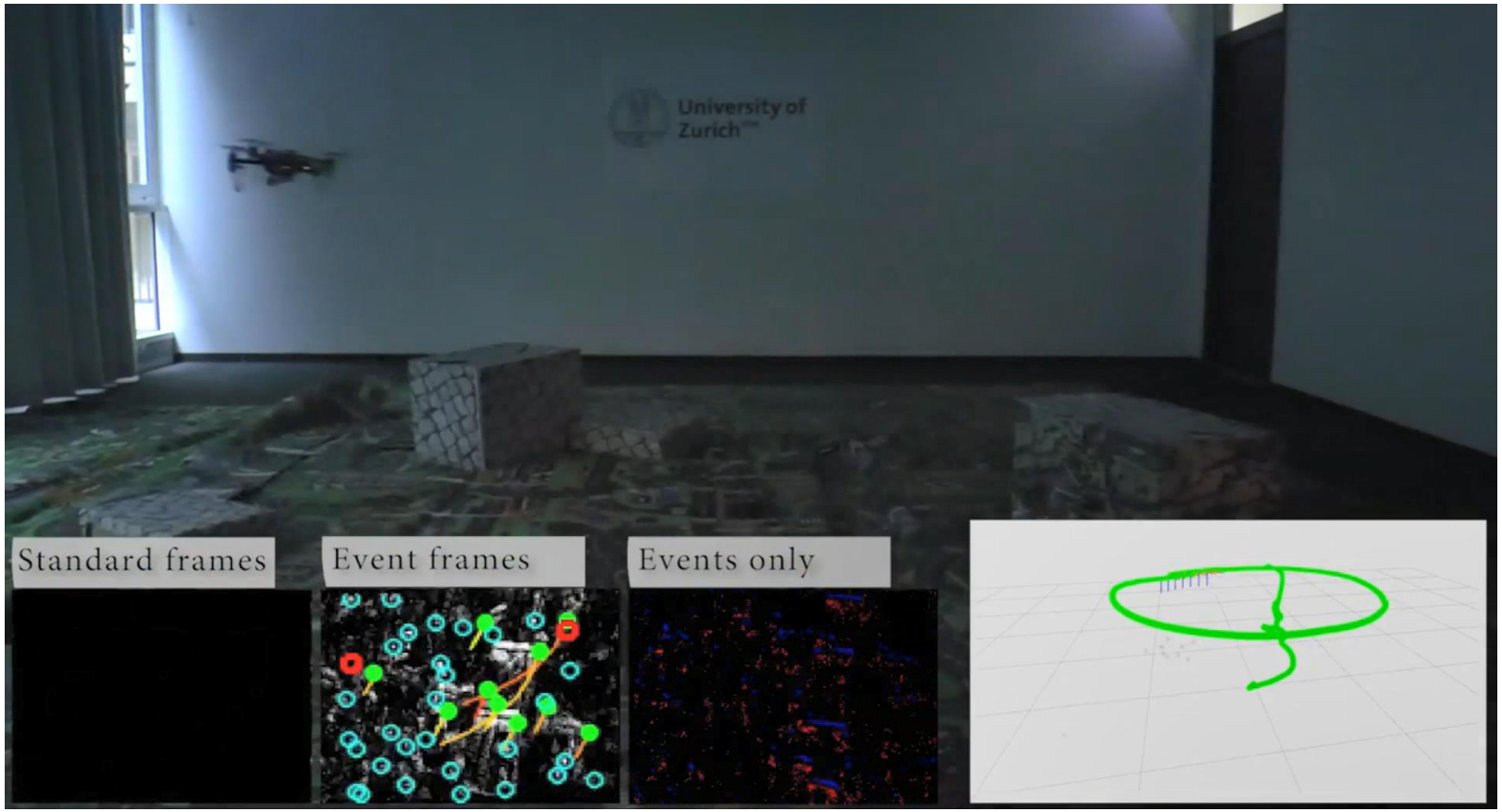
- **85%** accuracy gain over standard VIO in **HDR and high speed scenarios**



Rosinol-Vidal, Rebecq, Horstschaefer, Scaramuzza, *Ultimate SLAM? Combining Events, Images, and IMU for Robust Visual SLAM in HDR and High Speed Scenarios*, IEEE Robotics and Automation Letters (RAL), 2018 – PDF. Video. Best Paper Award Honorable Mention

Application 5: Autonomous Navigation in Low Light

- UltimateSLAM running on board (CPU: Odroid XU4)



