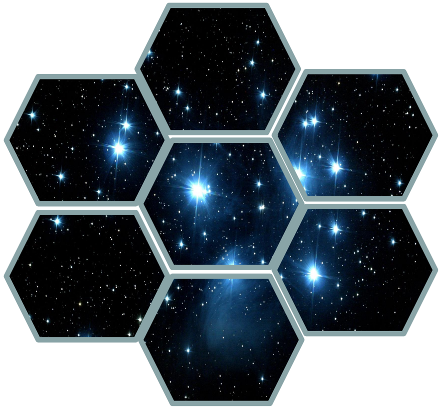
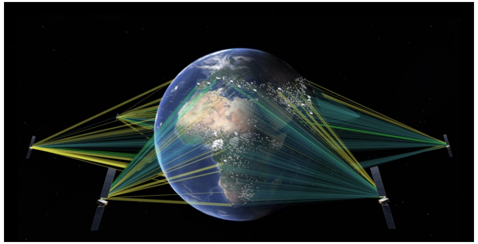
Phasing segmented telescopes via deep learning techniques



Maxime DUMONT, Jean-François SAUVAGE, Carlos CORREIA, Noah SCHWARTZ, Morgan GRAY, Jaime CARDOSO

Context

Earth observation from Low Earth Orbits (LEO)



- High **angular resolution** $\frac{\lambda}{D}$

  Limited by the **telescope aperture** and **wavelength**

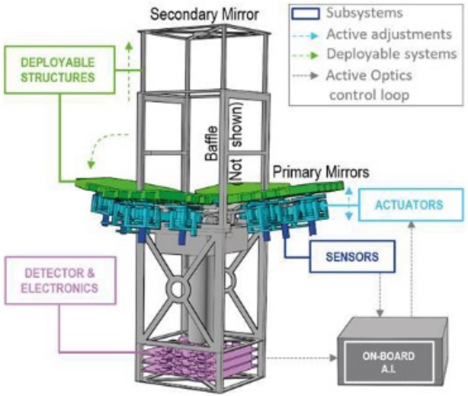
  ➡ **Increase the telescope size**

- High **revisit rate**

  Requires constellation of multiple satellites

  Limited by satellite cost i.e. **dimension**/manufacture

  ➡ **Reduce the satellite volume**



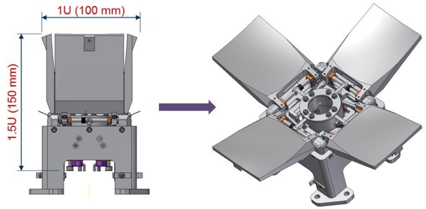
- Particularly interesting for LEO imaging at high resolution
  - Agriculture
  - Climate services
  - Disaster management
  - Defense

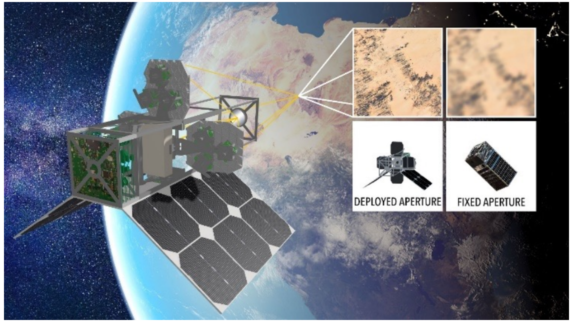
Needs **combine high angular resolution** and high **revisit rate**: fitting a **deployable telescope** inside a relatively small platform (CubeSat standard).

Science & Technology Facilities Council
UK Astronomy Technology Centre

Context

AZIMOV – The CubeSat deployable space telescope





3.0 m resolution
(D=10 cm at 500 km)

1.0 m resolution
(D=30 cm at 500 km)

Ground Sampling Distance	1 m at 600 nm
Field of View	>2 km (goal 5 km).
Wavelengths	400-800 nm
Deployment residual wavefront error	<2 waves at 800 nm PV / 400nmRMS
Total residual wavefront error	70 nm RMS
Aperture diameter	≥ 300 mm
M1-M2 distance	≥ 280 mm
Payload volume	4U

