IMO Localization and Tracking

using Probabilistic Distributions

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GRIFFIN Meeting

20th October 2022

Robotics
Vision
Control

Universidad de Sevilla

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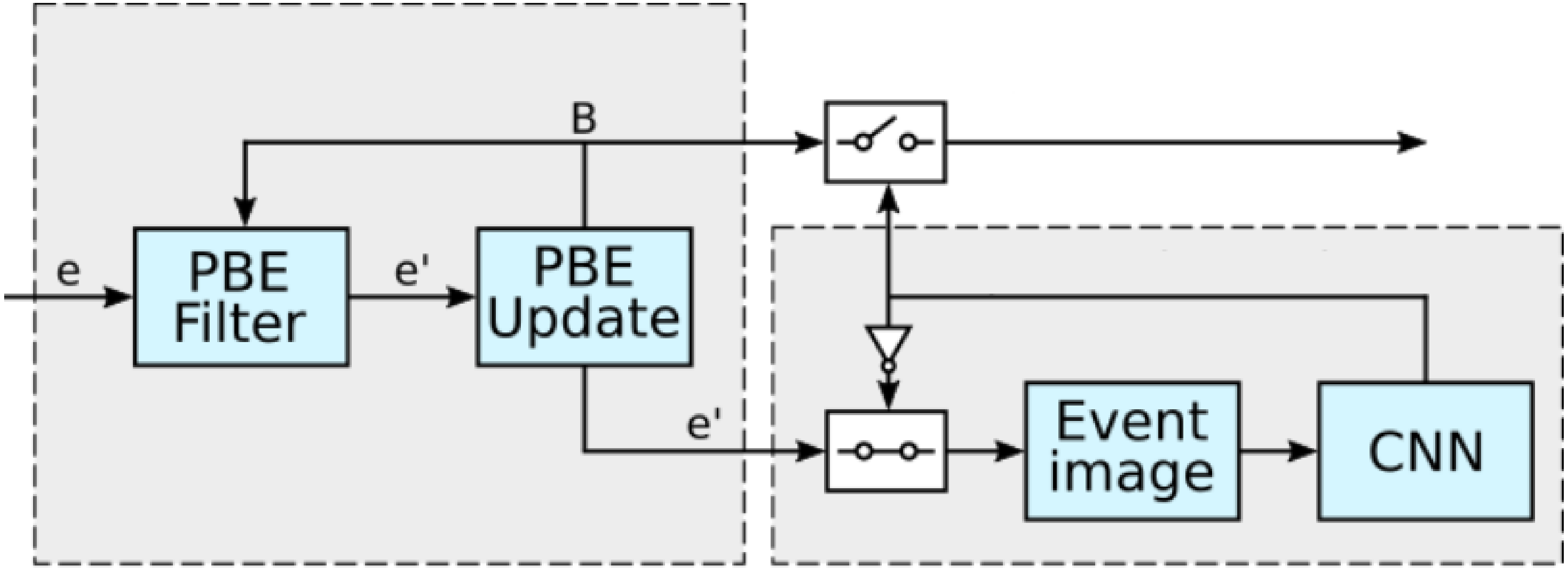
Introduction

- Efficient event-based IMO detection and tracking for online execution on board resource-constrained robots such as flapping-wing robots.
- Basic idea: Track the IMO using very low computational resources + Detect when needed.
- ↓Computation = ↑ free payload, ↓ energy consumption.
- **SoA.** Existing event-based detection methods have significant computational cost, and their online execution require onboard computers with considerable computational power.
- Some interesting ideas:
  - [1] Temporal event stream representation. They detect moving objects by model-fitting.
  - [2] IMO tracking using feature tracking + APM on UAS.
  - [3] Intrusion monitoring using CNN on UAS.
  - [4] Dataset for long time monitoring.