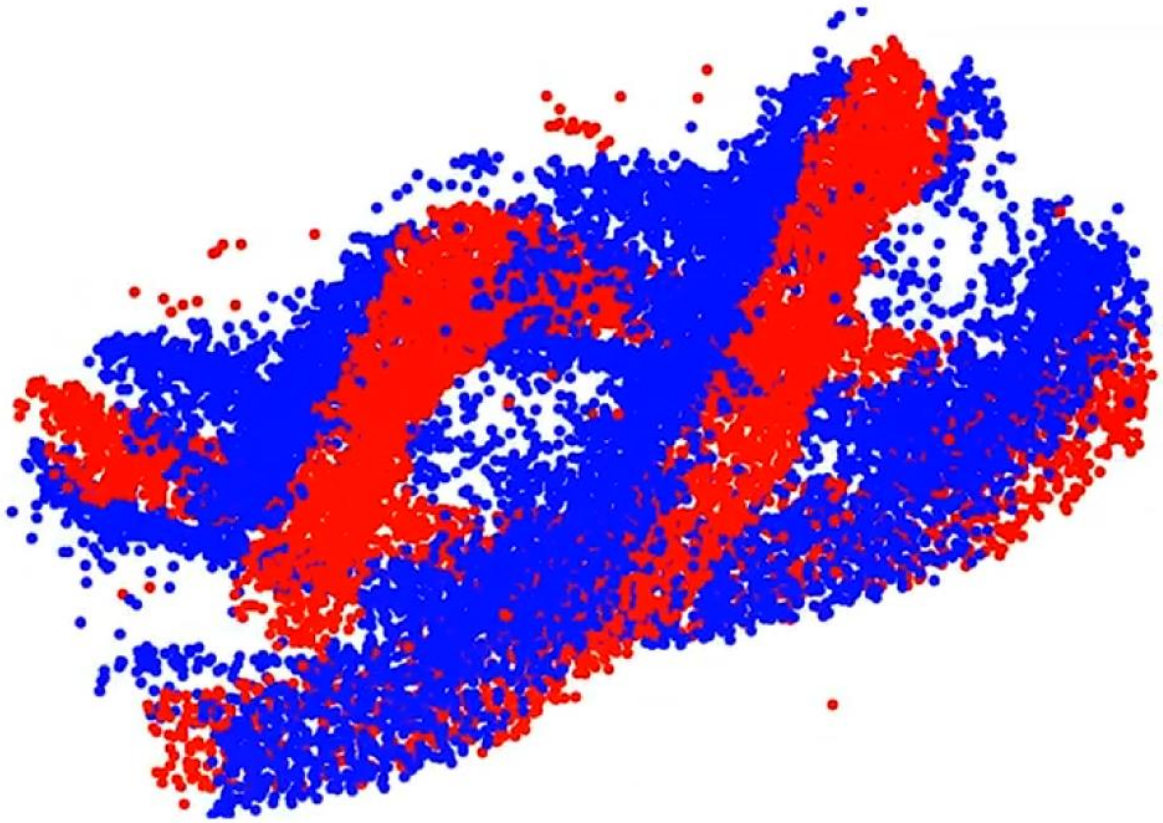
Rosinol-Vidal, Rebecq, Horstschaefer, Scaramuzza, *Ultimate SLAM? Combining Events, Images, and IMU for Robust Visual SLAM in HDR and High Speed Scenarios*, IEEE Robotics and Automation Letters (RAL), 2018 – PDF. Video. Best Paper Award Honorable Mention

Learning with Event Cameras

- Approaches using synchronous, Artificial Neural Networks (ANNs) designed for standard images
- Asynchronous, Sparse ANNs
- Approaches using asynchronous, Spiking neural networks (SNNs)

Input representation

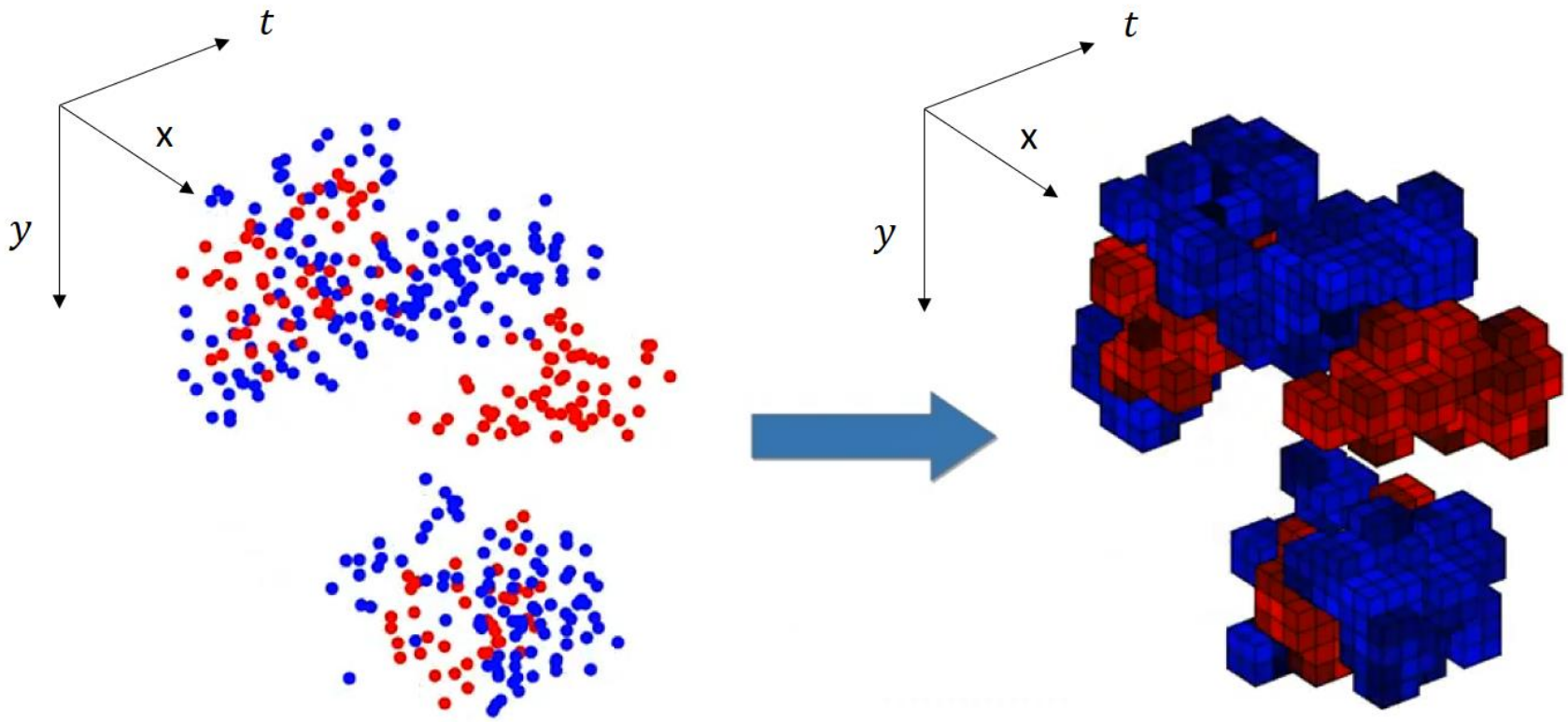
How do we pass sparse events into a convolutional neural network designed for standard images?