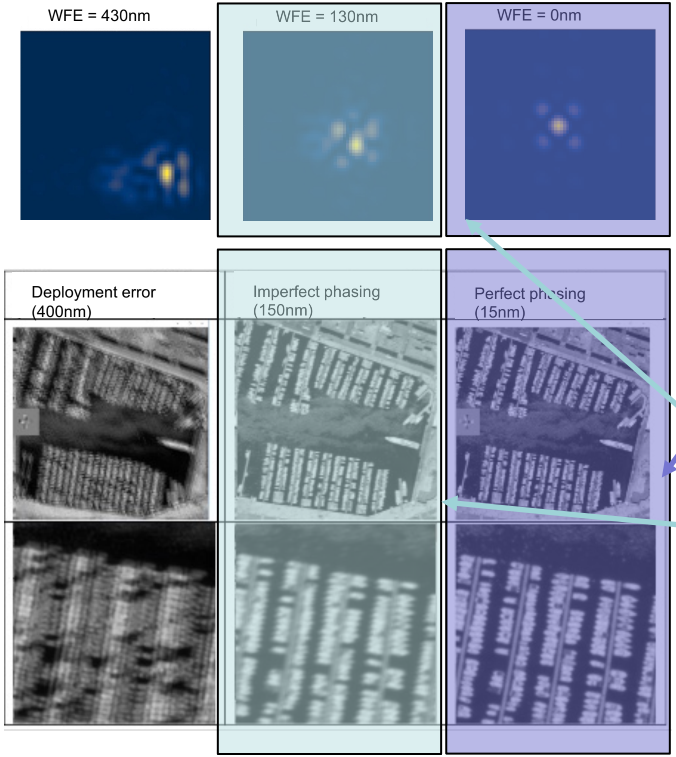
Requirement

From Schwartz, Noah, et al. "6U CubeSat deployable telescope for optical Earth observation and astronomical optical imaging." *Space Telescopes and Instrumentation 2022*SPIE, 2022.

Error budget

Point source
PSF

Extended scene
Abberated image



Ground Sampling Distance	1 m at 600 nm
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Wavelengths	800 nm
Deployment residual wavefront error	<2 waves at 800 nm PV / 400nmRMS
Total residual wavefront error	70 nm RMS
Aperture diameter	≥ 300 mm
M1-M2 distance	≥ 280 mm
Payload volume	4U

Equivalent resolution of a 10cm telescope

Error budget

Step	Capture range	Precision specification
Telescope initial deployment	-	Within the detector
Coarse phasing	Detector field of view	Sub-wavelength
Fine phasing	Few Wavelength	15nm RMS

Ground Sampling Distance	1 m at 600 nm
Field of View	>2 km (goal 5 km).
Wavelengths	800 nm
Deployment residual wavefront error	<2 waves at 800 nm PV / 400nmRMS
Total residual wavefront error	70 nm RMS
Aperture diameter	≥ 300 mm
M1-M2 distance	≥ 280 mm
Payload volume	4U

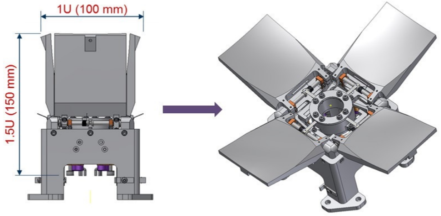
Total WFE of 70nm RMS includes :

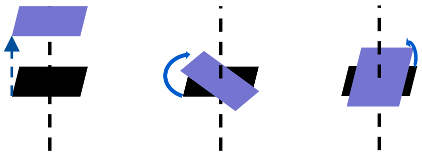
- **Measurement error**
- Latency
- Control errors
- Actuator resolution and drifts

Phasing under **15nm** in the visible is essential to reach diffraction limit resolution.

Constrains

Active control of the segment



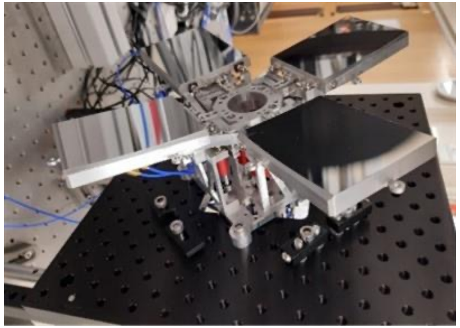


Piston **Tip** **Tilt**

12 coefficients to estimate,
PTT for each of the 4 segments

$$WFE = \sum_{\{k=0\}}^{\{4\}} \sqrt{\sum_{\{i=0\}}^{\{3\}} {c_k^i}^2}$$

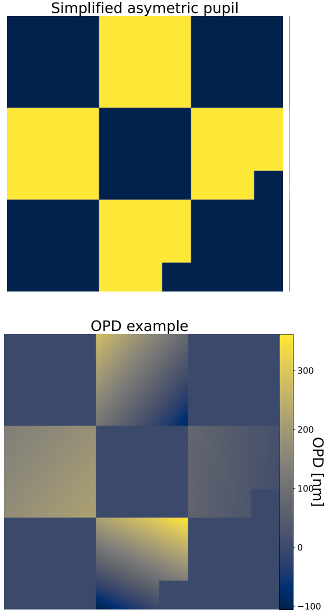
No additionnal optical path



- No WFS : only **focal plane wavefront sensing**.
- No defocused image, **1 image used** for the sensing.

