

Vol agile avec des micro-robots volants contrôlés par vision

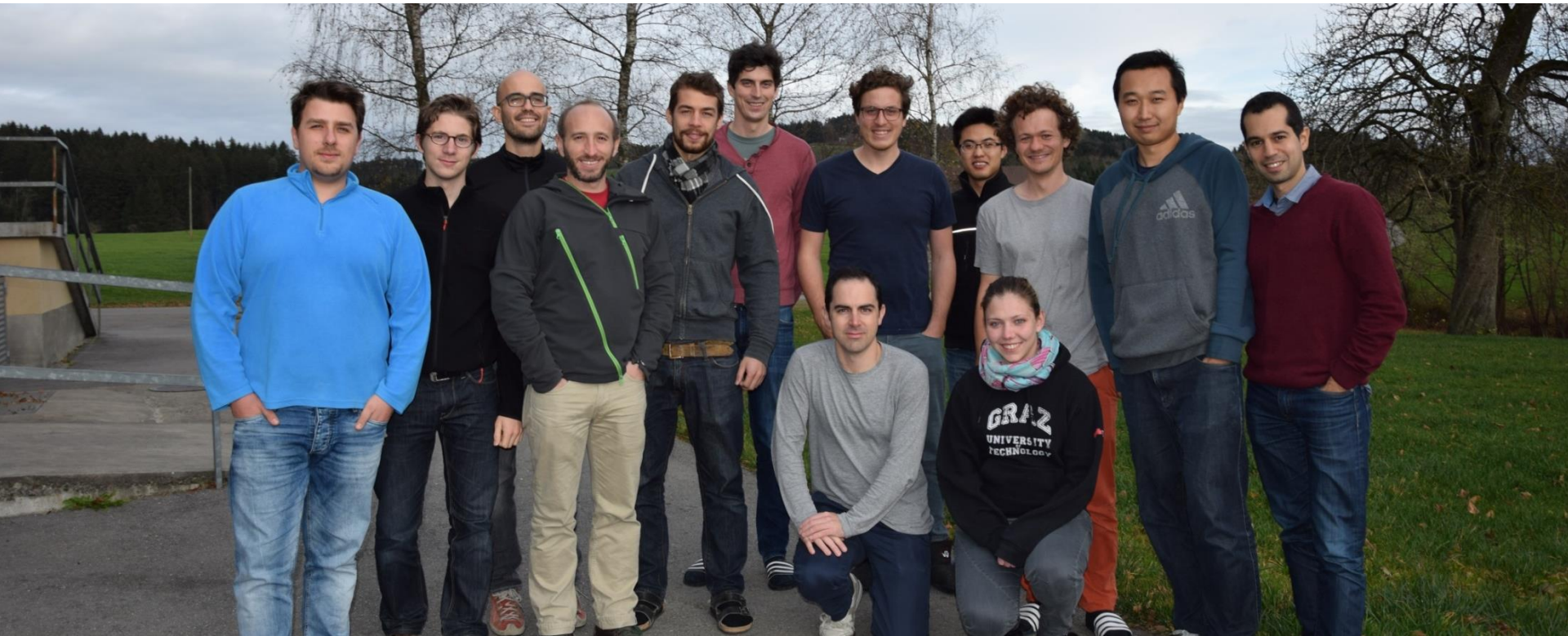
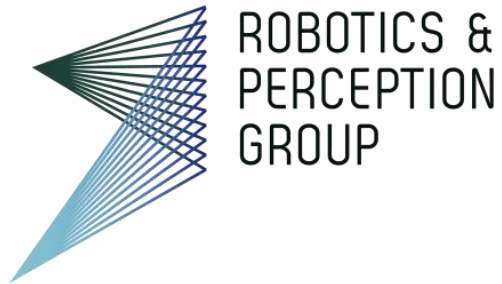
From Active Perception to Event-based Vision

Henri Rebecq

from Prof. Davide Scaramuzza's lab

GT UAV – 17 Novembre 2016, Paris

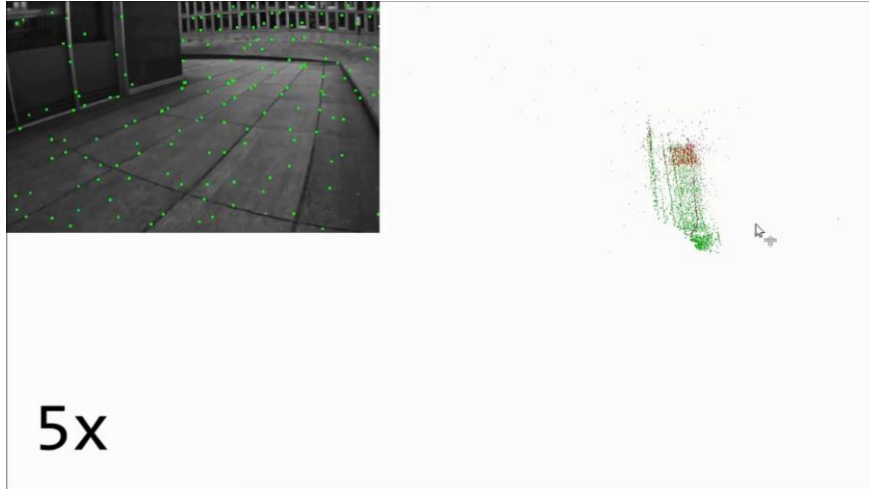
My Research Group



Our Research Areas

Visual-Inertial State Estimation

[IJCV'11, PAMI'13, RSS'15]



Dense Reconstruction

[ICRA'14, JFR'15]



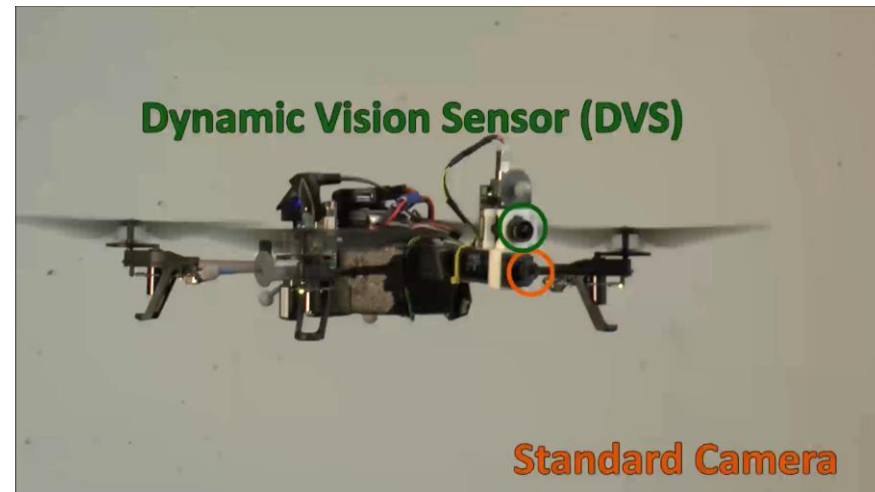
Vision-based Navigation of Flying Robots

[AURO'12, RAM'14, JFR'15]



Event-based Vision

[IROS'14, RSS'15]



Our Vision: Flying Robots to the Rescue!



Our Dream Robot

Agile, lightweight drones rapidly navigating to accomplish a given task

➤ **Challenges:** fast, lightweight, agile (low-latency perception & control)



Video credit: LEXUS commercial, 2013

State of the Art on GPS-denied Navigation



Mellinger, Michael, **Kumar**

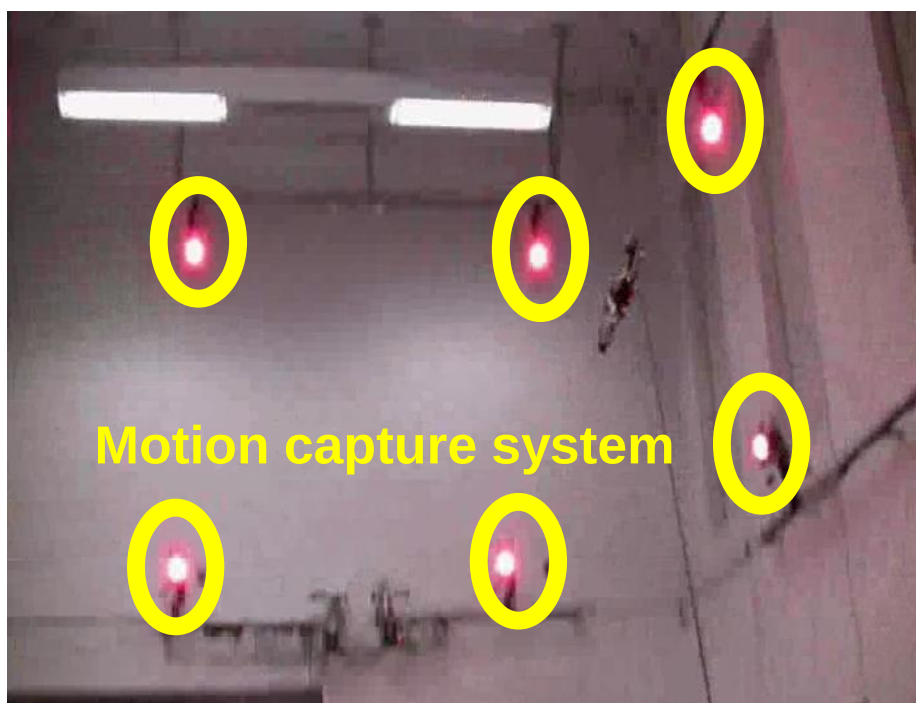


Fontana, Faessler, **Scaramuzza**

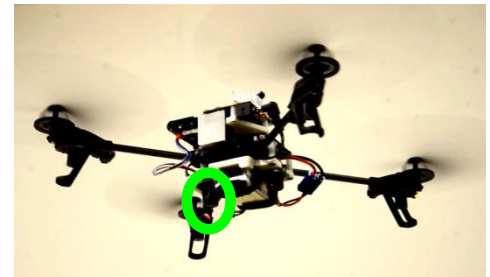


How do we Localize without GPS ?

