



Next-Generation Computer Vision Methods for Automated Navigation of Unmanned Aircraft

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Unmanned Aircraft Systems: Applications & Challenges

- Small flying devices using vision algorithm on onboard camera for autonomous navigation.
- Broadly used in various applications: security, corp analysis, entertainment.
- Level of autonomy requires a constant image quality in a various range of scenarios and presenting many challenges.



[source](#)

Integration

- Dimensions
- Weights
- Outdoor conditions
- Power consumption



Requirements

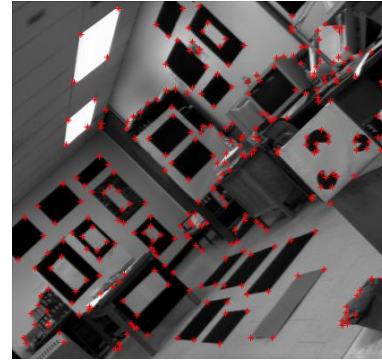
- Best image quality
- Extended FOV

Challenges of Drone Navigation: Overview

Navigation in a broad range of scenarios → Provide constant performance of computer vision algorithms

- **How to maintain constant performance of corner detection in varying illumination?**

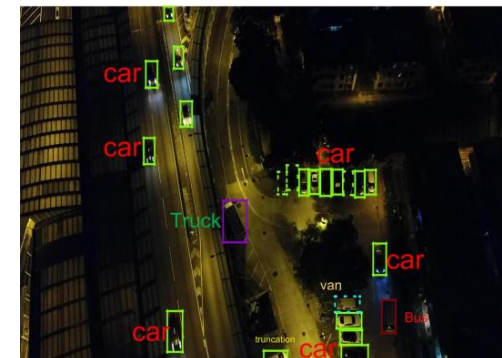
- How to compensate for the increase in spatial and temporal noise in low-light?
- How do we maintain real-time analysis?



[Kahaki, S.M.M.; Nordin, M.J.; Ashtari, A.F. Contour-Based Corner Detection and Classification by Using Mean Projection Transform. *Sensors* 2014, 14, 4126-4143. <https://doi.org/10.3390/s140304126>](#)

- **How to choose a camera for optimized performance of off-the-shelf neural networks?**

- Can we predict camera parameters' influence on learning-based algorithms?
- What is the impact of a camera degradation during its lifespan?
- Can we optimize camera parameters to minimize this impact?



[Zhu, Pengfei & Wen, Longyin & Bian, Xiao & Ling, Haibing & Hu, Qinghua. \(2018\). Vision Meets Drones: A Challenge.](#)

Use Case 1: Corner Detection Under Varying Illumination Scenarios

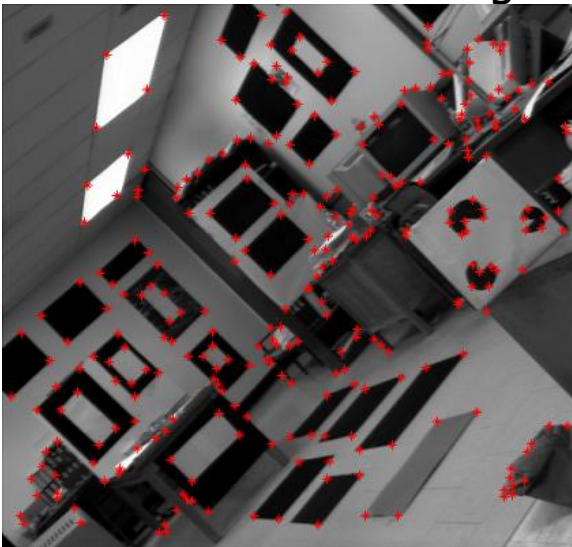
Corner Detection for Drone Navigation

Principle: Identify corners in an image using intensity variations to detect potential object, obstacle, and features of interest.

Obstacle avoidance:

The obstacle (tree branch) extremities can be detected using corner detection.

Improved autonomous navigation, lower risk of collision.



Kahaki, S.M.M.; Nordin, M.J.; Ashtari, A.H. Contour-Based Corner Detection and Classification by Using Mean Projection Transform. *Sensors* 2014, 14, 4126-4143. <https://doi.org/10.3390/s140304126>

Geometric pattern and QR Code recognition:

We can identify a precise geometric pattern.

Such patterns are used as target for:

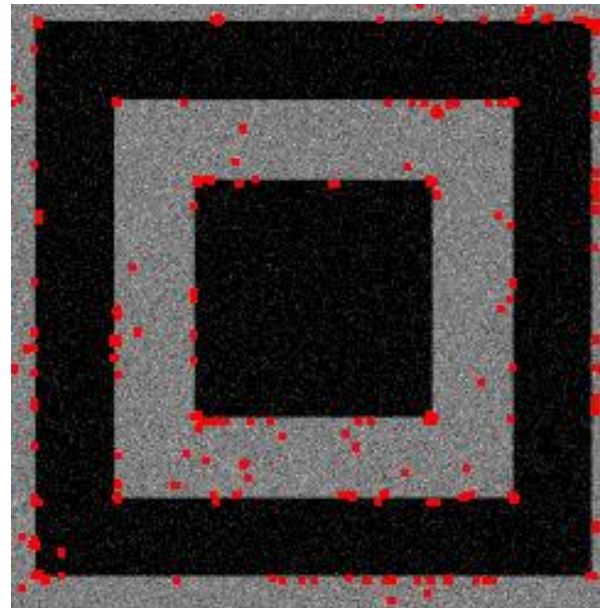
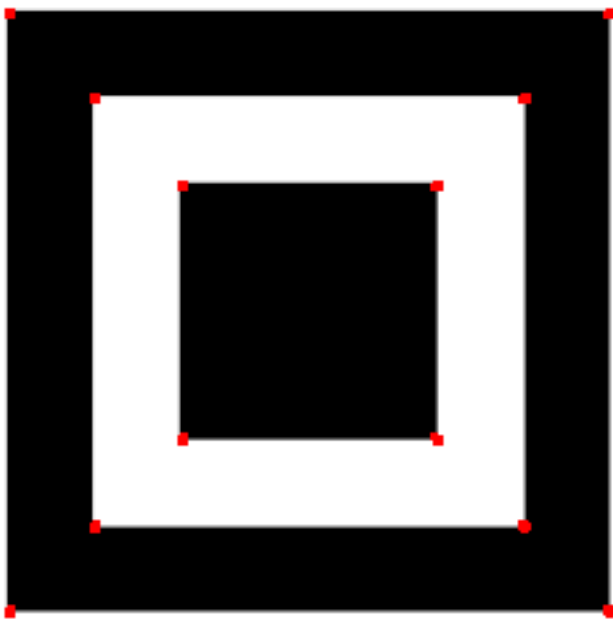
- Precision landing.
- Increasing drone autonomy.
- Landing without GPS information.