[1] A. Mitrokhin, et al. (2018) *Event-based Moving Object Detection and Tracking*. IROS2018.
[2] J. P. Rodríguez-Gómez, et al. (2021) *Auto-tuned event-based perception scheme for intrusion monitoring with UAS*. IEEE Access.
[3] M. Pérez-Cutiño, et al. (2021) *Event-based human intrusion detection in UAS using deep learning*. ICUAS2021.
[4] T. Bolten, et al. (2021) *DVS-OUTLAB: A Neuromorphic Event-Based Long Time Monitoring Dataset for Real-World Outdoor Scenarios*. CVPR2021ws.

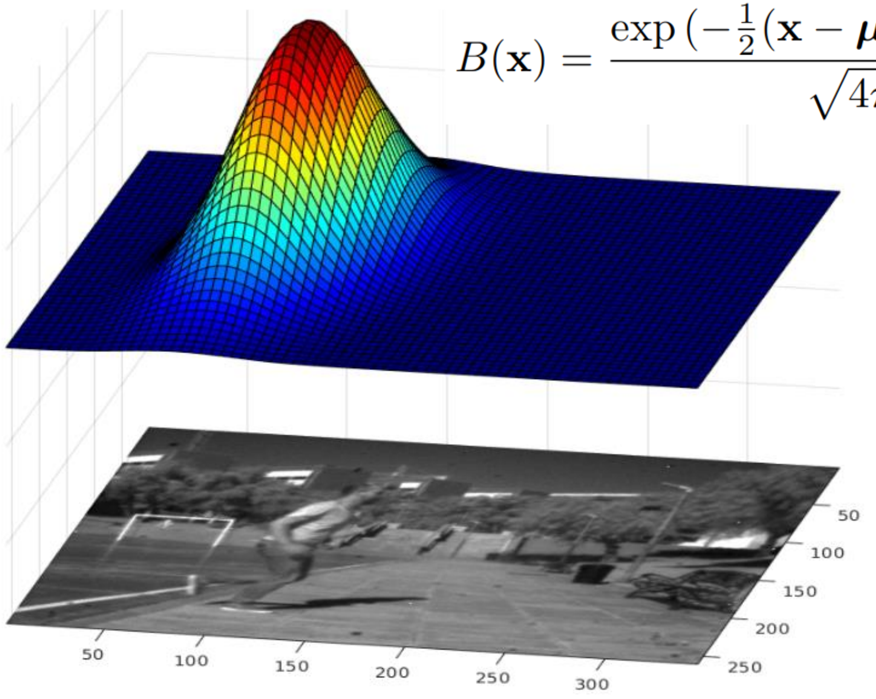
Method Description



Tracking

Detection

Target Tracking



$$B(\mathbf{x}) = \frac{\exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)}{\sqrt{4\pi^2|\boldsymbol{\Sigma}|}}$$

Given an event:

$$\hat{\mathbf{x}}_k = (\hat{x}, \hat{y})^T$$

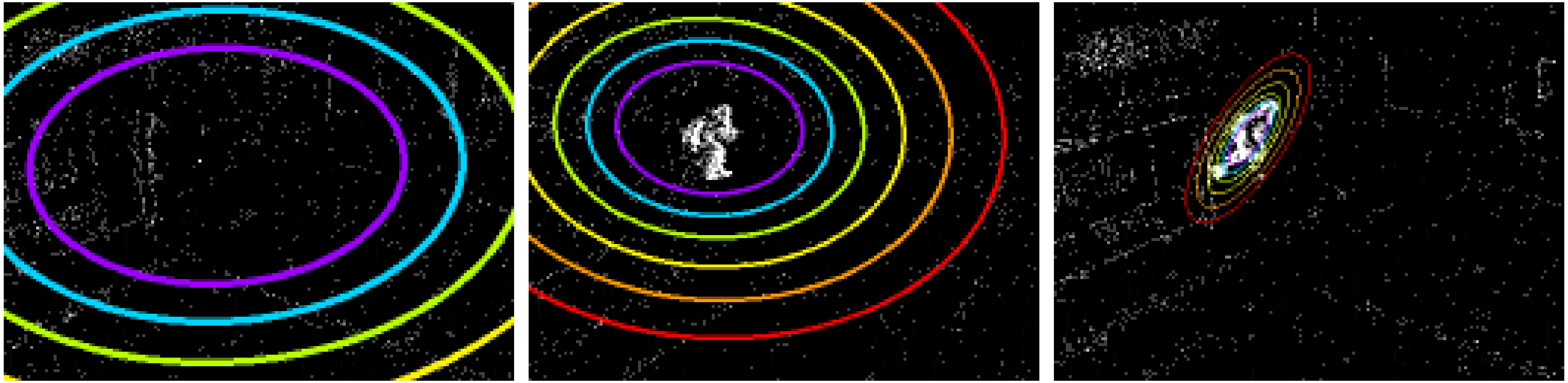
Update de PBF:

$$\boldsymbol{\mu} := \boldsymbol{\mu} + \frac{1}{N}(\hat{\mathbf{x}}_N - \hat{\mathbf{x}}_1)$$

$$\boldsymbol{\varepsilon} := \boldsymbol{\varepsilon} + \begin{bmatrix} \hat{x}_N^2 - \hat{x}_1^2 & \hat{x}_N\hat{y}_N - \hat{x}_1\hat{y}_1 \\ \hat{x}_N\hat{y}_N - \hat{x}_1\hat{y}_1 & \hat{y}_N^2 - \hat{y}_1^2 \end{bmatrix}$$

$$\boldsymbol{\Sigma} := \frac{\boldsymbol{\varepsilon}}{N} - \begin{bmatrix} \mu_{\hat{x}}^2 & \mu_{\hat{x}}\mu_{\hat{y}} \\ \mu_{\hat{x}}\mu_{\hat{y}} & \mu_{\hat{y}}^2 \end{bmatrix}$$

Target Tracking

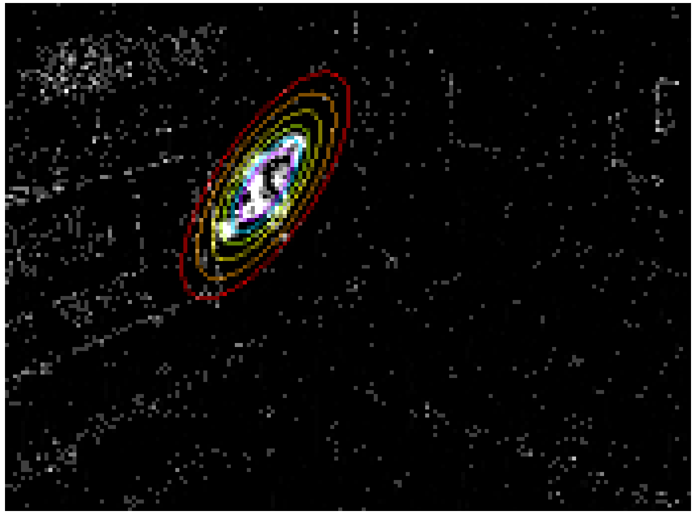


$$\frac{(\bar{x}\cos\theta + \bar{y}\sin\theta)^2}{s\lambda_1} + \frac{(\bar{x}\sin\theta - \bar{y}\cos\theta)^2}{s\lambda_2} \le 1$$