This robot is «*blind*»



This robot can «*see*»



Problems with Vision-controlled Drones

Drones have the **potential to navigate quickly** through unstructured environments but

- Autonomous operation is currently **restricted to controlled environments**
- **Vision-based** maneuvers still **slow** and **inaccurate** wrt motion-capture systems

Why?

- Perception algorithms are **mature but not robust**
 - Unlike mocap systems, **localization accuracy** depends on **distance & texture!**
 - **Control & Perception** have been mostly **considered separately!**
 - Algorithms and sensors have **big latencies** (50-200 ms) → need faster sensors!

Outline

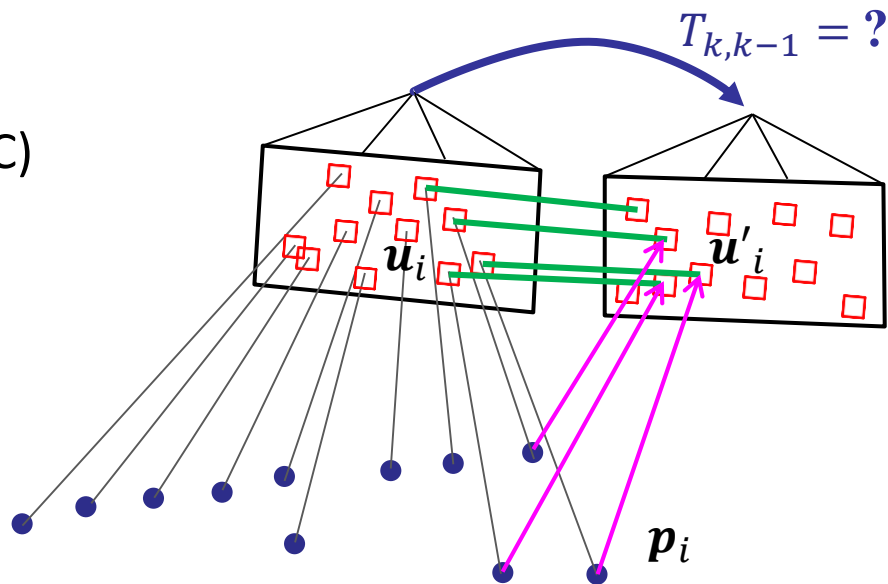
- Visual-Inertial State Estimation
- Active Vision
- Low-latency, Event-based Vision

Visual-Inertial State Estimation

Feature-based methods

1. Extract & match features (+RANSAC)
2. Minimize **Reprojection error** minimization

$$T_{k,k-1} = \arg \min_T \sum_i \| \mathbf{u}'_i - \pi(\mathbf{p}_i) \|_{\Sigma}^2$$

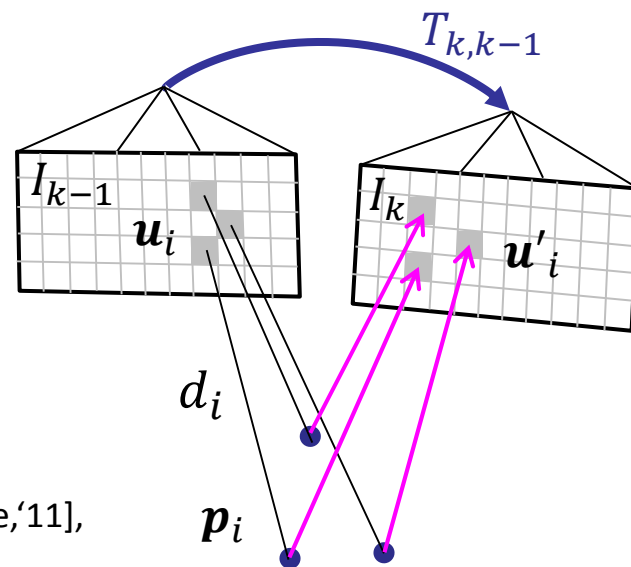


Direct methods

1. Minimize **photometric error**

$$T_{k,k-1} = \arg \min_T \sum_i \| I_k(\mathbf{u}'_i) - I_{k-1}(\mathbf{u}_i) \|_{\sigma}^2$$

where $\mathbf{u}'_i = \pi(T \cdot (\pi^{-1}(\mathbf{u}_i) \cdot d))$



Feature-based methods

1. Extract & match features (+RANSAC)
2. Minimize **Reprojection error** minimization

- ✓ Large frame-to-frame motions
- ✗ Slow due to costly feature extraction and matching

Our solution:

SVO: *Semi-direct* Visual Odometry [ICRA'14]

Combines feature-based and direct methods

$$T_{k,k-1} = \arg \min_T \sum_i \|I_k(\mathbf{u}_i) - I_{k-1}(\mathbf{u}_i)\|_{\sigma}$$

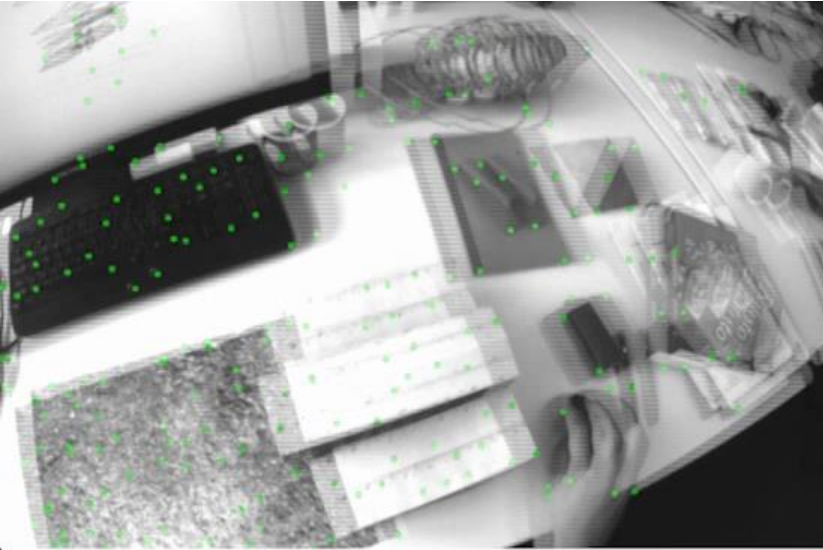
frame

per

where $\mathbf{u}'_i = \pi(T \cdot (\pi^{-1}(\mathbf{u}_i) \cdot d))$

- ✗ Limited frame-to-frame motion

SVO Results: Fast and Abrupt Motions



Open Source

[Forster, Pizzoli, Scaramuzza, «SVO: Semi Direct Visual Odometry», ICRA'14]

Processing Times of SVO

Laptop (Intel i7, 2.8 GHz)

400 frames per second



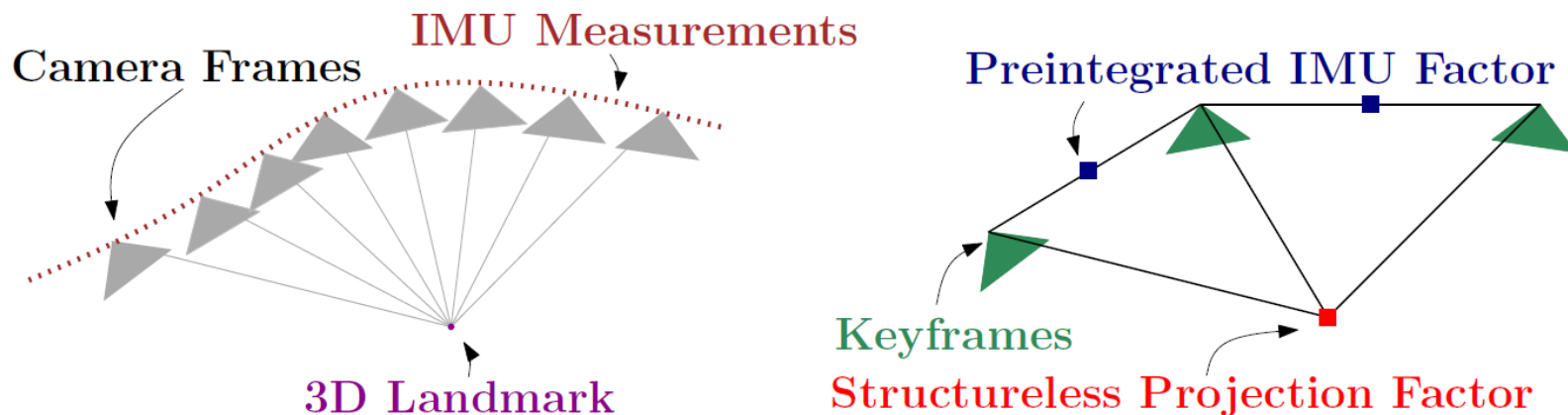
Embedded ARM Cortex-A9, 1.7 GHz

Up to 70 frames per second



Visual-Inertial Fusion [RSS'15]