Yang, Tao & Ren, Qiang & Zhang, Fangbing & Xie, Bolin & Ren, Hailei & Li, Jing & Zhang, Yanning. (2018). Hybrid camera array-based UAV auto-landing on moving UGV in GPS-denied environment. *Remote Sensing*. 10. 1829. 10.3390/rs10111829.

Problem Statement:

- Traditional navigation camera performs well in daylight.
- Challenging lighting conditions impact pixel quality and then CV algorithm accuracy.



Corner detection for the same pattern under different levels of light

Examples:

- The decreasing signal in low-light reduces the amount of information available for scene understanding.
- The increased level of noise in low-light can bias the algorithm, which is then more likely to perform false detections.

Solution:

- Camera modules and algorithms must be customized for low-light conditions.

Existing Solutions: Optimize the Camera Sensor

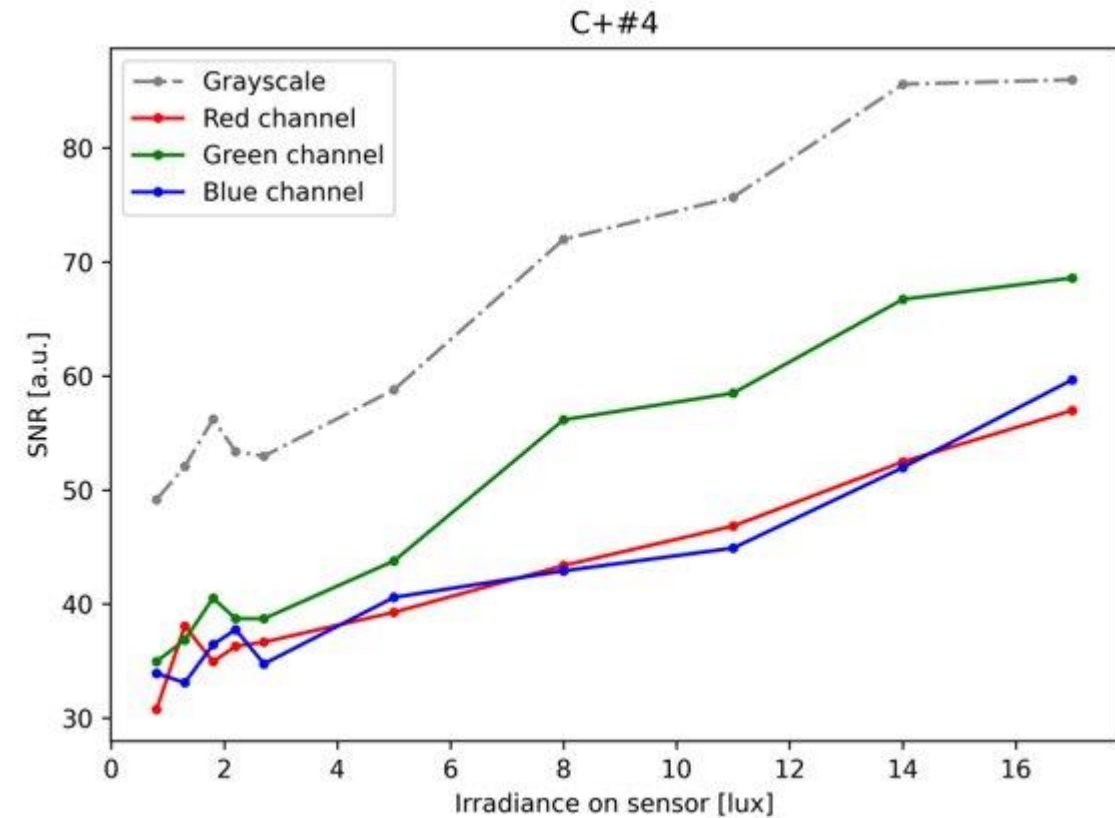
Current methods for better image quality in low-light sensor optimization:

- Use a gray-scale sensor to increase the SNR
- Increase pixel size

Promising methods usually affect the image quality for higher illumination.

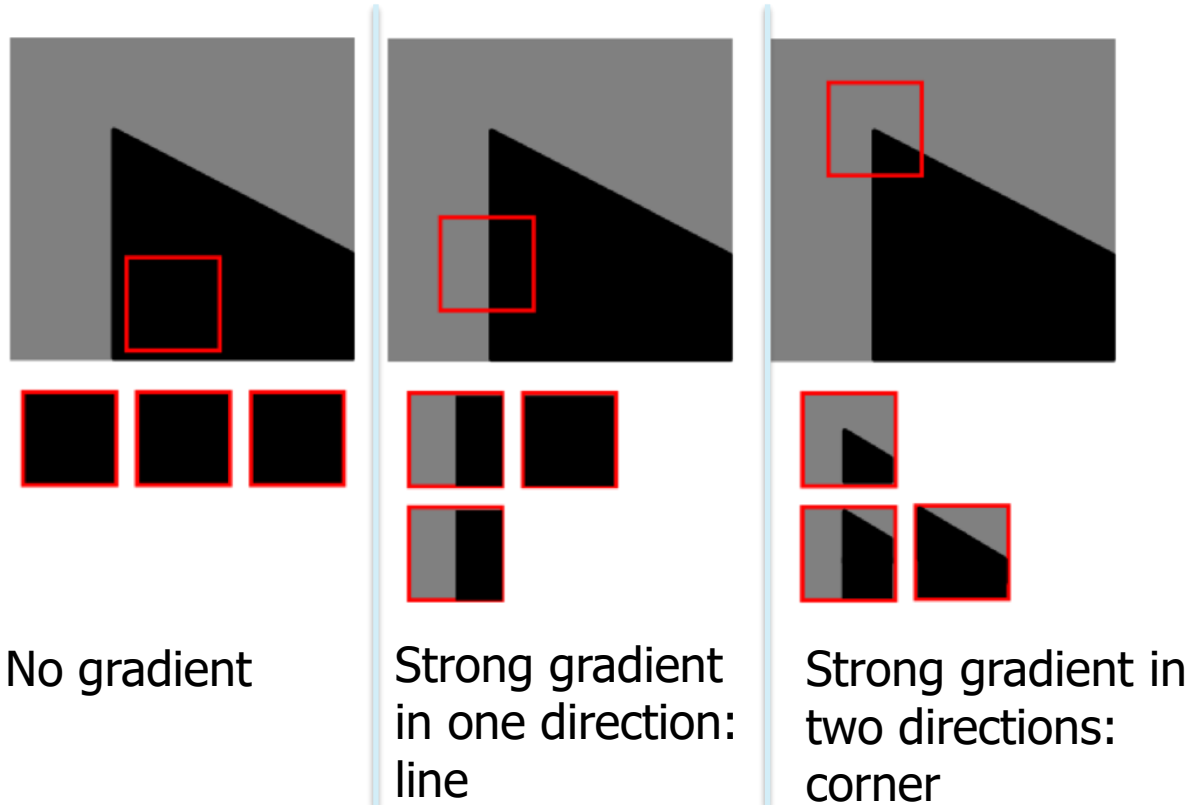
Complement this sensor optimization with corner detector optimization.