Video from here

Input representation

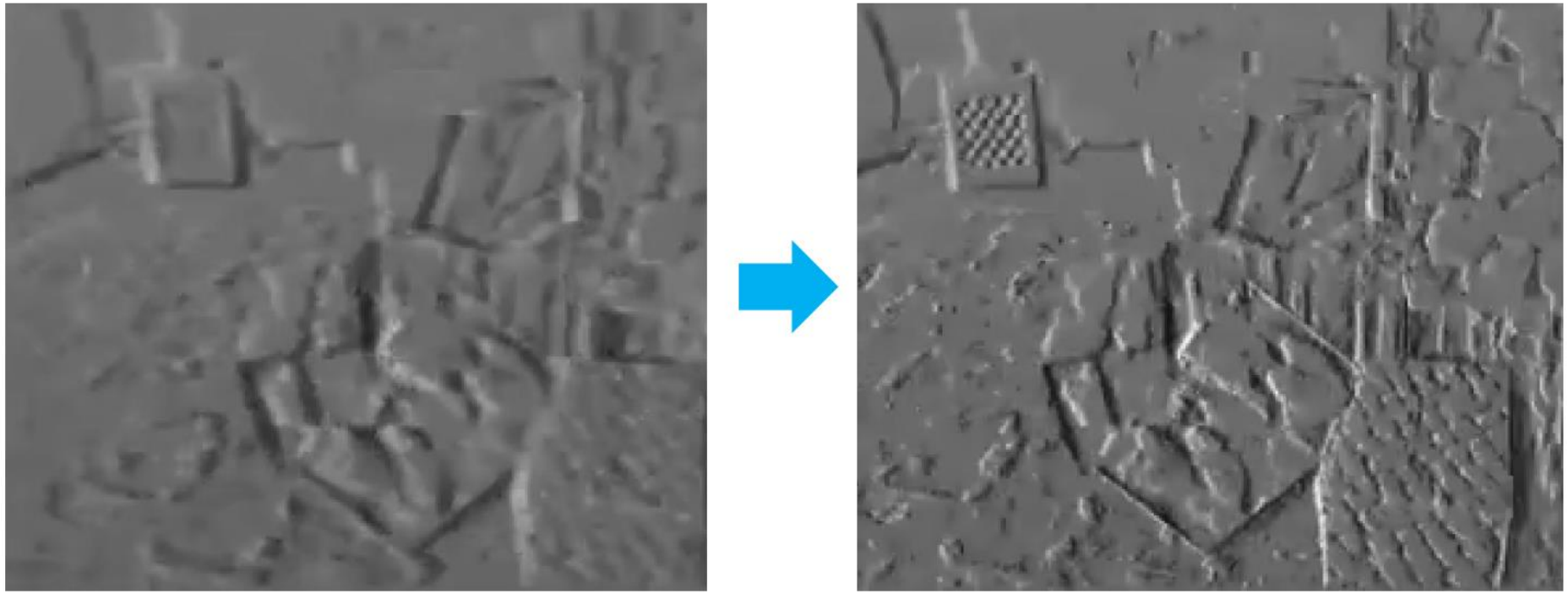
Represent events in space-time into a 3D voxel grid (x, y, t): each voxel contains sum of positive and negative events falling within the voxel



Video from here

Contrast as Loss Function for Unsupervised Learning

- **Idea**: maximize sharpness of the aggregated event image



Video from here

Zhu, Yuan, Chaney, Daniilidis, *Unsupervised Event-based Learning of Optical Flow, Depth and Egomotion*, CVPR 19. PDF.