- Fusion solved as a *non-linear optimization problem* (no filters)
- Increased accuracy over filtering methods



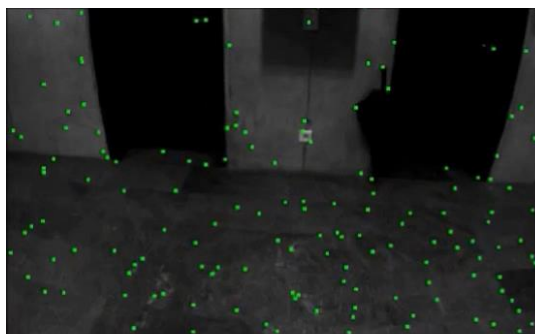
$$\sum_{(i,j) \in \mathcal{K}_k} \|\mathbf{r}_{\mathcal{I}_{ij}}\|_{\Sigma_{ij}}^2 + \sum_{i \in \mathcal{K}_k} \sum_{l \in \mathcal{C}_i} \|\mathbf{r}_{\mathcal{C}_{il}}\|_{\Sigma_c}^2$$

IMU residuals *Reprojection residuals*



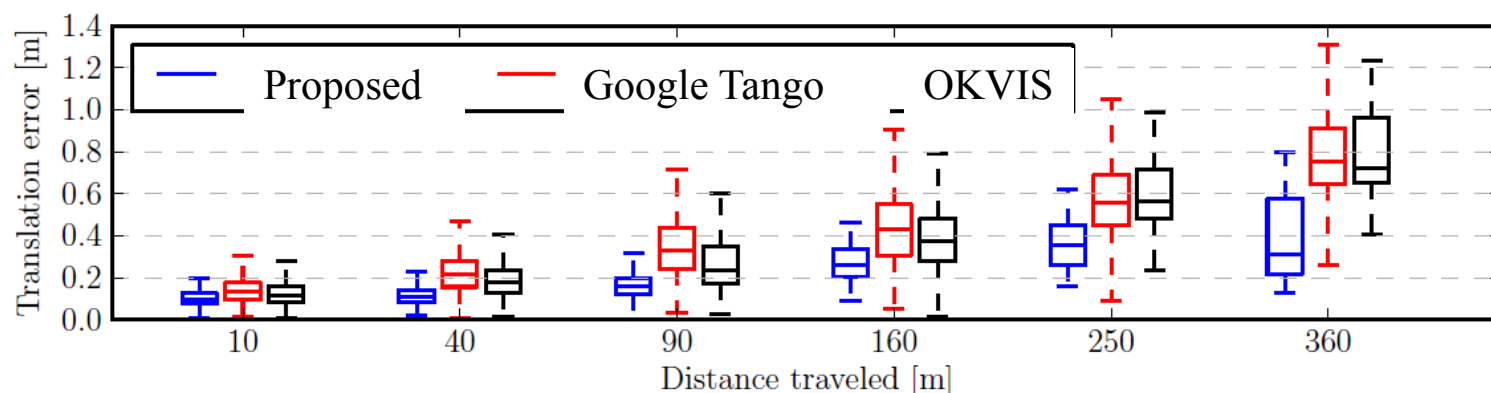
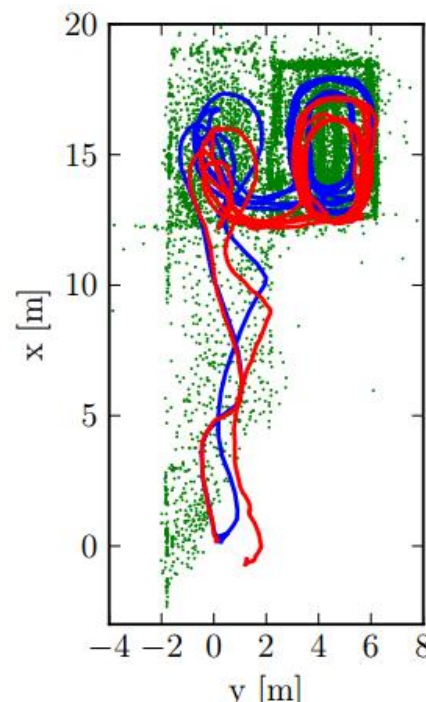
Comparison with Previous Works

Open Source



5x

Accuracy: 0.1% of the travel distance



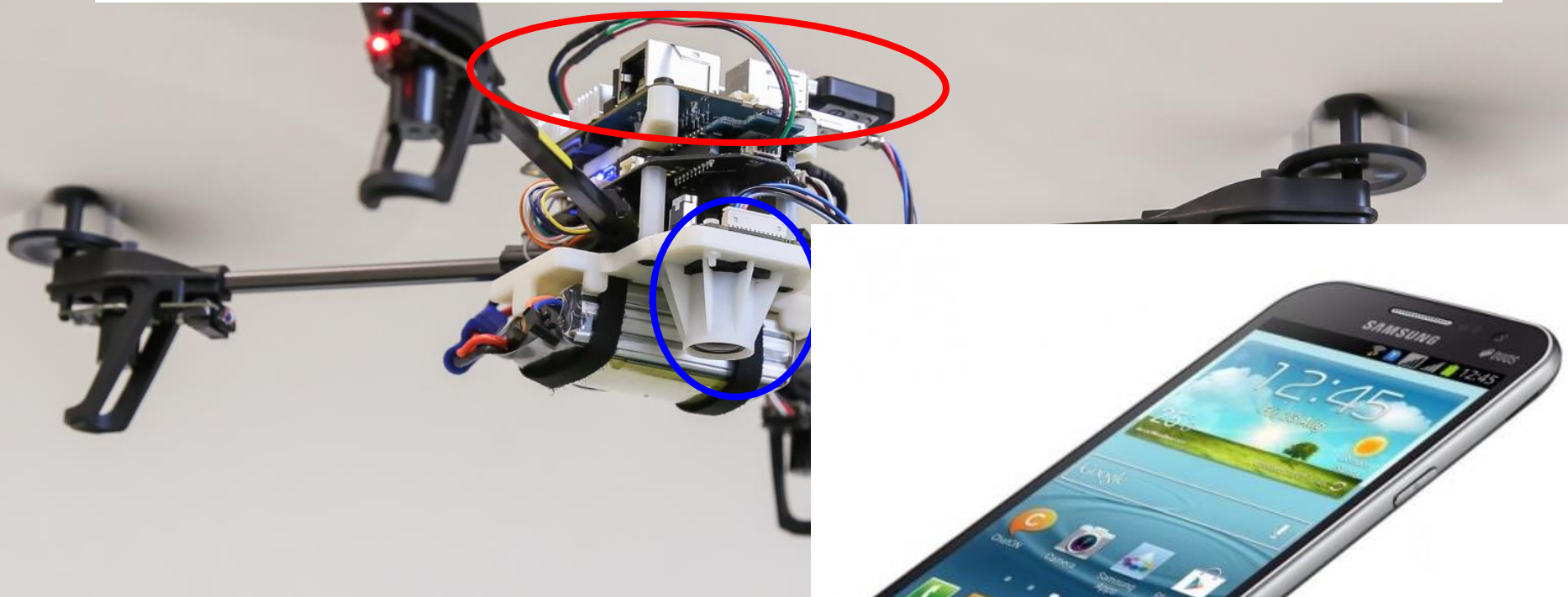
Forster, Carlone, Dellaert, Scaramuzza, IMU Preintegration on Manifold for efficient Visual-Inertial Maximum-a-Posteriori Estimation, *Robotics Science and Systems*'15, **Best Paper Award Finalist**

Integration on a Quadrotor Platform

Quadrotor System

Odroid XU4 Computer

- Quad Core Odroid (ARM Cortex A-9) used in Samsung Galaxy S4 phones
- Runs Linux Ubuntu and ROS



450 grams

Indoors and outdoors experiments



Position error: 5 mm, height: 1.5 m – Down-looking camera



Speed: 4 m/s, height: 1.5 m – Down-looking camera



Faessler, Fontana, Forster, Mueggler, Pizzoli, Scaramuzza, Autonomous, Vision-based Flight and Live Dense 3D Mapping with a Quadrotor Micro Aerial Vehicle, **Journal of Field Robotics**, 2015.