Provide constant corner detection in a broad range of illumination.



Existing Solution: Traditional Corner Detectors

- **Harris detector:** Corner detection using the gradient at one point (x,y)



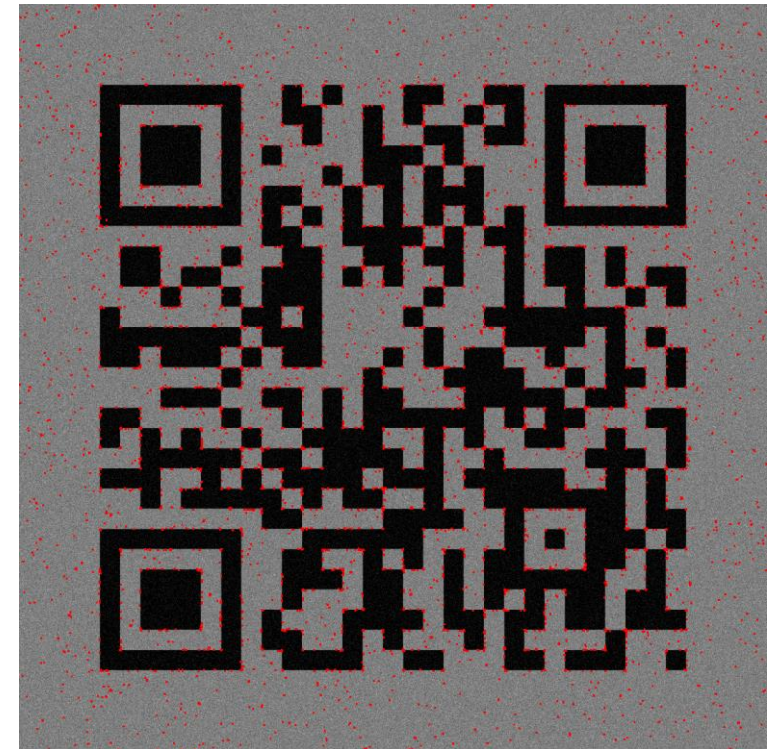
$$M = \sum_{(x,y) \in W} \begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix} = \begin{bmatrix} \sum_{(x,y) \in W} I_x^2 & \sum_{(x,y) \in W} I_x I_y \\ \sum_{(x,y) \in W} I_y I_x & \sum_{(x,y) \in W} I_y^2 \end{bmatrix}$$

if $(R = \det(M) - K \text{tr}(M) > \text{threshold}) \rightarrow \text{corner}$

Threshold is customized depending on the camera and the outdoor conditions.

- **Detection highly depends on illumination conditions**
- In low light: the intensity of a corner is similar to the noise level: False detection

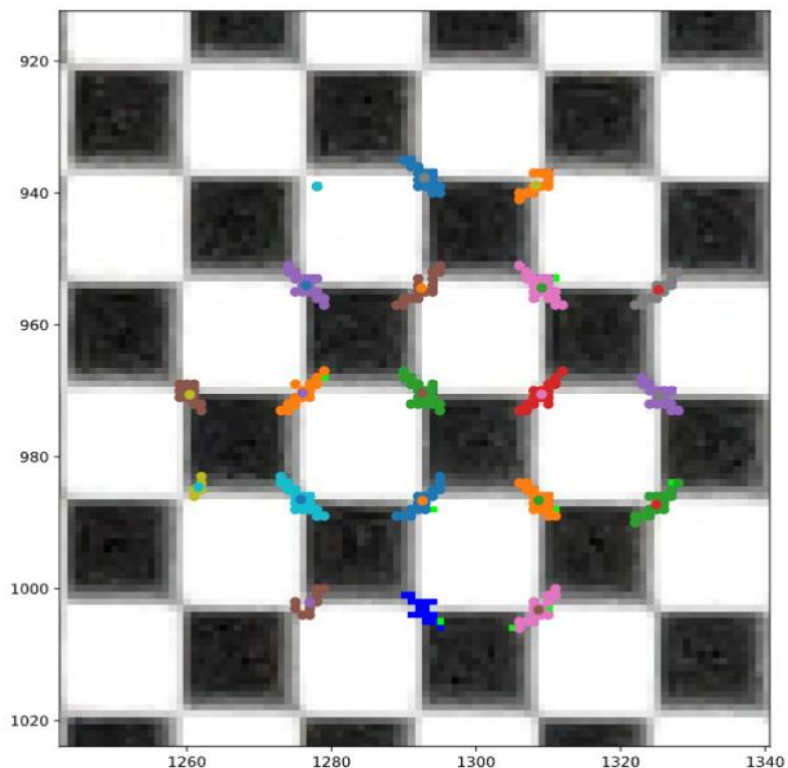
**Add feature clustering to create a more robust detection
(elimination of spatial noise).**



Our Method: Spatial Noise Reduction Using Feature Clustering

Feature clustering :

Each corner is associated to one feature of interest.
We identify a cluster by computing its barycenter.