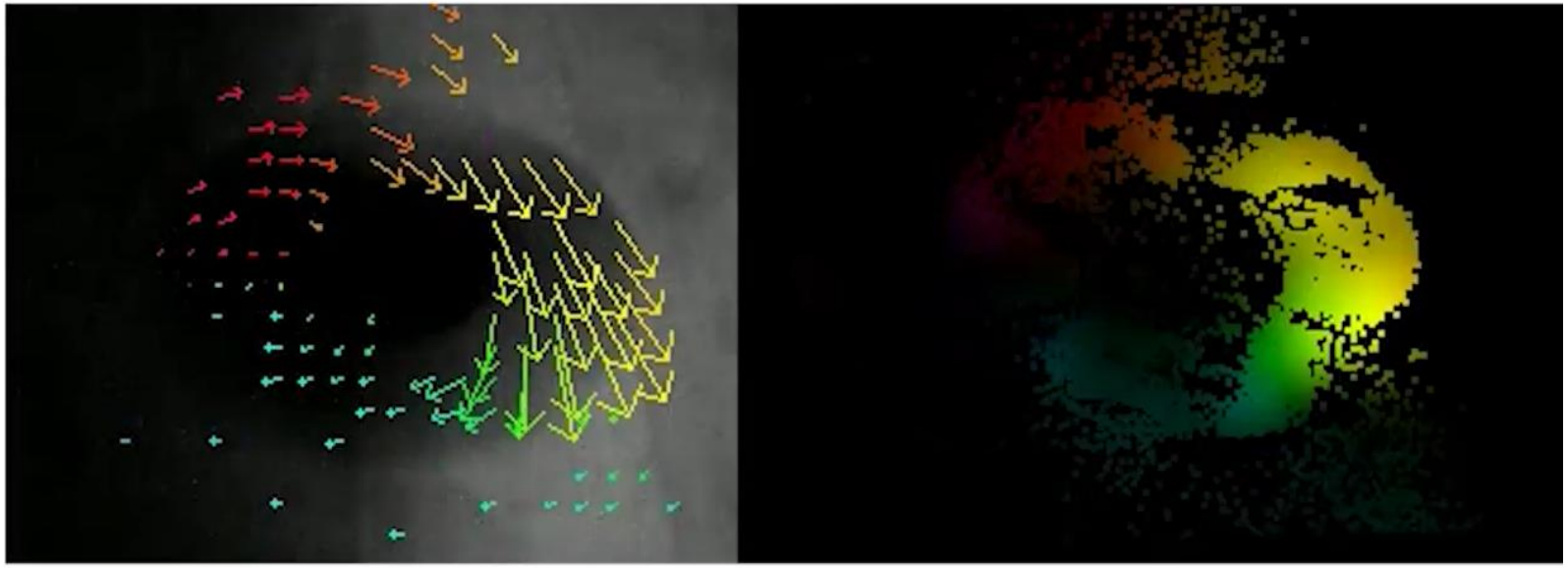
Gallego, Gehrig, Scaramuzza, *Focus Is All You Need: Loss Functions for Event-based Vision*, CVPR19, PDF.

Application1: Unsupervised Learning of Optical Flow

- **Idea**: maximize sharpness of the aggregated event image

Fidget Spinner w/ Challenging Lighting

Penn Engineering | GRASP Laboratory
General Robotics, Automation, Sensing & Perception Lab



Grayscale Image w/ Sparse Flow Quiver

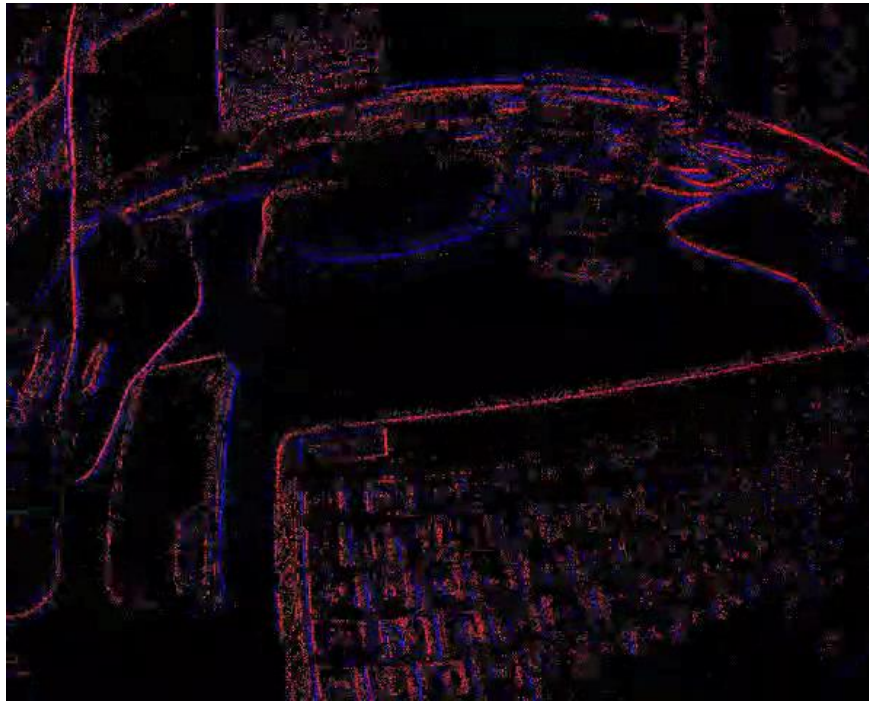
Dense Flow Output

1x realtime

Zhu, Yuan, Chaney, Daniilidis, *Unsupervised Event-based Learning of Optical Flow, Depth and Egomotion*, CVPR 19. PDF.