Application: Autonomous Inspection of Bridges and Power Masts

Project with Parrot: Autonomous vision-based navigation



Parrot senseFly

Albris drone

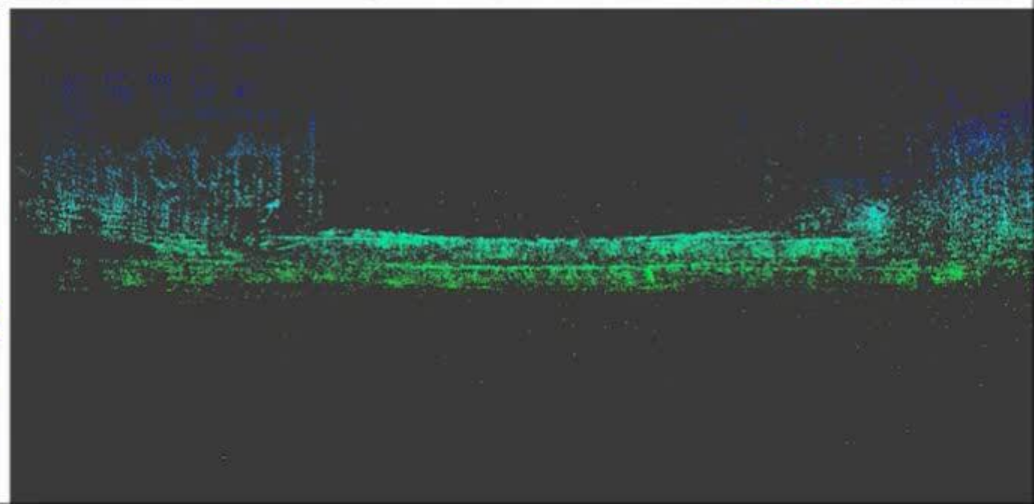
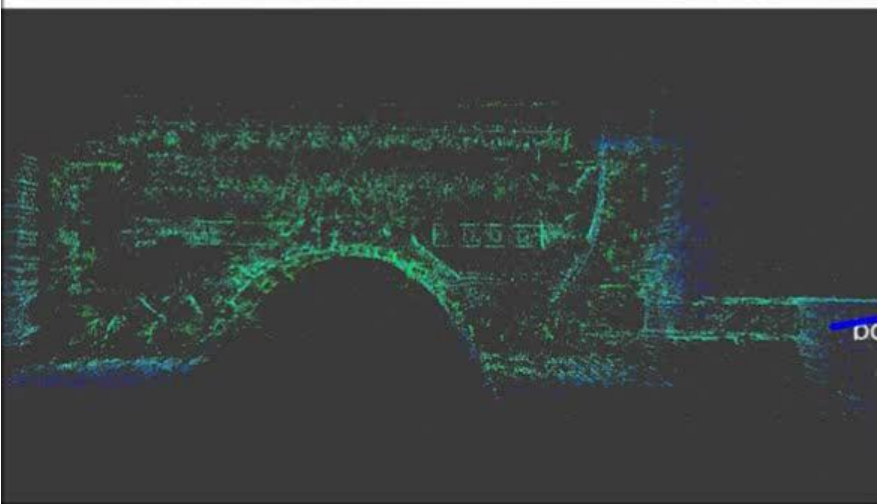