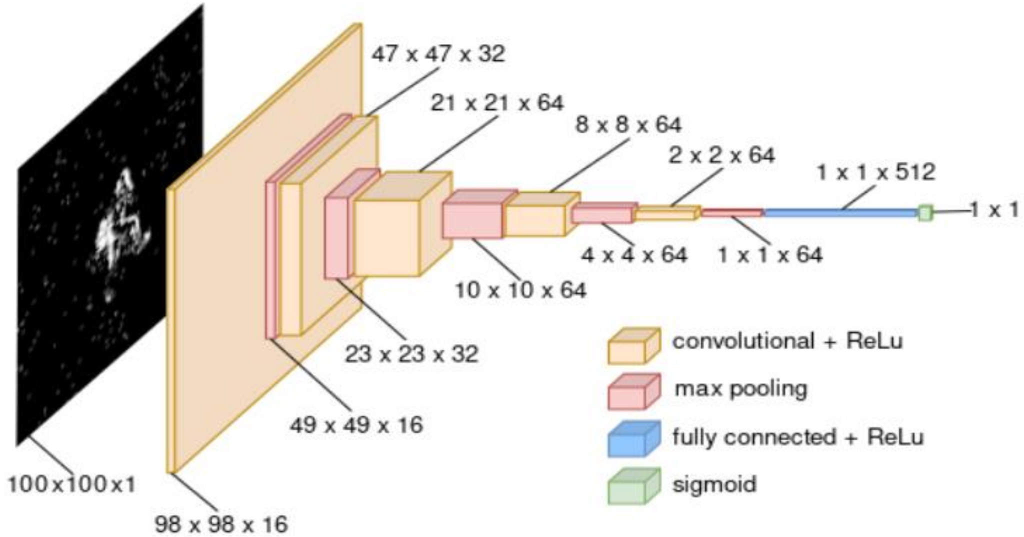
where $s = -2\log(1-\pi)$ and $\theta = \arctan(v_y v_x^{-1})$

since $\pi = \frac{1}{2}\int_0^s e^{-\frac{1}{2}s} ds = 1 - e^{-\frac{1}{2}s}$

Target Detection



$$\rho(t) = \frac{1}{[\Pi]} \sum_{\forall t_i | e_i \in \Pi} \exp(-\frac{t - t_i}{\tau})$$



Five convolutional layers with ReLu activation functions + 2×2 maxpooling.
Fully connected to a layer with 512 neurons with ReLu activation functions.
Fully connected to a sigmoid node for classification output.