Application 2: Image Reconstruction from Events

Events



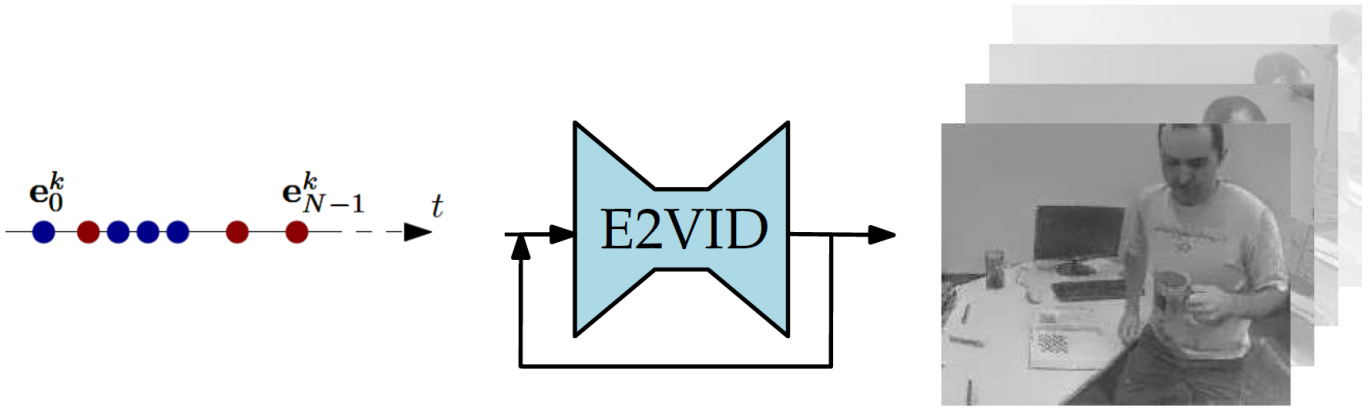
Reconstructed image from events

Code & datasets: https://github.com/uzh-rpg/rpg_e2vid

Rebecq, Ranftl, Koltun, Scaramuzza, *High Speed and High Dynamic Range Video with an Event Camera*, T-PAMI, 2019. PDF Video Code