5 vision sensors

Startup: Zurich-Eye – www.zurich-eye.com

Vision-based Localization and Mapping Solutions for Mobile Robots

Founded in Sep. 2015, **became part of Facebook-Oculus in Sep. 2016**



Active Perception

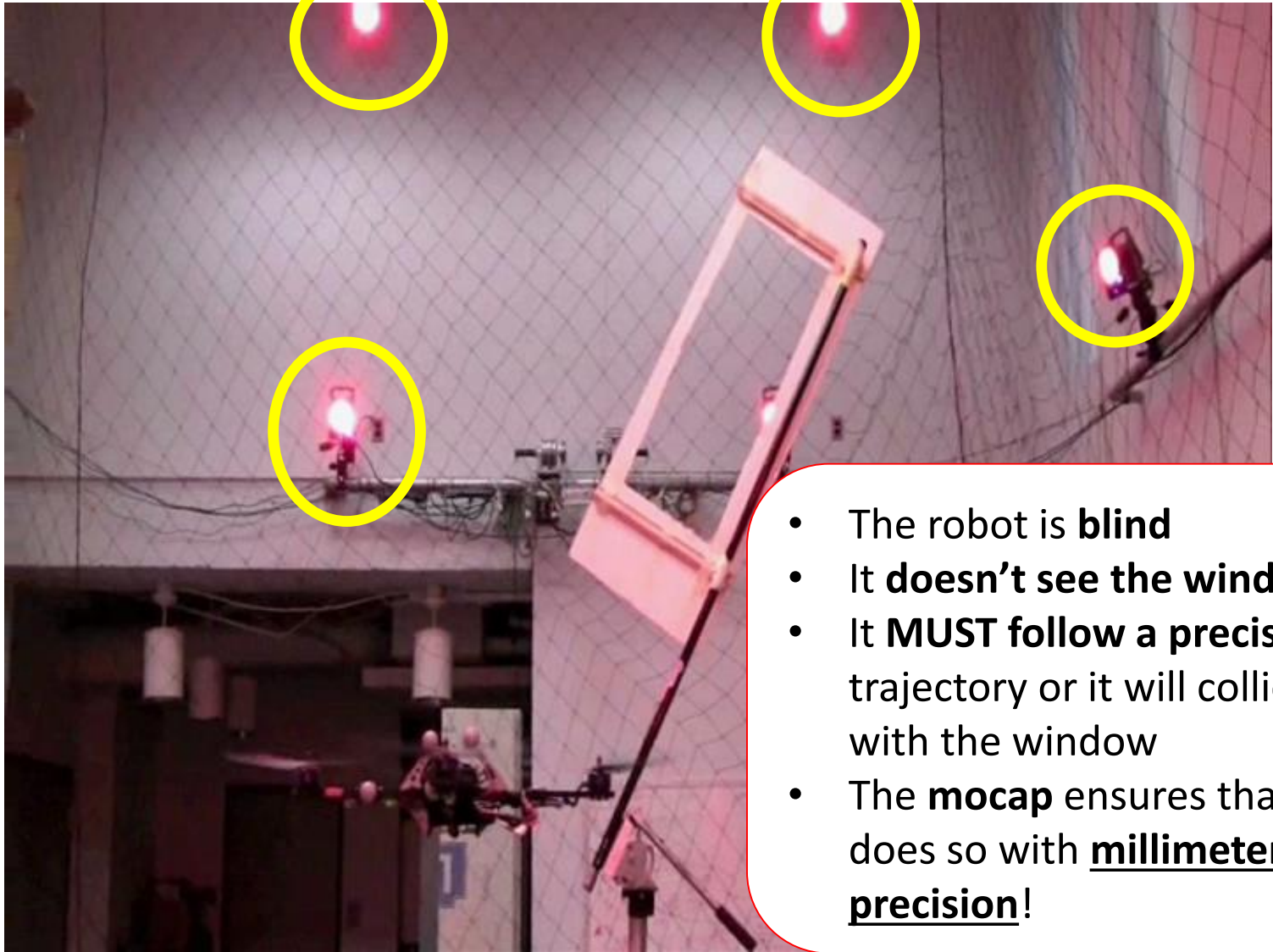
Flight through Narrow Windows



Autonomous Flight through Narrow Windows



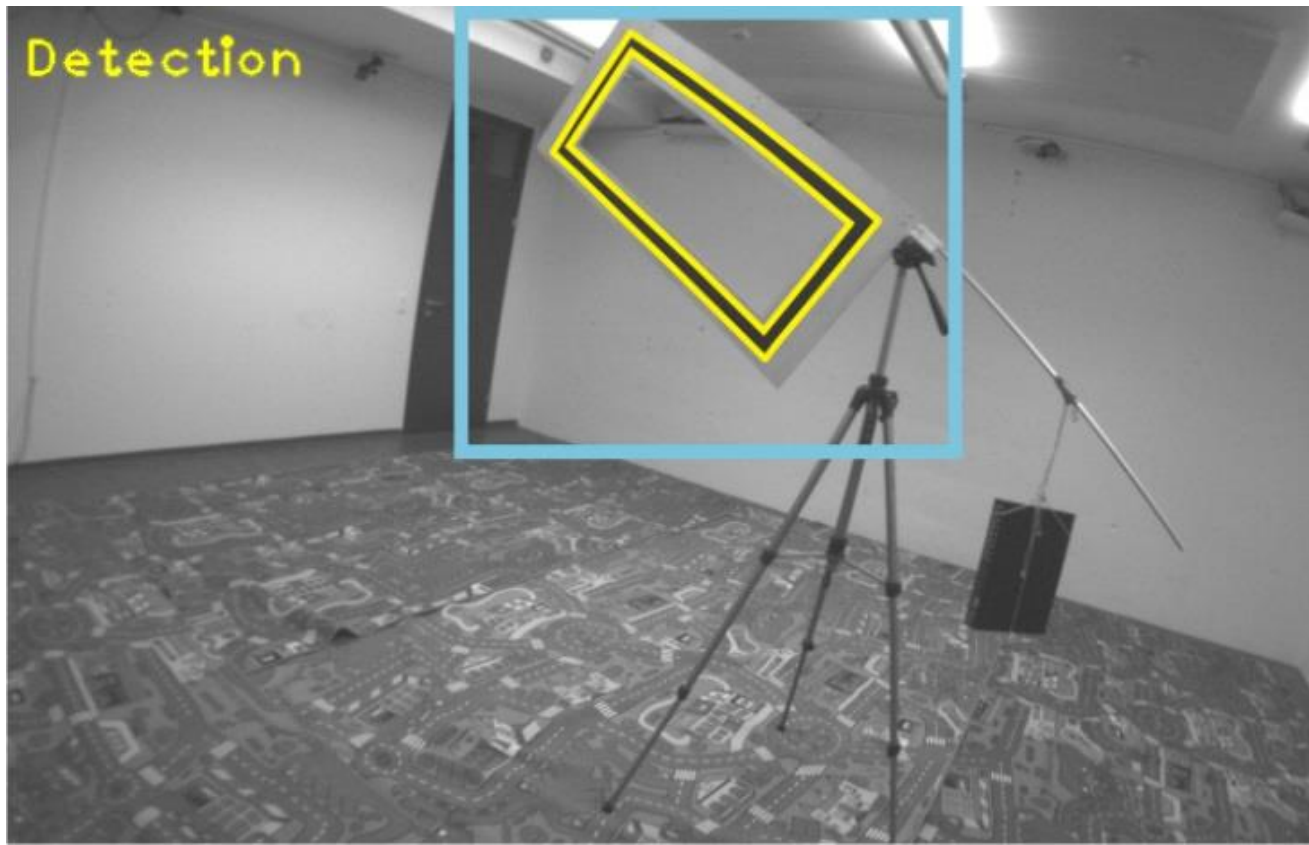
D. Mellinger, N. Michael, V. Kmar



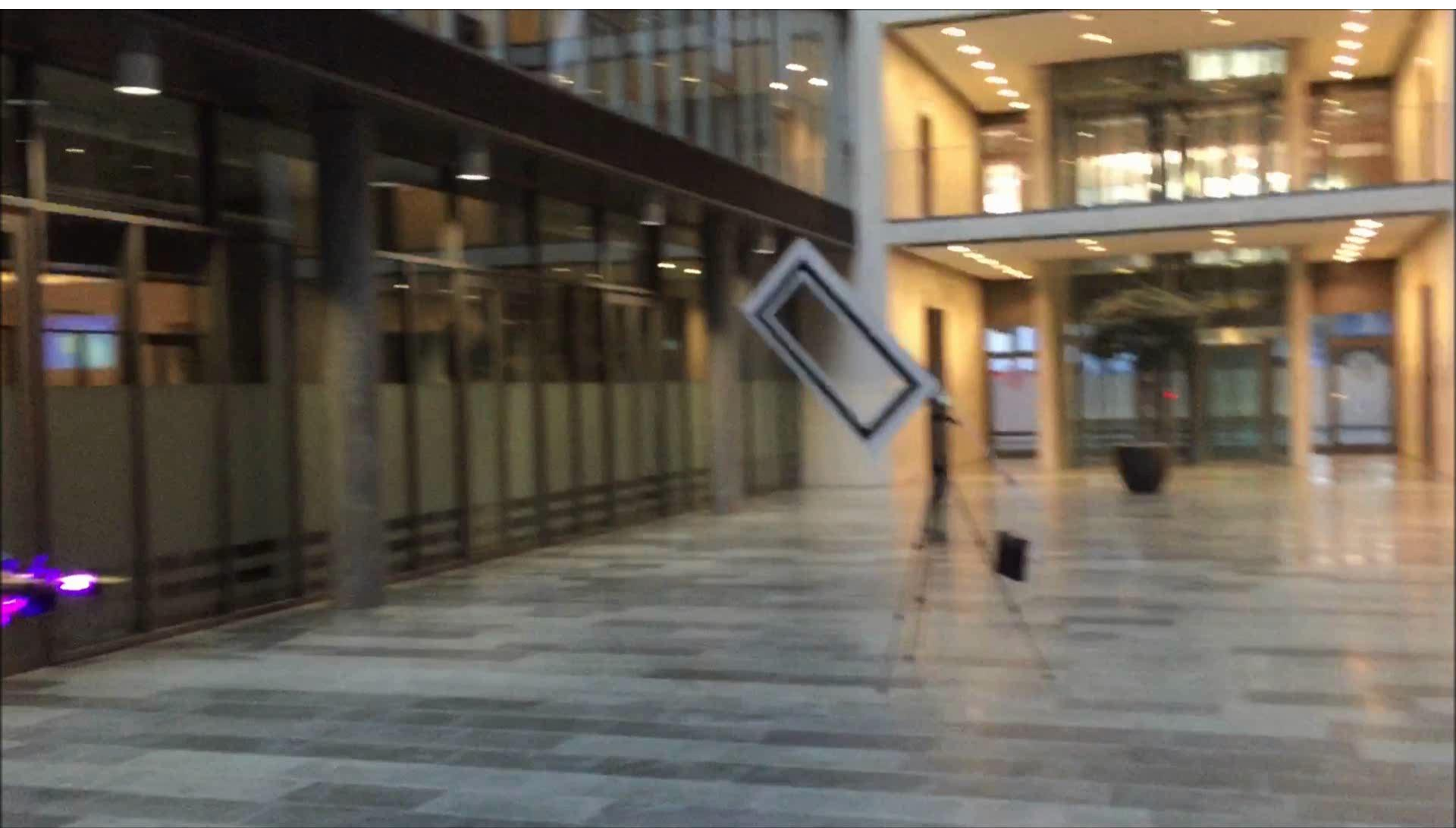
- The robot is **blind**
- It **doesn't see the window**
- It **MUST follow a precise trajectory** or it will collide with the window
- The **mocap** ensures that it does so with **millimeter precision!**

Vision-based Flight through Narrow Windows

Can we pass through narrow windows using only a single onboard camera?



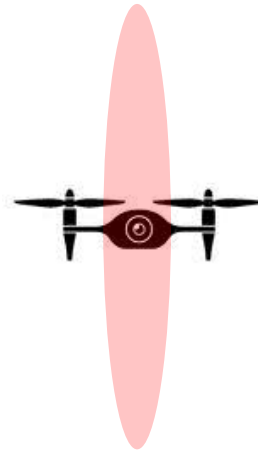
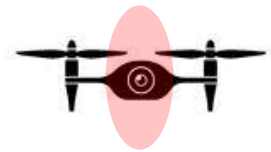
How would a professional drone pilot perform?



Challenge I

➤ How to localize?

- Use a **window detector** plus **IMU**
- Pose uncertainty increases **quadratically with the distance**: $\sigma \propto d^2$



Challenge 2

➤ What is the optimal trajectory in (x, v, a) ?

- **Dynamic constraints**

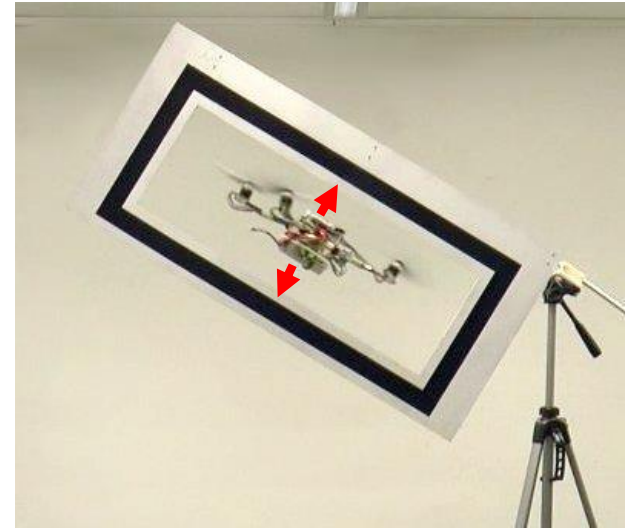
- Continuous up to the Jerk
- Minimize the snap (energy)

- **Geometric constraints**

- Maximize the distance from the edges of the window

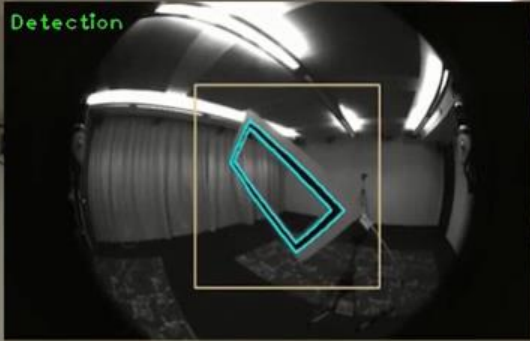
- **Perception constraints**

- Always face the window to enable localization (active vision!)
- Challenge: how can we **plan in the position and angle domains?**