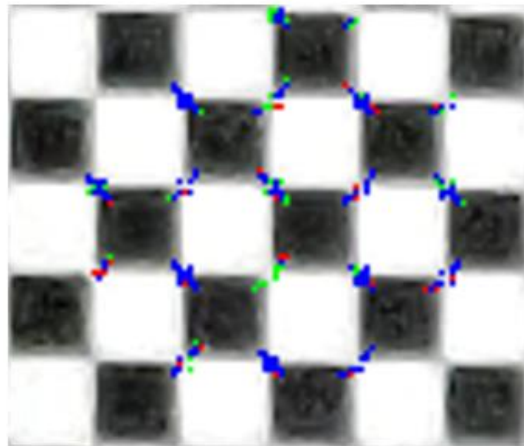
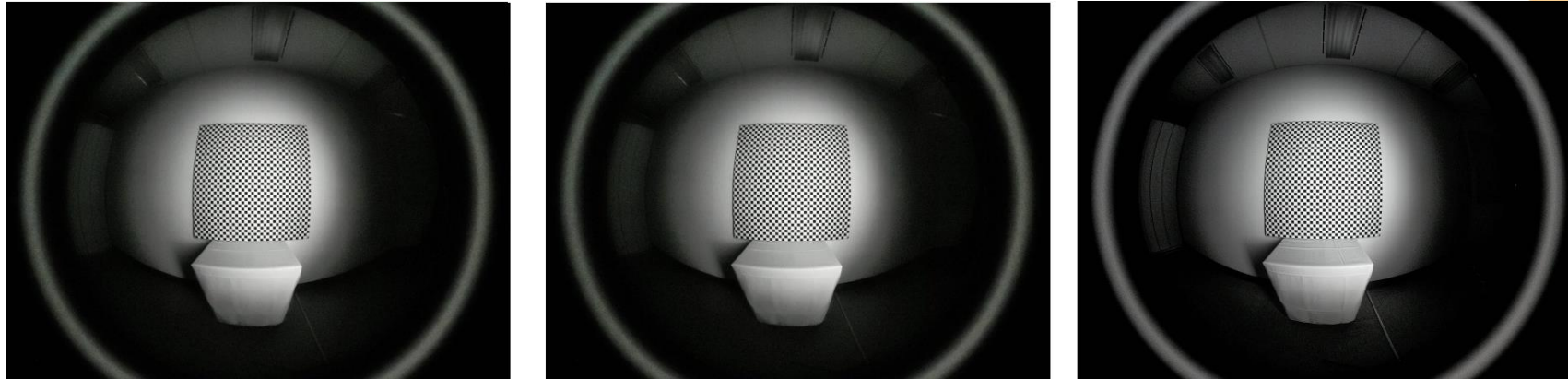
0.5 Lux

Results:

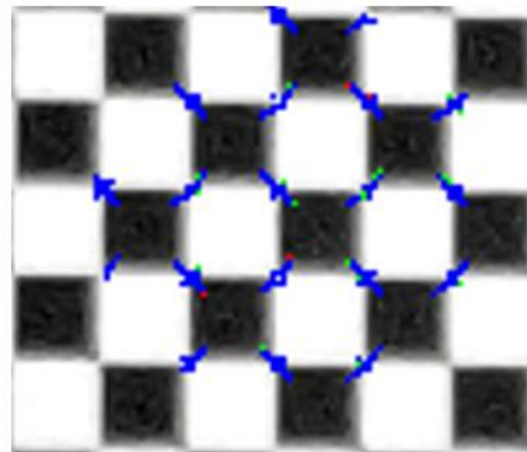
- Outliers (clusters with too few pixels) are avoided
- Spatial noise is reduced
- All corners are detected at 0.5 Lux

We obtain the same corner detection as in daylight for extremely low light (0.5 lux)

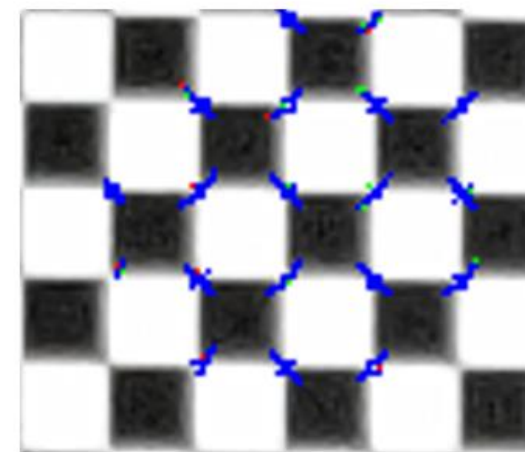
Results after Temporal Noise Reduction



0.5 Lux



3 Lux



15 Lux




**All levels of illumination provide accurate corner detection
100% of corners are detected.**

Limitations: Residual Temporal Noise

There is still residual temporal noise which induces a variation of the estimated position of the corner:

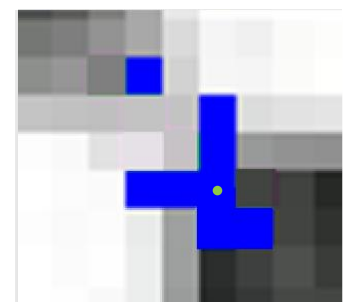
- Applying noise reduction on low-light images might induce a loss of information.
- Averaging corner detection on several frames will limit all applications requiring real-time.

We will evaluate the impact of the temporal noise on each frame compared to the ground truth (average position estimated from 20 frames).

-  **True Positive** : Corners detected in ground truth and current frame
-  **False Negative** : Corners only identified in the ground truth
-  **False Positive** : Corners only identified in the current frame