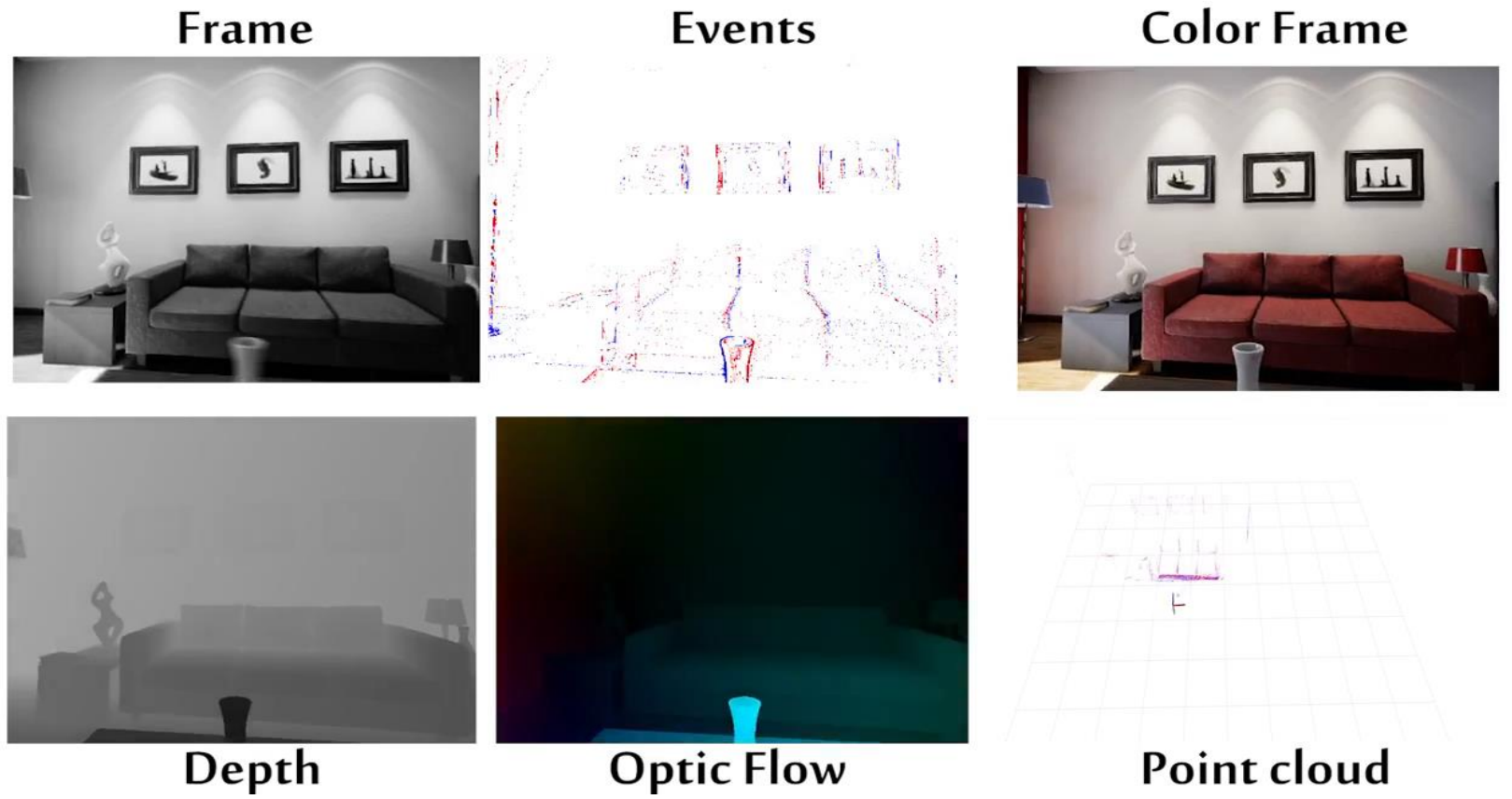
Overview

- **Recurrent neural network** (main module: Unet)
- Input: sequences of *event tensors* (3D spatio-temporal volumes of events[3])
- **Trained in simulation only**, without seeing a single real image
- To improve robustness **we randomize the contrast sensitivity** during simulation.
- Event camera simulator (ESIM): http://rpg.ifi.uzh.ch/esim.html



Rebecq, Ranftl, Koltun, Scaramuzza, *High Speed and High Dynamic Range Video with an Event Camera*, T-PAMI, 2019. PDF Video Code

ESIM: Event Camera Simulator



Open Source: http://rpg.ifi.uzh.ch/esim.html

Rebecq, Gehrig, Scaramuzza, *ESIM: an Open Event Camera Simulator*, Conference on Robot Learning (CORL), 2018. PDF. Video. Code.

Bullet shot by a gun (1,300 km/h)

Recall: trained in simulation only!

Huawei P20 Pro (240 FPS)

Our reconstruction (5400 FPS)

Code & datasets: https://github.com/uzh-rpg/rpg_e2vid

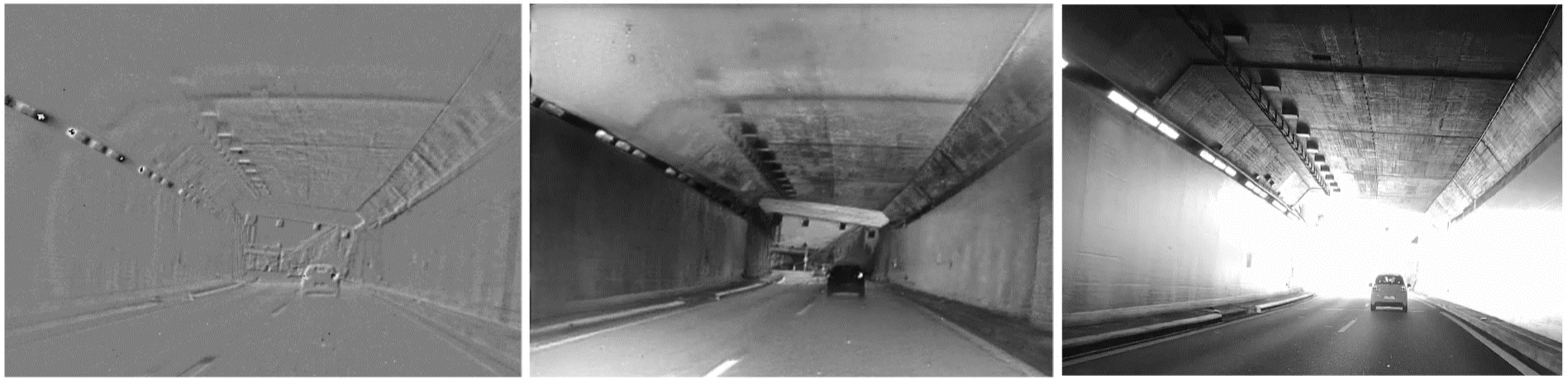
100 x slow motion

Rebecq, Ranftl, Koltun, Scaramuzza, *High Speed and High Dynamic Range Video with an Event Camera*, T-PAMI, 2019. PDF Video Code

HDR Video: Driving out of a tunnel

Recall: trained in simulation only!