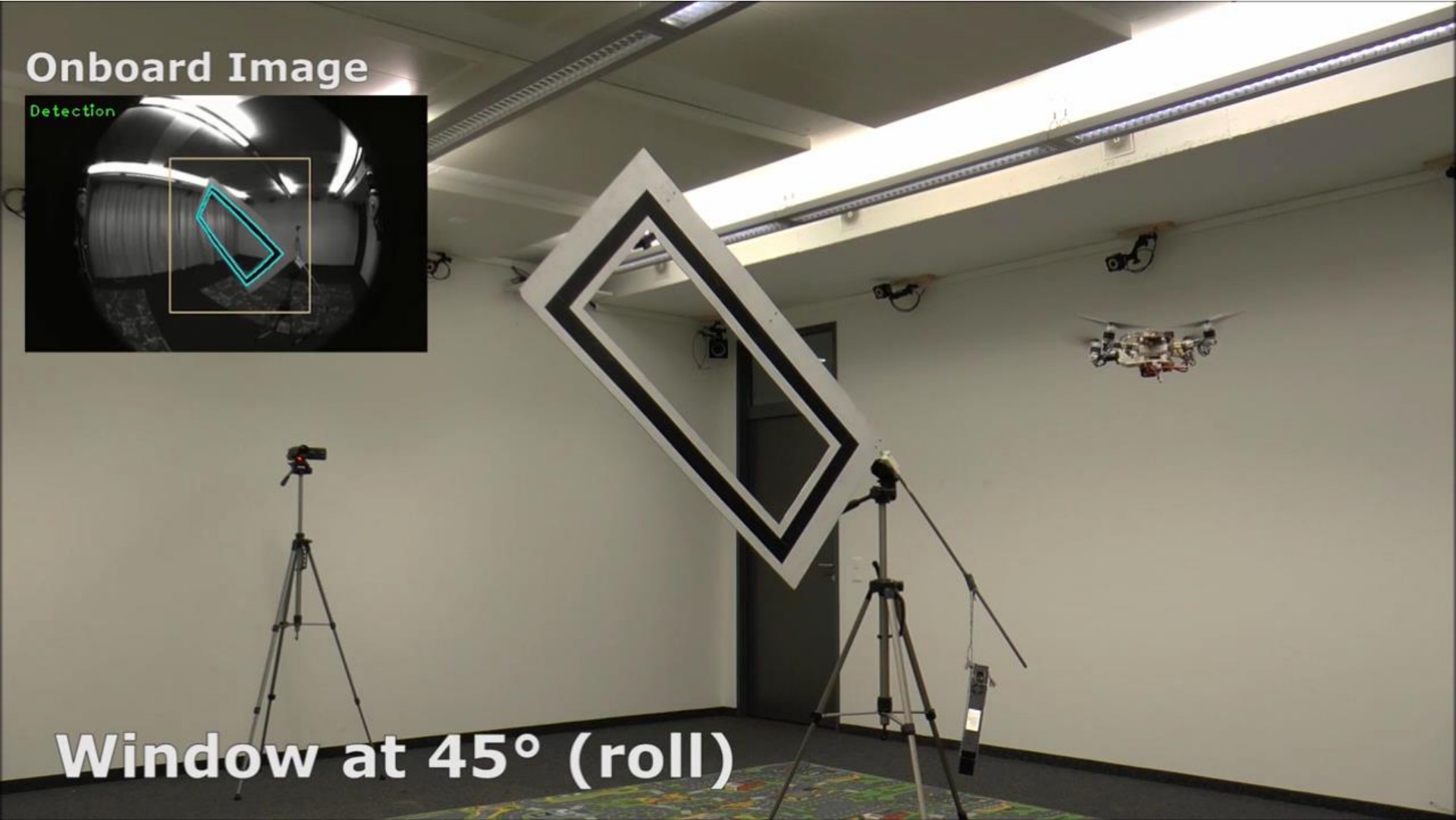


Autonomous Flight through Narrow Gaps

Onboard Image



Window at 45° (roll)



[Falanga, Mueggler, Faessler, Scaramuzza, «Aggressive Quadrotor Flight through Narrow Gaps with onboard Sensing and Computing», Submitted, ICRA'16] **Featured on IEEE Spectrum**

Low-latency, Event-based Vision

Open Problems and Challenges with Micro Helicopters

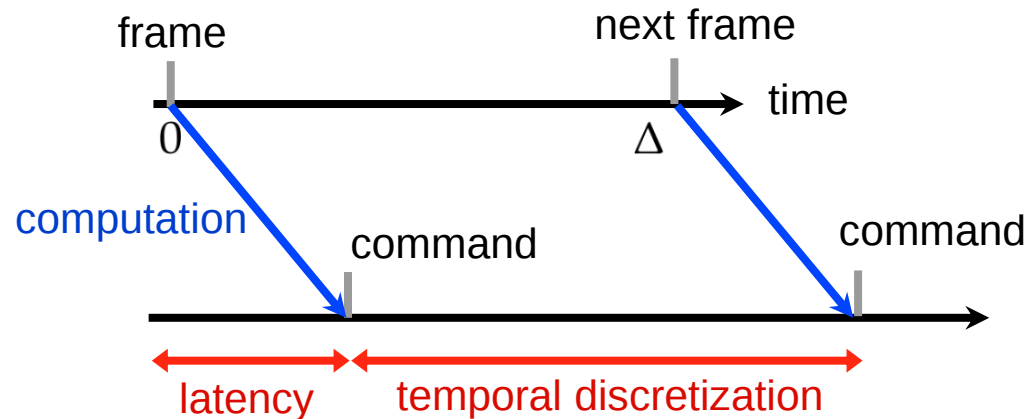
Current flight maneuvers achieved with onboard cameras are still too slow compared with those attainable by birds or FPV pilots



FPV-Drone race

To go faster, we need faster sensors!

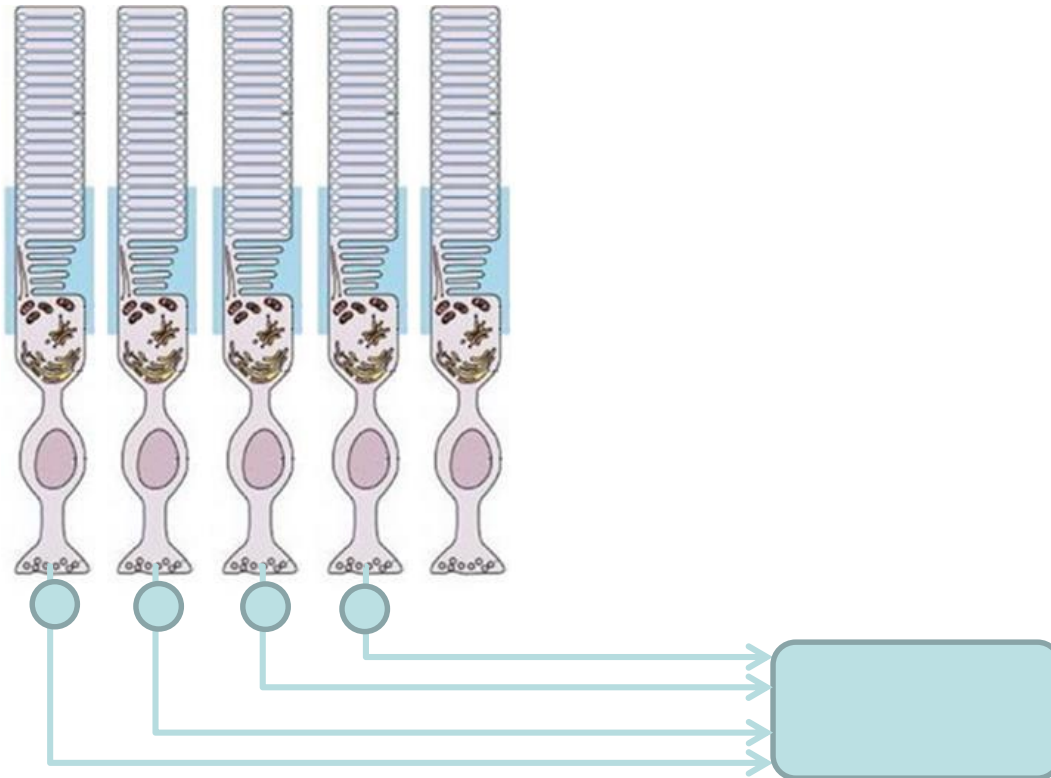
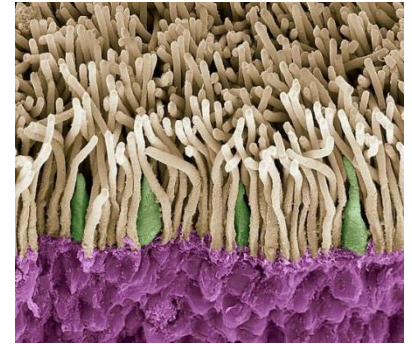
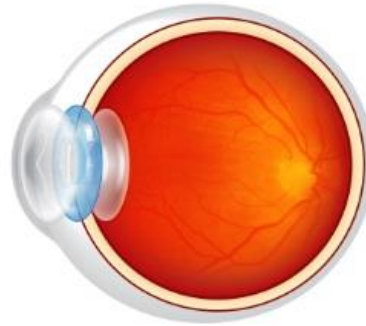
- At the current state, the agility of a robot is limited by the latency and temporal discretization of its sensing pipeline.
- Currently, the average robot-vision algorithms have latencies of 50-200 ms. This puts a hard bound on the agility of the platform.



- **Can we create a low-latency and low-discretization perception pipeline?**
 - Yes, if we use **event-based cameras**

Human Vision System

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



Dynamic Vision Sensor (DVS)

- **Event-based camera** developed by Tobi Delbruck's group (ETH & UZH).
- Temporal resolution: **1 μ s**
- High dynamic range: **140 dB**
- Low power: **20 mW**
- Cost: 2,500 EUR

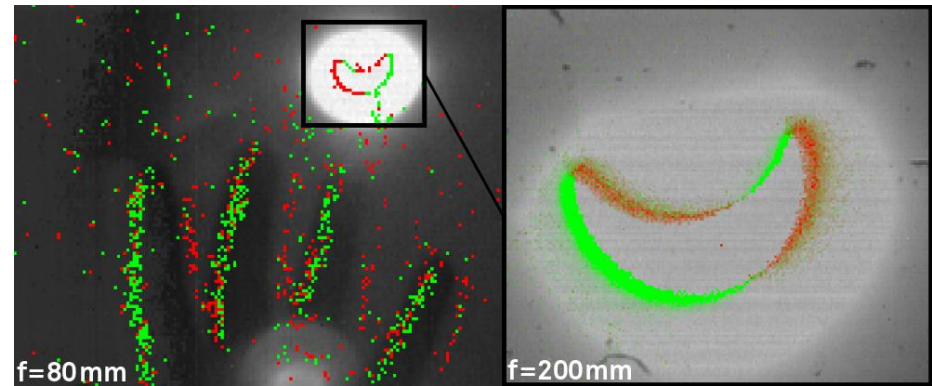
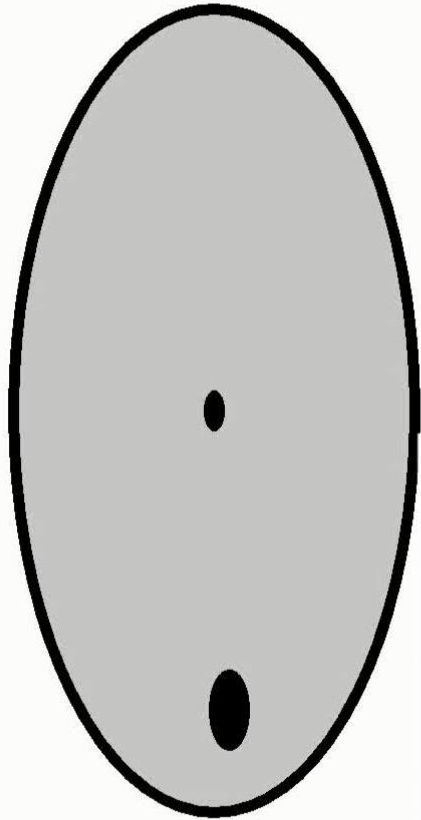