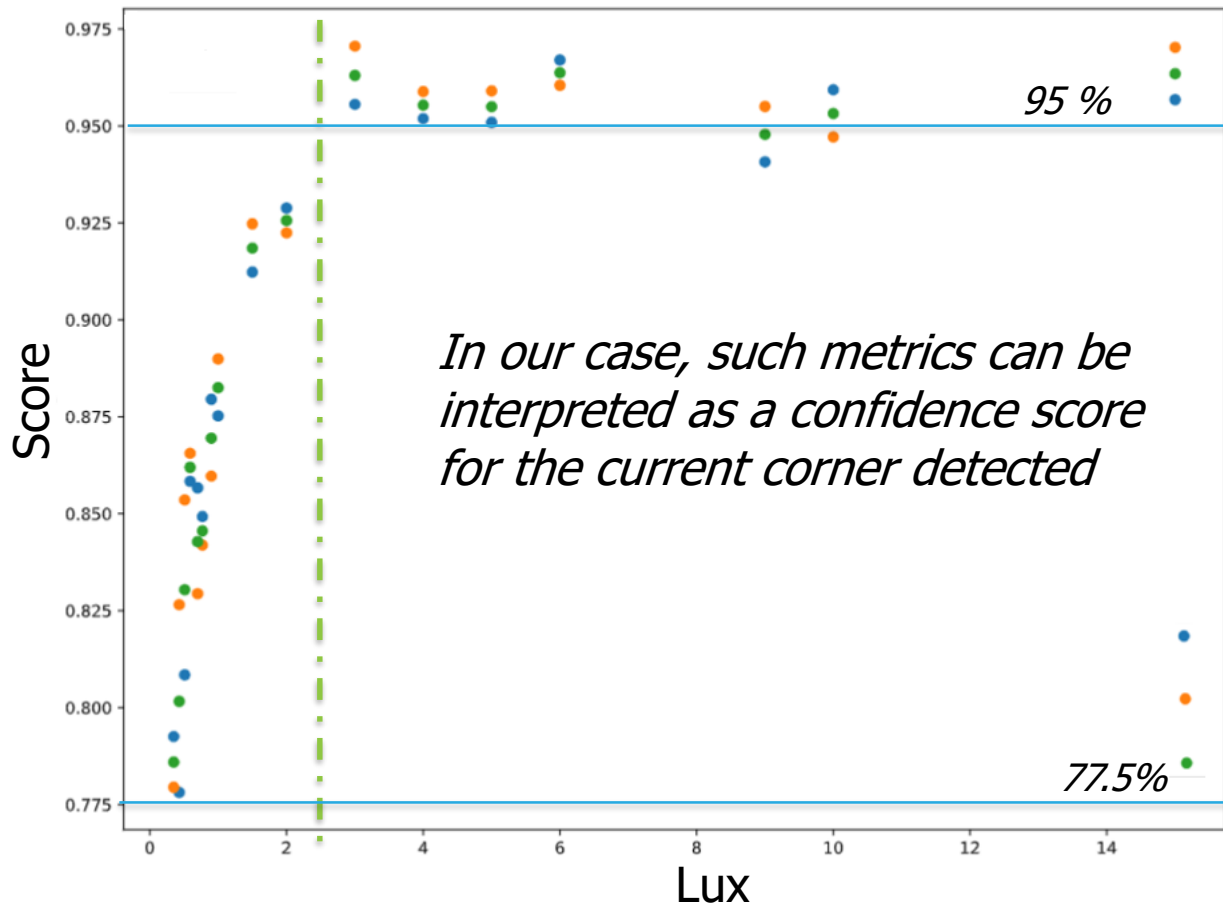
Frame n



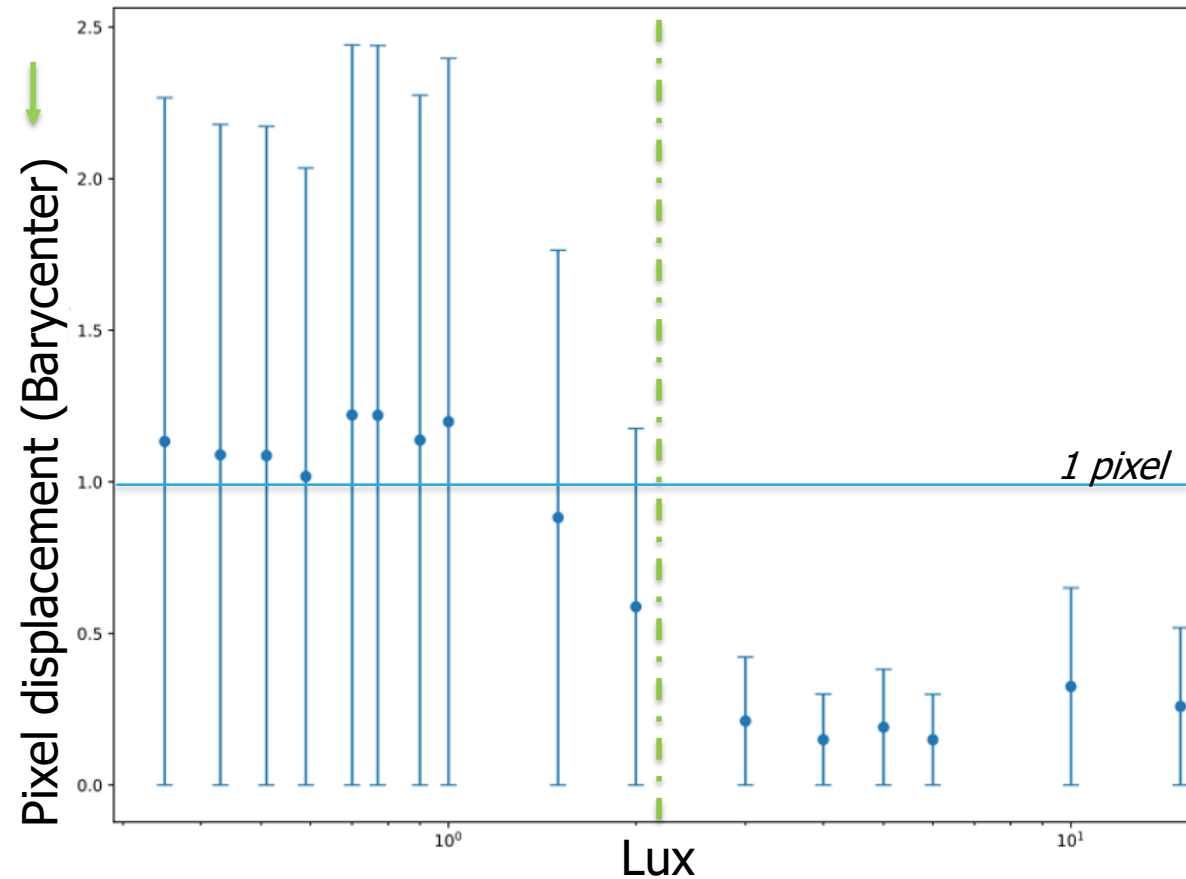
Frame n+5

Evaluation of the Residual Temporal Noise

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F1 = \frac{2 * R * P}{R + P}$$



Corresponding displacement of cluster center:



Conclusions on Low-Light Illumination Corner Detection

- Corner detection algorithms can be adapted to a broad range of illumination by using spatial filtering methods such as feature clustering.
 - This also reduces the temporal noise which allows consistent corner location across time.
- Each frame can provide accurate corner detection independently, which makes the algorithm able to run real-time.

An algorithm optimized for constant performance across illumination levels becomes a powerful KPI for camera evaluation in a context of machine vision.

Use Case 2 : Object Detection With Varying Blur from Camera Defocus

2D Object Detection and Identification

Goals:

- Detecting an object and labelling it as one out of many available classes of object.
- Providing a better scene understanding to improve decision making.

Current Solution:

- Yolov4 pretrained on MSCoco : Real-time and lighter architecture.
- Broadly used in automotive : Good candidate for drone navigation.