Driving out of a tunnel



Events **Our reconstruction** **Phone camera**

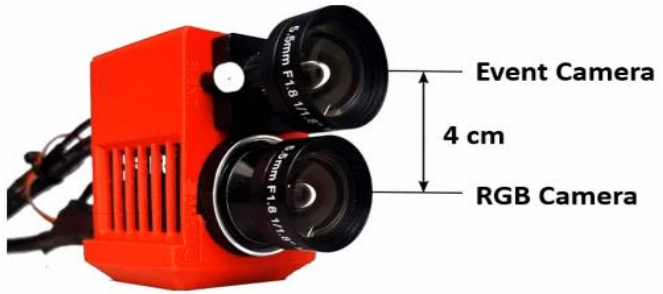
Code & datasets: https://github.com/uzh-rpg/rpg_e2vid

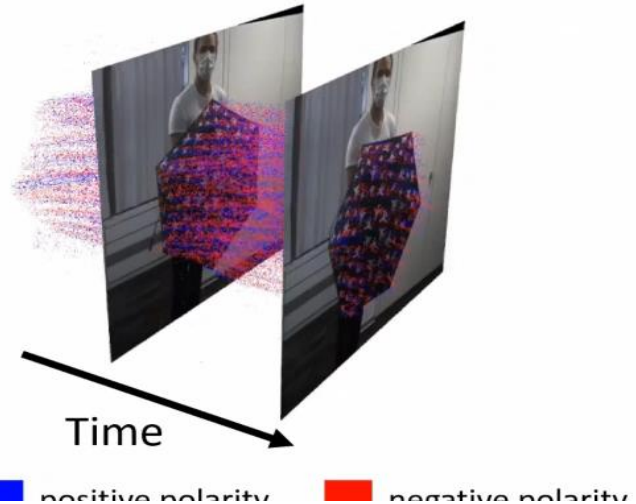
Rebecq, Ranftl, Koltun, Scaramuzza, *High Speed and High Dynamic Range Video with an Event Camera*, T-PAMI, 2019. PDF Video Code

Application 3: Slow Motion Video

- We can combine an event camera with an HD RG camera
- We use events to **upsample low-framerate video** by over **50 times** with **only 1/40th of the memory** footprint!

It does this by leveraging event cameras which provide a compressed stream of visual information in the blind-time between frames.





Code & Datasets: http://rpg.ifi.uzh.ch/timelens

Tulyakov et al., TimeLens: *Event-based Video Frame Interpolation*, CVPR'21. PDF. Video. Code.

Application 3: Slow Motion Video

- We can combine an event camera with an HD RG camera
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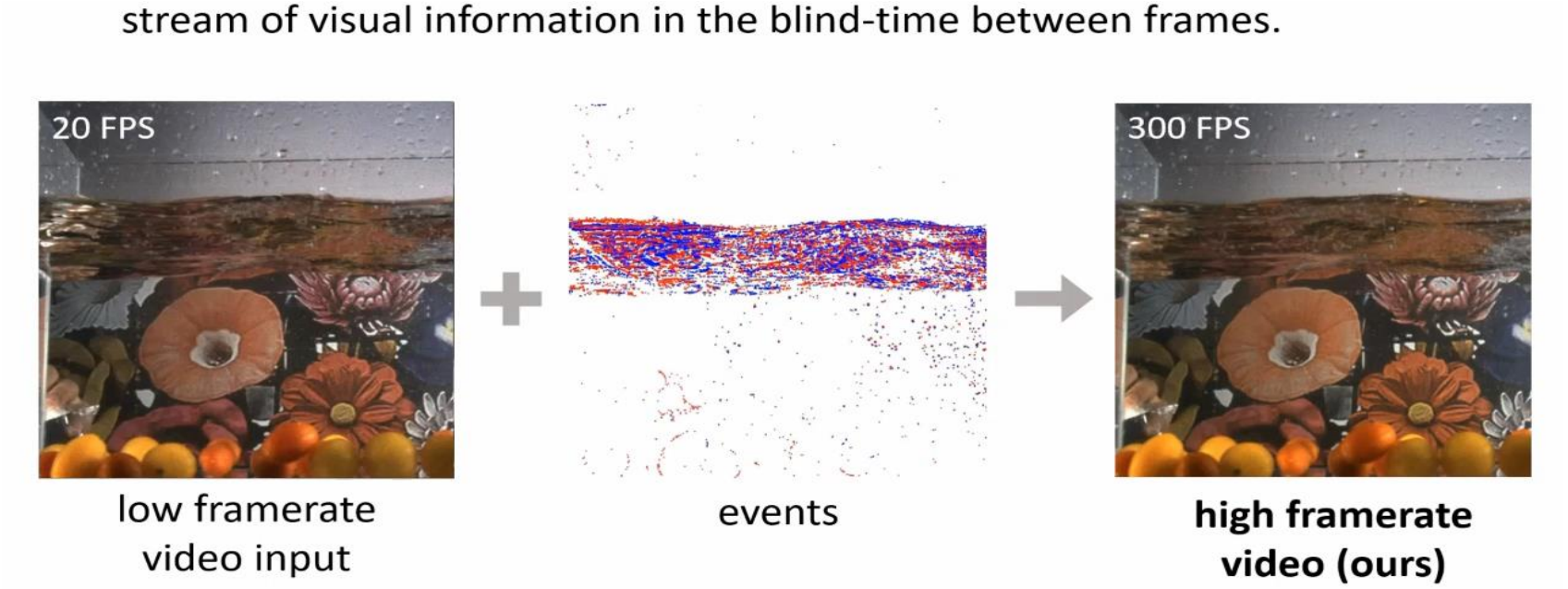


Code & Datasets: http://rpg.ifi.uzh.ch/timelens

Tulyakov et al., TimeLens: *Event-based Video Frame Interpolation*, CVPR'21. PDF. Video. Code.