Image of the solar eclipse (March'15) captured by a DVS (courtesy of IniLabs)

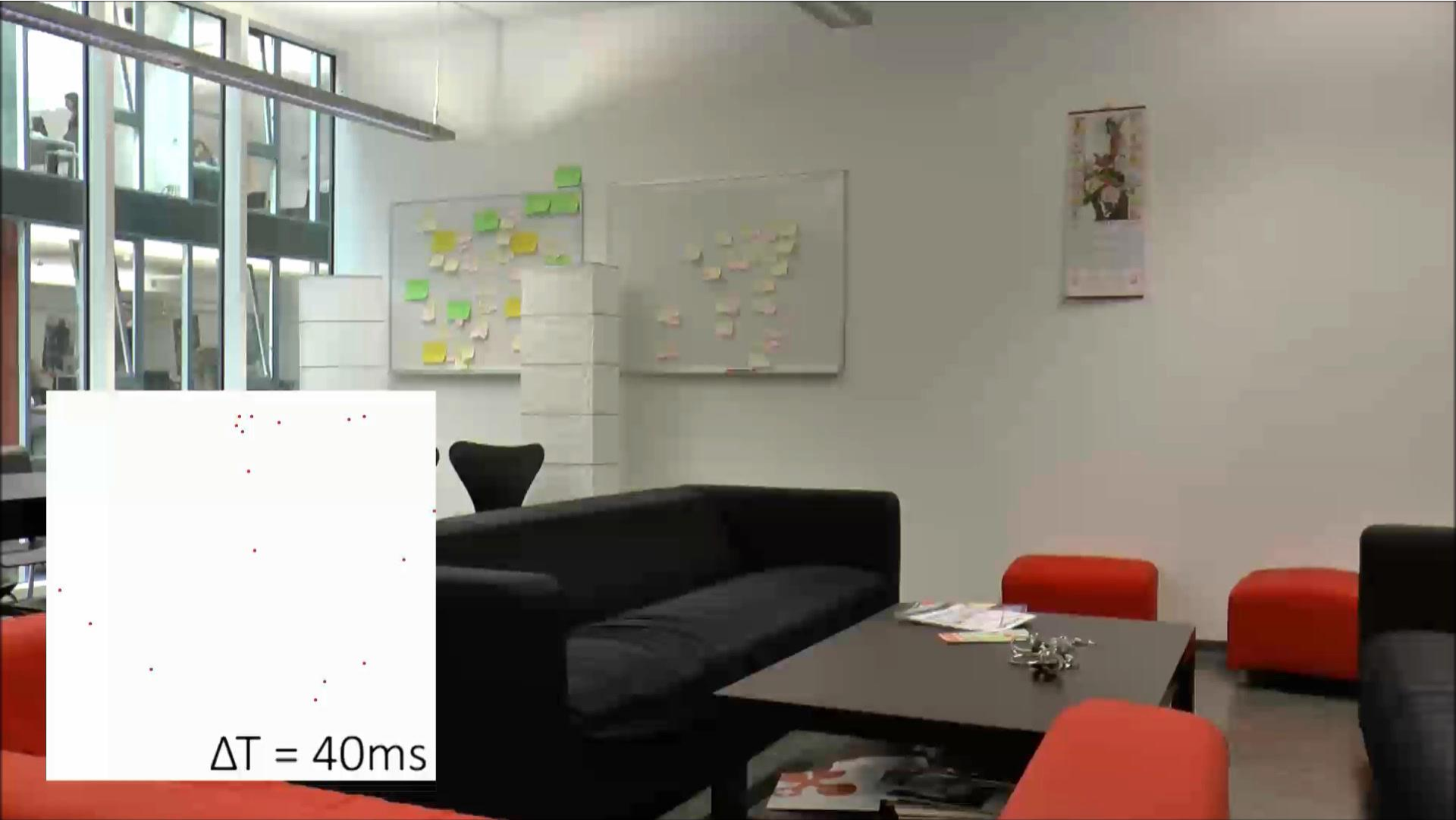
Camera vs Dynamic Vision Sensor



**standard
camera
output:**



Camera vs Dynamic Vision Sensor



Dynamic Vision Sensor (DVS)



Advantages

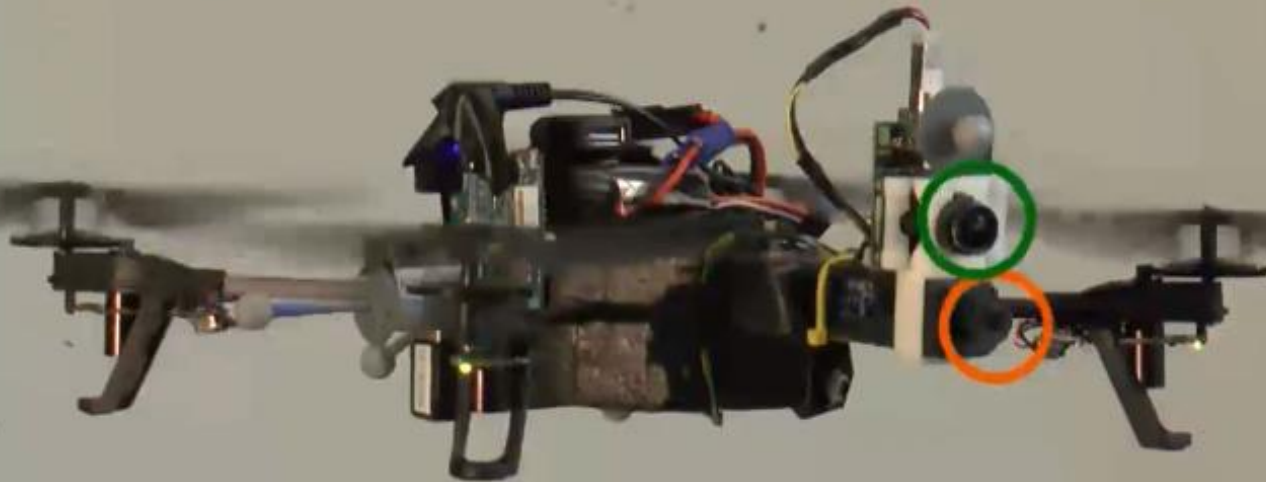
- **low-latency** (~ 1 micro-second)
- **high-dynamic range** (140 dB instead 60 dB)
- **Low storage capacity, processing time, and power**

Disadvantages

- Require totally **new vision algorithms**
- **No intensity information** (only binary intensity changes)

DVS mounted on a quadrotor AR Drone

Dynamic Vision Sensor (DVS)

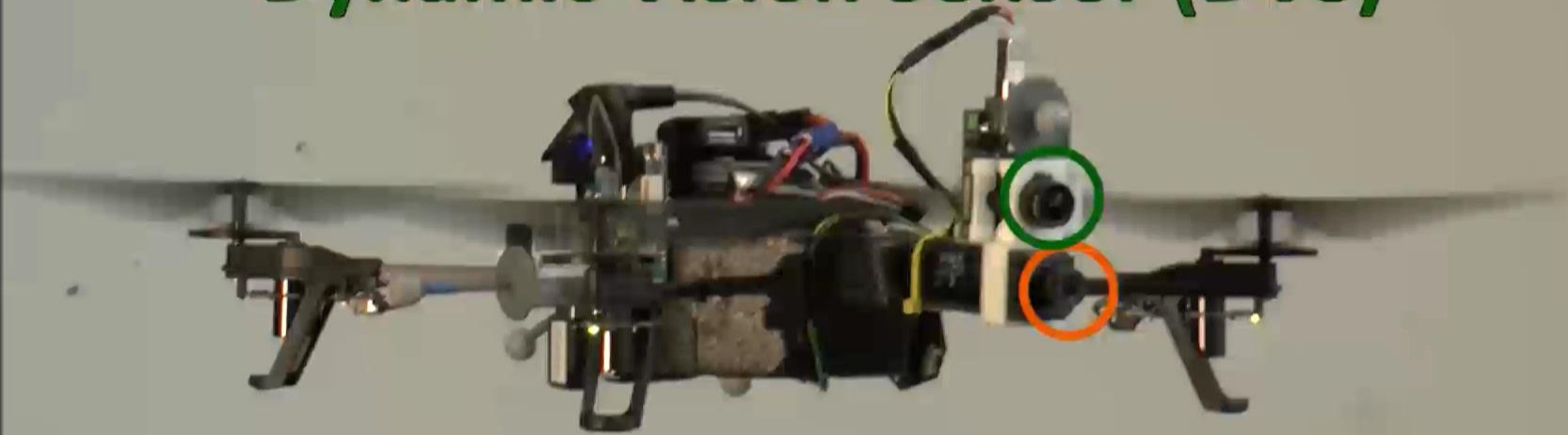


Standard Camera

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

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

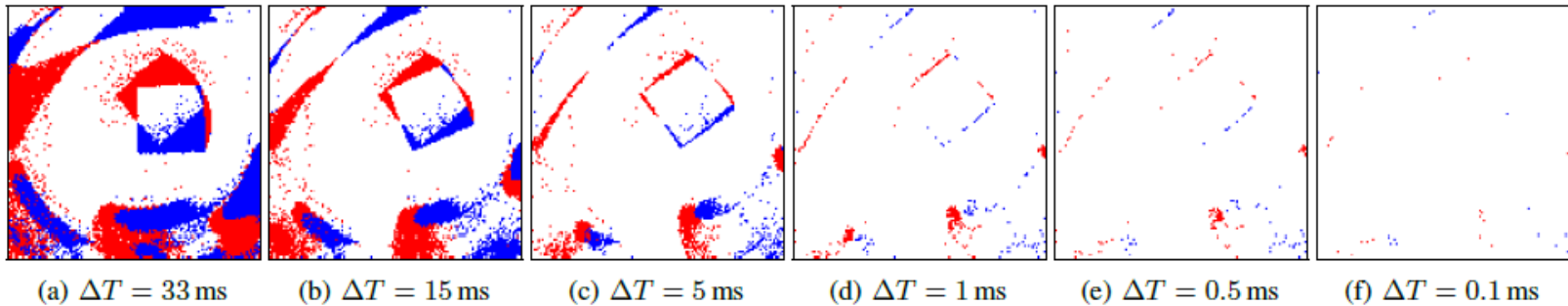
Dynamic Vision Sensor (DVS)