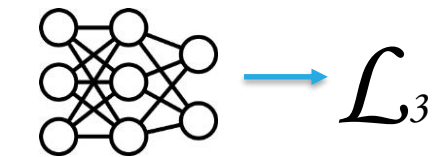
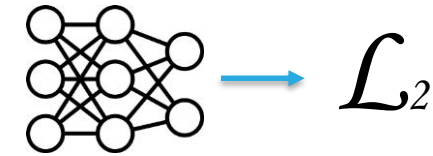
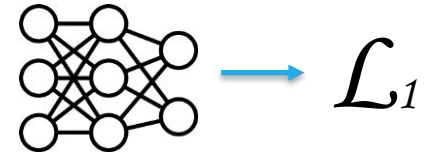
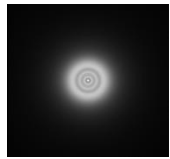
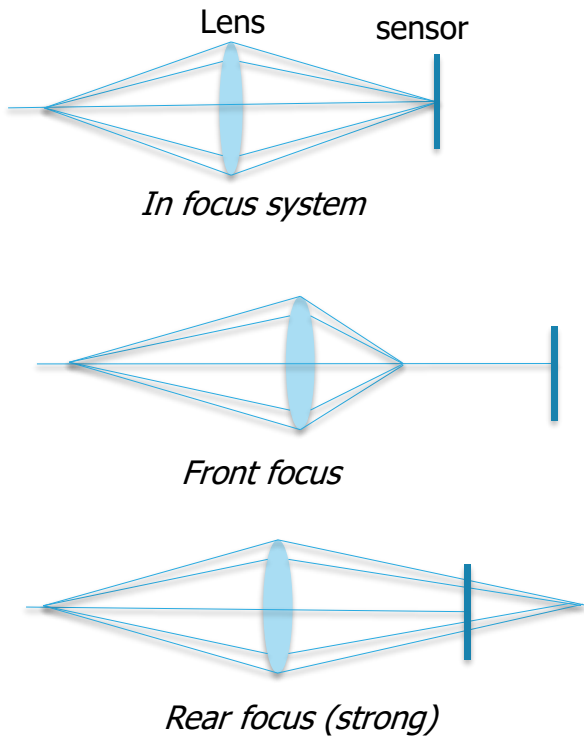


2D Object Detection and Identification

- Image quality is not constant when a camera is exposed to outdoor condition (motion, temperature shifts etc.).
- What is the impact of image quality degradation on neural network performance?
- Is it possible to optimize a camera to minimize this impact?



Our Camera Simulation Algorithm



Aberration-free image

Camera simulation with different degradations

Resulting degraded image

Performance on off-the-shelf neural network

Experimental Procedure

Protocol:

- PixSet dataset : 29 000 images taken on Canadian roads (urban environment) via a 180° road-facing camera placed on the rear-view mirror.
- We generate 21 datasets each corresponding to the same automotive camera with a value of defocus.



Metrics:

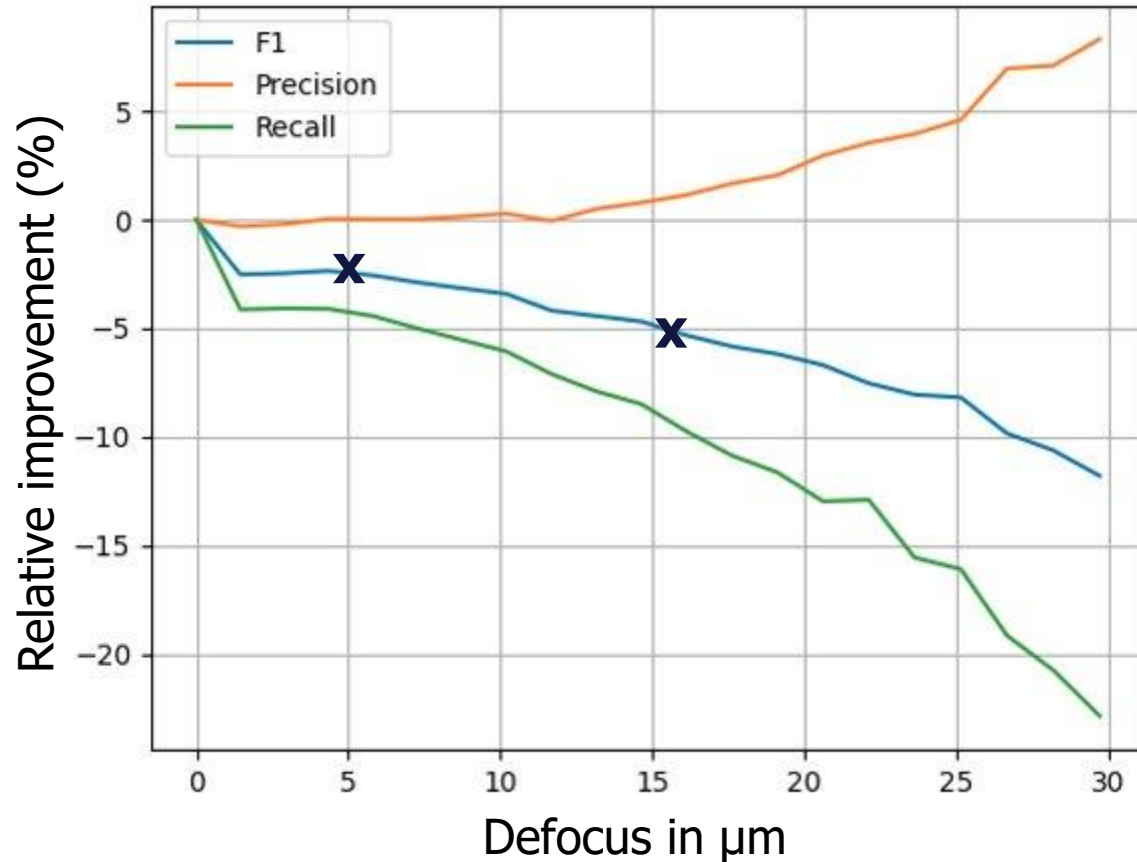
$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F1 = \frac{2 * R * P}{R + P}$$

- Precision: How many objects identified are correct
- Recall: How many detections are correct among all objects to detect (sensitivity)
- F1: combination of both (global evaluation)

Predicted label

| | | True label | |
|------------------------|----------|---------------------|---------------------|
| | | Positive | Negative |
| Predicted label | Positive | True Positive (TP) | False Positive (FP) |
| | Negative | False Negative (FN) | True Negative (TN) |

Results



- Stationary results below 5 μm of defocus (only 2.5% drop on F1-score)
- Slow drop until reaching 5% at 15.38 μm

At $\lambda=550$ nm:

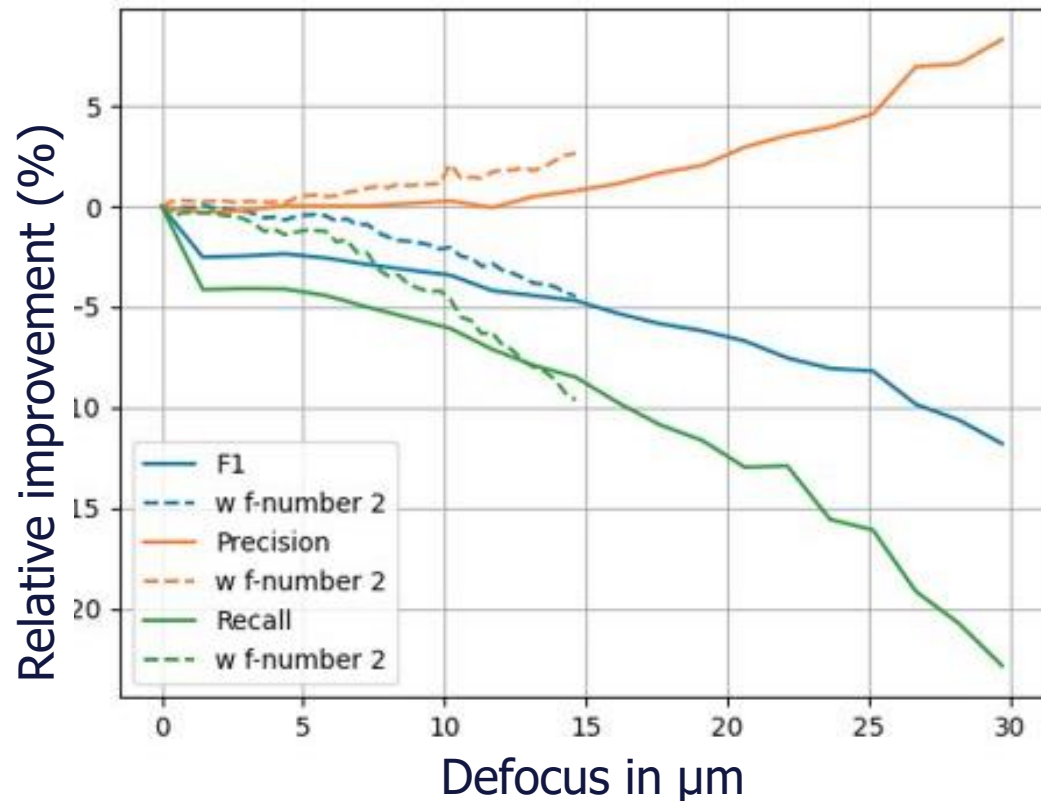
A drop of 2% is observed for a defocus of 5.84 μm and corresponds to a temperature shift of 23.19 $^{\circ}\text{C}$

Results: Zoom-in



Defocus increases from upper left to bottom right video: (in μm : 0, 5.81, 14.64, 22.12).
Large defocus reduces the accuracy of object detection algorithm.

Optimization of the Camera



- Stationary results with a relative drop of 0.6% until 6 μm
- Linear decrease down to -2% (still acceptable) at 10 μm
- The evolution with defocus is the same as before but the amplitude of the drop is way smaller

At $\lambda=550 \text{ nm}$:

A drop of 2% is observed for a defocus of 10.21 μm and corresponds to a temperature shift of 43.67 $^{\circ}\text{C}$ (this corresponds to an altitude variation of 6.5 km).

We can limit the impact of defocus on 2D Object detection by optimizing camera parameters.

Here, a smaller f-number is beneficial due to the small pixel size (1 μm) which might differ if we consider another camera module with different initial optical parameters.

Conclusions on Object Detection with Image Quality Degradation

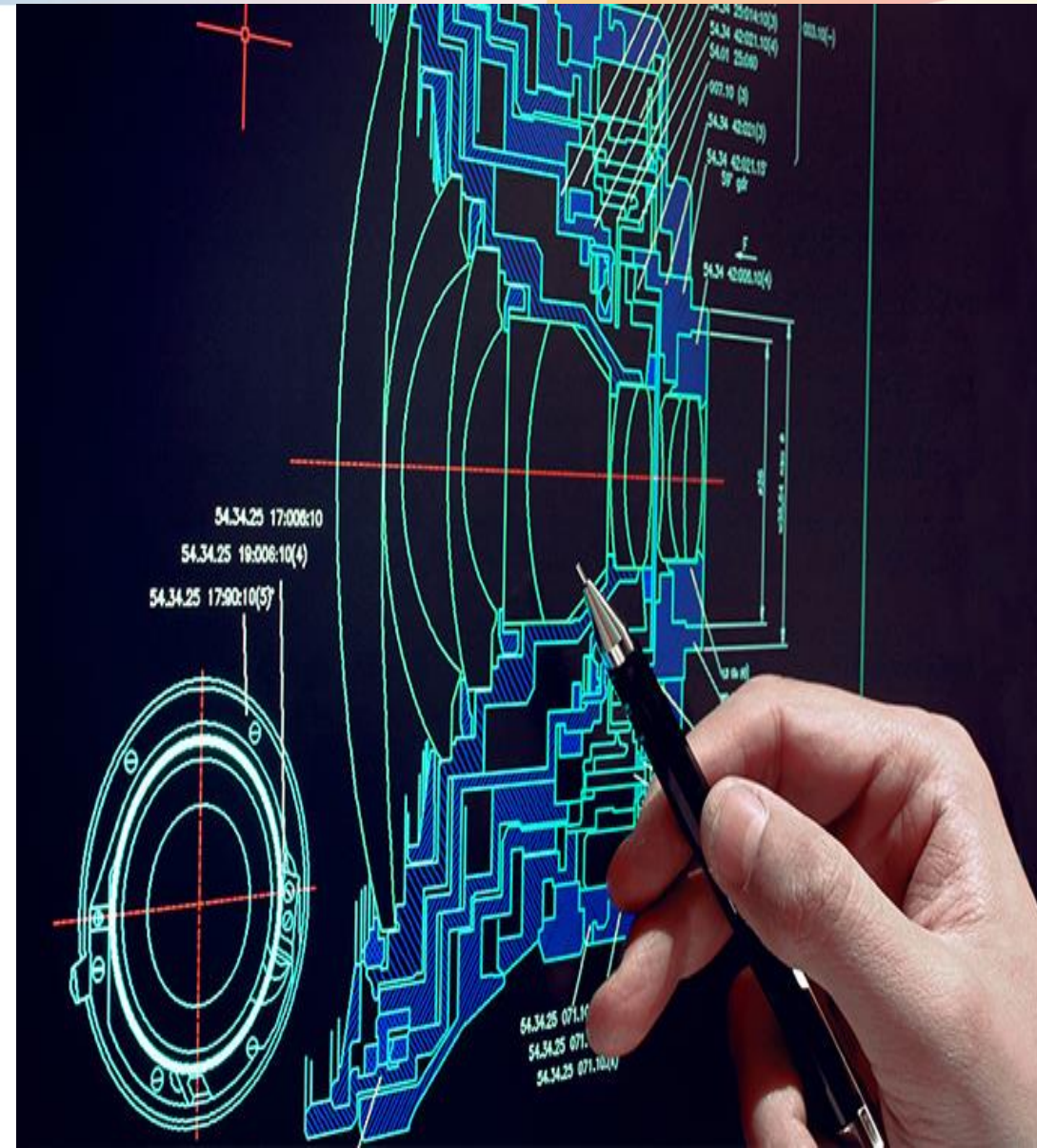
- Simulating image quality degradation is useful to predict its impact on the performance of learning-based algorithms.
- By integrating the camera in the simulation, it is possible to predict its performance during its lifespan.