Application 3: Slow Motion Video

- We can combine an event camera with an HD RG camera
- We use events to **upsample low-framerate video** by over **50 times** with **only 1/40th of the memory** footprint!

low framerate video input **Time Lens (this work)**

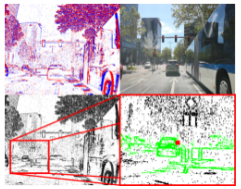
Code & Datasets: http://rpg.ifi.uzh.ch/timelens

Tulyakov et al., TimeLens: *Event-based Video Frame Interpolation*, CVPR'21. PDF. Video. Code.

We have student projects on event cameras

http://rpg.ifi.uzh.ch/student_projects.php

Asynchronous Processing for Event-based Deep Learning - Available

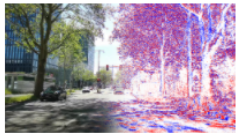


Description: Event cameras such as the Dynamic Vision Sensor (DVS) are recent sensors with large potential for high-speed and high dynamic range robotic applications. Since their output is sparse traditional algorithms, which are designed for dense inputs such as frames, are not well suited. The goal of this project is explore ways to adapt existing deep learning algorithms to handle sparse asynchronous data from events. Applicants should have experience in C++ and python deep learning frameworks (tensorflow or pytorch), and have a strong background in computer vision.

Goal: The goal of this project is explore ways to adapt existing deep learning algorithms to handle sparse asynchronous data from events.

Contact Details: Daniel Gehrig (dgehrig at ifi.uzh.ch)
Thesis Type: Semester Project / Master Thesis
See project on SiROP

Designing a New Event Camera with Events and Images - Available

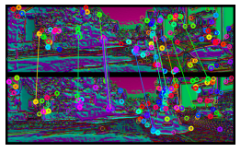


Description: Event cameras such as the Dynamic Vision Sensor (DVS) are recent sensors with a lot of potential for high-speed and high dynamic range robotic applications. They have been successfully applied in many applications, such as high speed video and high speed visual odometry. Due to their high speed and

Goal: The goal of this project is to design a new event camera that combines events and standard images.

Contact Details: Daniel Gehrig (dgehrig (at) ifi (dot) uzh (dot) ch), Mathias Gehrig (mgehrig (at) ifi (dot) uzh (dot) ch)
Thesis Type: Semester Project / Master Thesis
See project on SiROP

Data-driven Keypoint Extractor for Event Data - Available

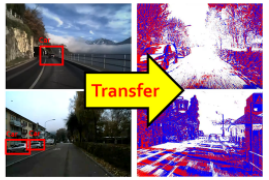


Description: Neuromorphic cameras exhibit several amazing properties such as robustness to HDR scenes, high-temporal resolution, and low power consumption. Thanks to these characteristics, event cameras are applied for camera pose estimation for fast motions in challenging scenes. A common technique for camera pose estimation is the extraction and tracking of keypoints on the camera plane. In the case of event cameras, most existing keypoint extraction methods are handcrafted manually. As a new promising direction, this project tackles the keypoint extraction in a data-driven fashion based on recent advances in frame-based keypoint extractors.

Goal: The project aims to develop a data-driven keypoint extractor, which computes interest points in event data. Based on the current advances of learned keypoint extractors for traditional frames, the approach will leverage neural network architectures to extract and describe keypoints in an event stream. The student should have prior programming experience in a deep learning framework and completed at least one course in computer vision.

Contact Details: Contact Details: Nico Messikommer [nmessi (at) ifi (dot) uzh (dot) ch], Mathias Gehrig [mgehrig (at) ifi (dot) uzh (dot) ch]
Thesis Type: Semester Project / Master Thesis
See project on SiROP

Domain Transfer between Events and Frames - Available



Description: During the last years, a vast collection of frame-based datasets was collected for countless tasks. In comparison, event-based datasets represent only a tiny fraction of the available datasets. Thus, it is highly promising to use labelled frame datasets to train event-based networks as current data-driven approaches heavily rely on labelled data.

Goal: In this project, the student extends current advances from the UDA literature for traditional frames to event data in order to transfer multiple tasks from frames to events. The approach should be validated on several tasks (segmentation, object detection, etc.) in challenging environments (night, high-dynamic scenes) to highlight the benefits of event cameras. As several deep learning methods are used as tools for the task transfer, a strong background in deep learning is required. If you are interested, we are happy to provide more details.

Contact Details: Nico Messikommer [nmessi (at) ifi (dot) uzh (dot) ch], Daniel Gehrig [dgehrig (at) ifi (dot) uzh (dot) ch]
Thesis Type: Semester Project / Master Thesis
See project on SiROP

Understanding Check

Are you able to answer the following questions?

- What is an event camera 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 an event camera (formula). Can you derive its 1^{st} order approximation?
- What is a DAVIS sensor?
- What is the focus maximization framework and how does it work? What is its advantage compared with the generative model?