Standard Camera

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

Camera and DVS renderings

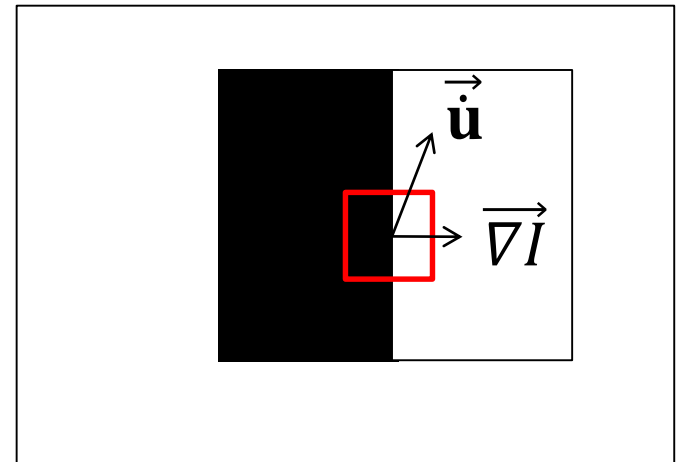
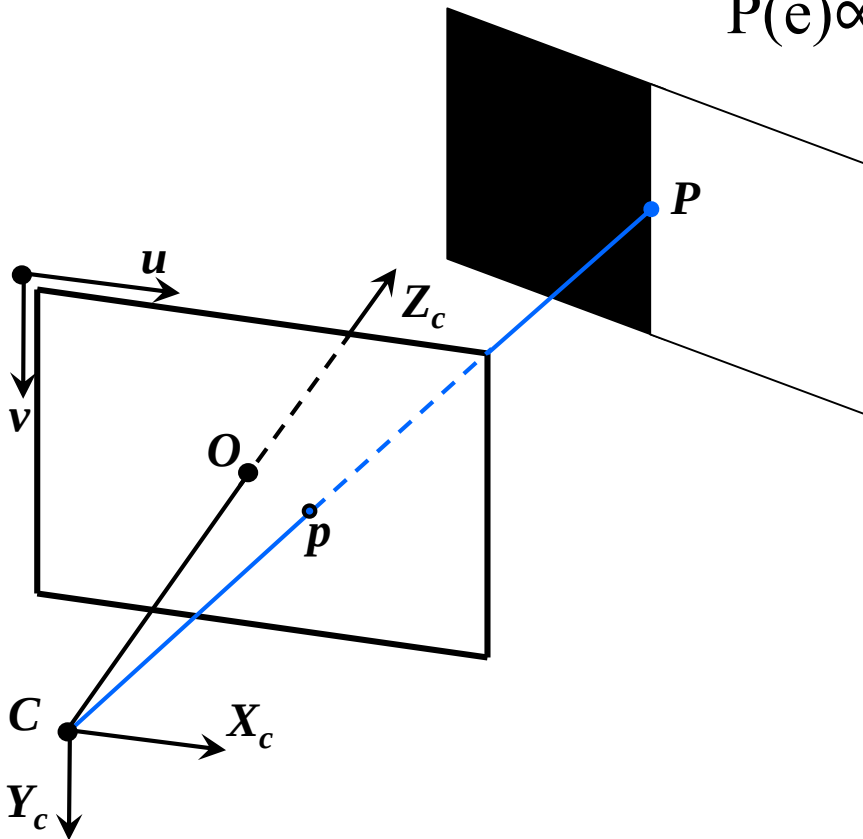


[Mueggler, Huber, Scaramuzza, Event-based, 6-DOF Pose Tracking for High-Speed Maneuvers, IROS'14]

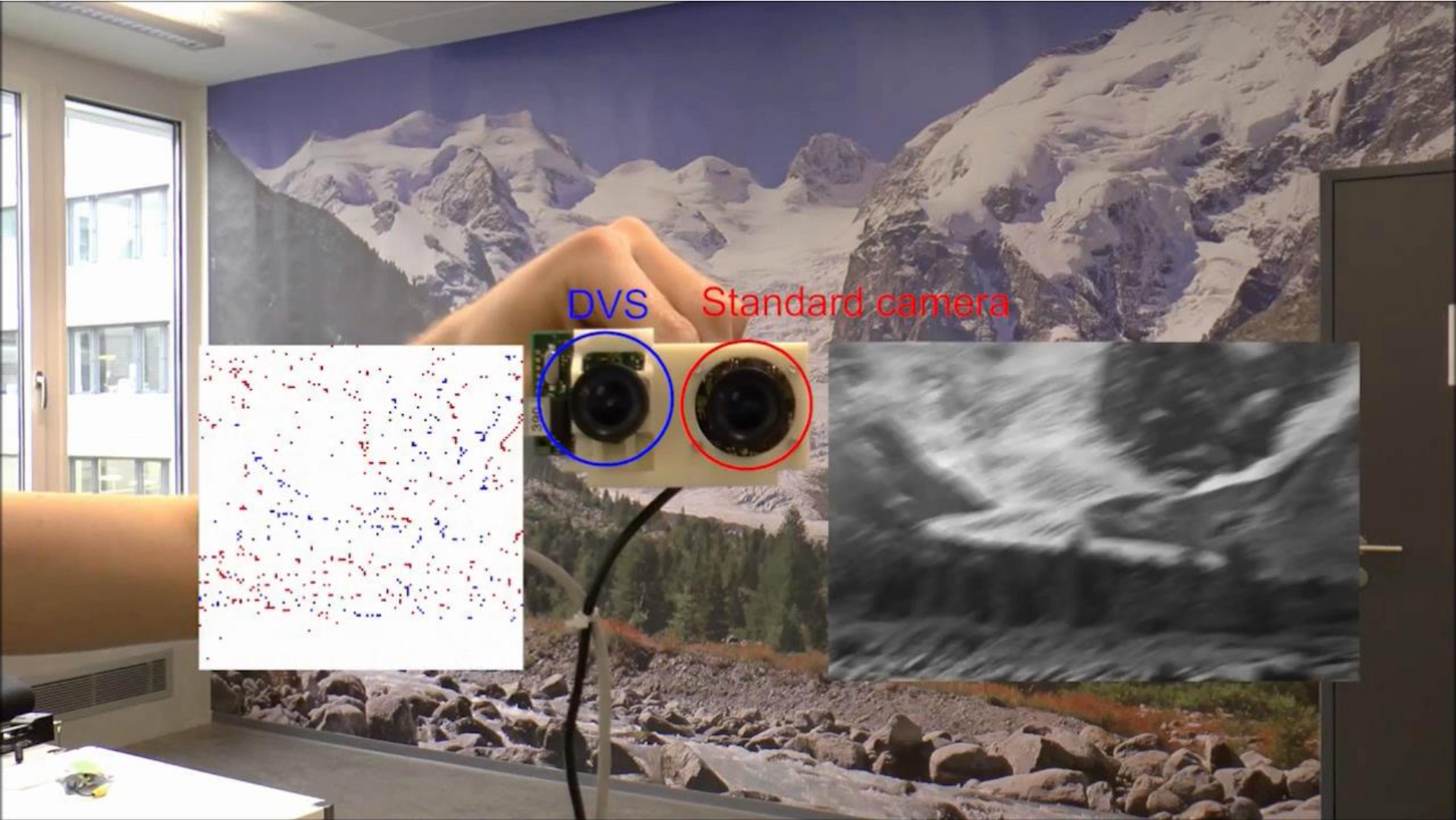
Generative Model [Censi & Scaramuzza, ICRA'14]

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 $\dot{\mathbf{u}}\Delta t$

$$P(e) \propto |\langle \nabla I, \dot{\mathbf{u}} \Delta t \rangle|$$



Event-based 6DoF Pose Estimation Results



[Event-based Camera Pose Tracking using a Generative Event Model, Arxiv]

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

Robustness to Illumination Changes and High-speed Motion



Conclusions

- Agile flight (**like birds**) is still far (10 years?)
- Agile flight requires success at different levels
 - **perception, planning, and control**
- **Perception and control** need to be considered **jointly!**
- **Event cameras** open enormous possibilities!
 - Ideal for high speed motion estimation and robustness to illumination changes