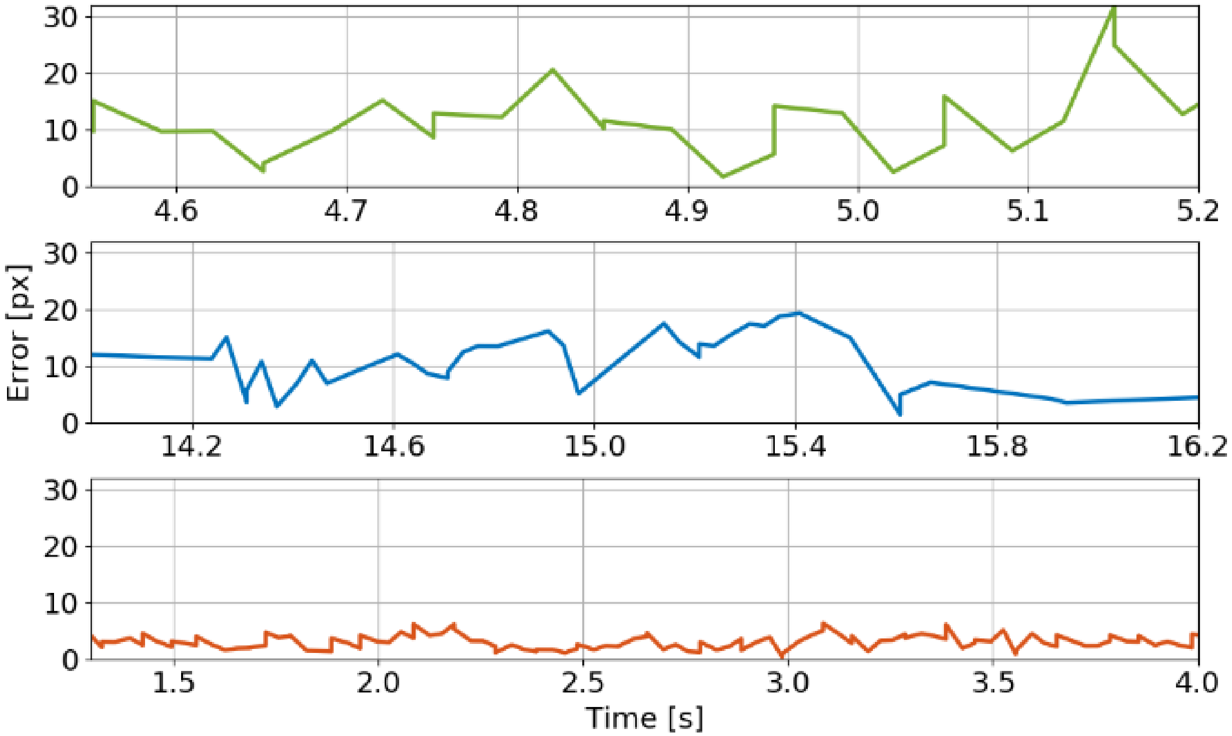
Some results

Detection

Scenario	Distance	Precision	Recall	Accuracy
Daylight close	(5, 10) m	99.95	98.04	99.49
Daylight middle	(10, 25) m	99.98	95.12	98.11
Daylight far	(25, 40) m	99.48	92.68	97.65
Night	-	92.91	95.43	96.22

(*) Using YOLOv5 as ground truth

Tracking



(*) Using the centroid of YOLOv5 bb as ground truth

Some results

(*) YOLOv5 fails

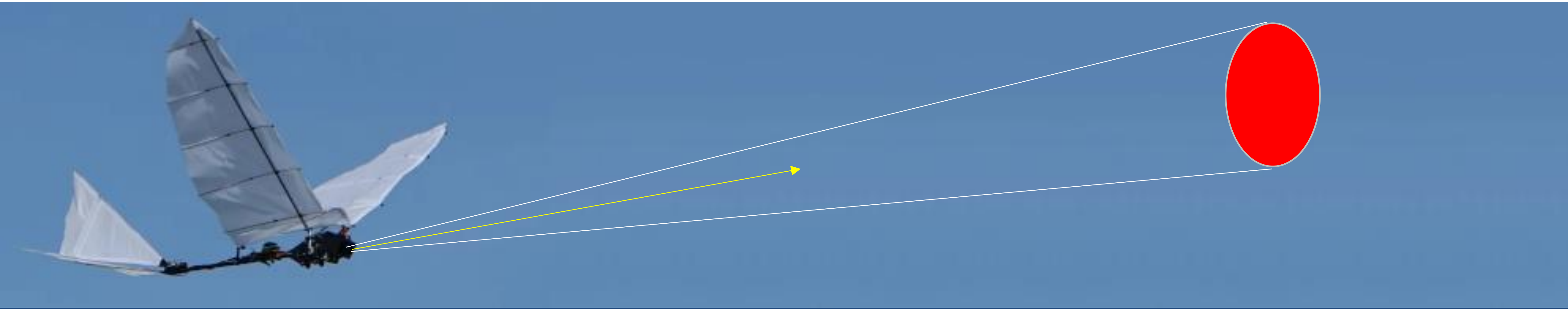
Ongoing Work

- Preliminary version of the method already published*.
- Integration on flapping wing robots:
  - Static camera, dynamic target: Ok (but not interesting with FWR).
  - Dynamic camera, static target: Ok.
  - Dynamic camera, dynamic target: Some considerations already required.
- Extension to multi-object detection and tracking.

[*] F.J. Gañán, J.A. Sanchez-Diaz, R. Tapia, J.R. Martinez-de Dios and A. Ollero, (2022). *Efficient Event-based Moving Object Localisation and Tracking using Probabilistic Distributions.* SSRR2022.

GRIFFIN Demo

- Use of event-by-event updated PBFs + Visual Servoing.
- Detect a static target and fly towards it.
- Ask Rafael, Honorio, Diego, Jose Manuel, Anibal if suitable.



GRIFFIN Outdoor Perching

- Based on the previous approach.
- Use of event-by-event updated PBFs + IBVS.
- Fuse information with event-based/conventional line detectors.

QUESTIONS