We can optimize optical parameters to limit the impact of image quality degradation on vision algorithms.

(This is a case study; the precise required resolution needed and the tolerated temperature shift need to be evaluated for each use case.)

Take Aways

- **Traditional computer vision can be adapted to fit drone navigation by using spatial noise filtering for improved performance in low light.**
- **Being able to simulate a camera and image quality degradation during its lifespan can help optical parameter optimization for improved performance of learning-based algorithms.**
- **Optimized algorithms can be used as KPI in a context of machine vision.**



Immervision website: <https://www.immervision.com/>

Previous publications:

[Xavier Dallaire, Julie Buquet, Patrice Roulet, Jocelyn Parent, Pierre Konen, Jean-François Lalonde, Simon Thibault, "Enhancing learning-based computer vision algorithms accuracy in sUAS using navigation wide-angle cameras," Proc. SPIE 11870, Artificial Intelligence and Machine Learning in Defense Applications III, 1187009 \(12 September 2021\); <https://doi.org/10.1117/12.2600197>](#)

[J. Buquet, S.-G. Beauvais, J. Parent, P. Roulet, S. Thibault, "Next-generation of sUAS 360 surround vision cameras designed for automated navigation in low-light conditions," Proc. SPIE 12274, Emerging Imaging and Sensing Technologies for Security and Defence VII, 122740L \(7 December 2022\); <https://doi.org/10.1117/12.2639024>](#)

[YOLOv4: Optimal Speed and Accuracy of Object Detection, Alexey Bochkovskiy, Chien-Yao Wang, Hong-Yuan Mark Liao, 2020](#)

[PixSet : An Opportunity for 3D Computer Vision to Go Beyond Point Clouds With a Full-Waveform LiDAR Dataset, Jean-Luc Déziel, Pierre Merriault, Francis Tremblay, Dave Lessard, Dominique Plourde, Julien Stanguennec, Pierre Goulet, Pierre Olivier, 2021](#)

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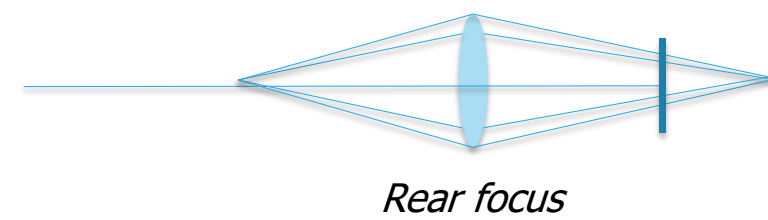
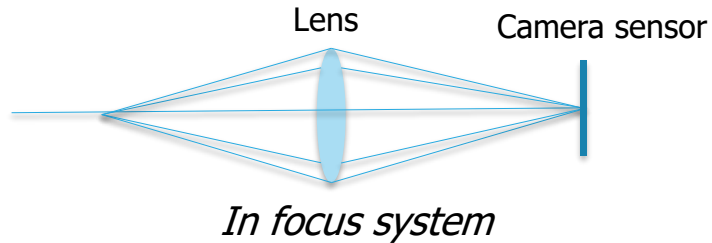
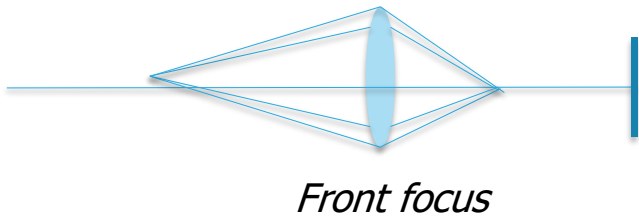
THANK YOU

Blur induced by a camera defocus

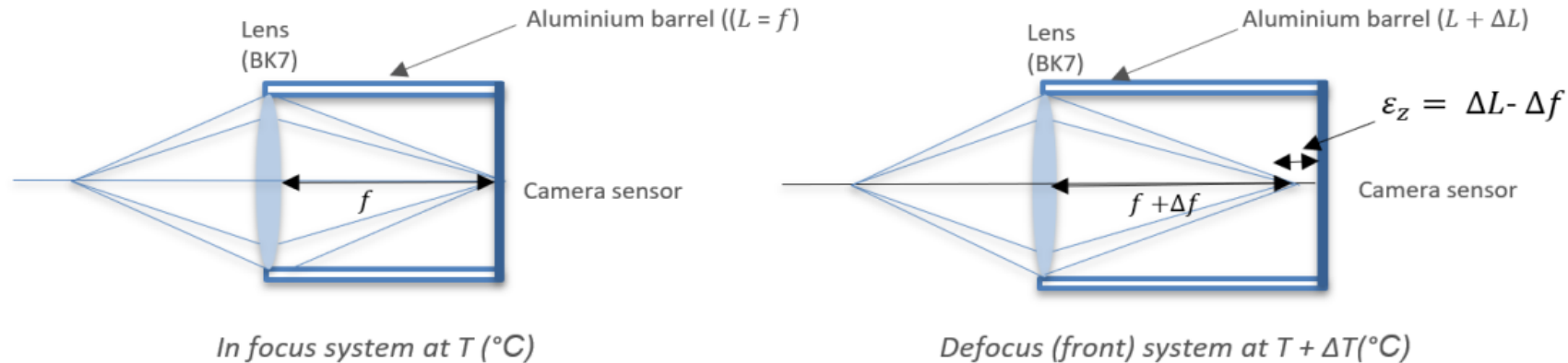


Positive defocus

Negative defocus

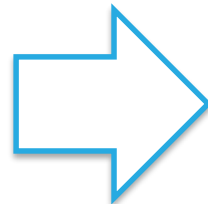


Defocus due to temperature shift



$$\Delta f = \delta_G f \Delta T$$

$$\Delta L = \beta f \Delta T$$



At $\lambda = 550\text{nm}$ a **drop of 2%** in the performances :

$$f_{\#} = 4 : 5.81 \mu\text{m} / \mathbf{23.19} \text{ }^{\circ}\text{C}$$

$$f_{\#} = 2 : 10.94 \mu\text{m} / \mathbf{43.67} \text{ }^{\circ}\text{C}$$