Requires diversity

Amplitude diversity [1]



Crop 5% of the total collecting area

(1) F. Martinache (2013)

Methods – Focal Plane wavefront sensing

Classical FP Methods

Phase diversity [2]

Minimize a numerical criterion

- Iterative
- Model dependent
- Initial guess

Image Sharpening [3]

Optimize an optical criterion

- Iterative
- Model-free
- Initial guess
- Requires active correction at each iteration

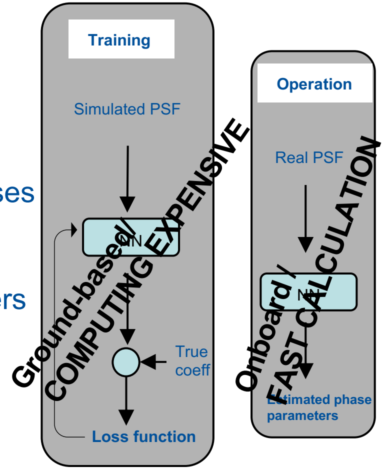
Deep Learning

Optimize a numerical criterion to adjust filters, weights and biaises.

- Data-Driven
- ”Model-free”
- Stochastic learning
- Deterministic estimation

How it works ?

- ➢ Dataset :
  - ➢ Realisations representative of real cases
  - ➢ Coherent numbers of samples
- ➢ Training : Optimize HP
- ➢ Operation : NN models infere phase parameters



(2) L. M. Mugnier,(2006)
(3) N. Schwartz (2020),

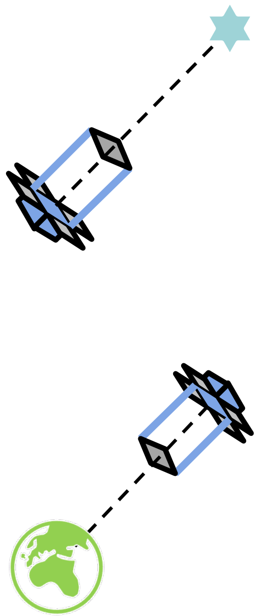
Objectives

- **Study NN ability for FPWFS**
  - Model sizes
  - Noise propagation
  - Robustness to Higher-Order aberrations
  - Comparison to SoTA
- **Uses NN as phasing strategy for AZIMOV**
  - Full telescope phasing
  - Closed-loop

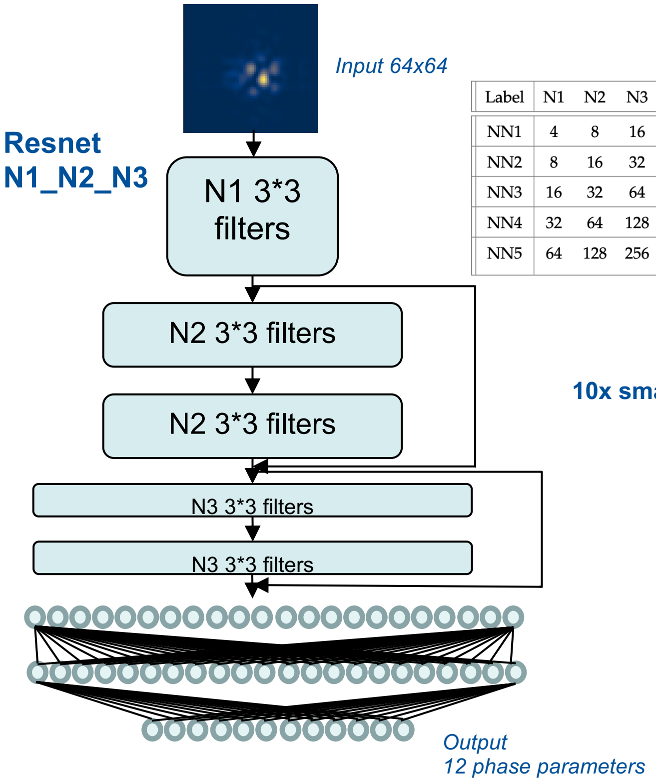
Point source

- **How about Earth observation ?**

Extended scene

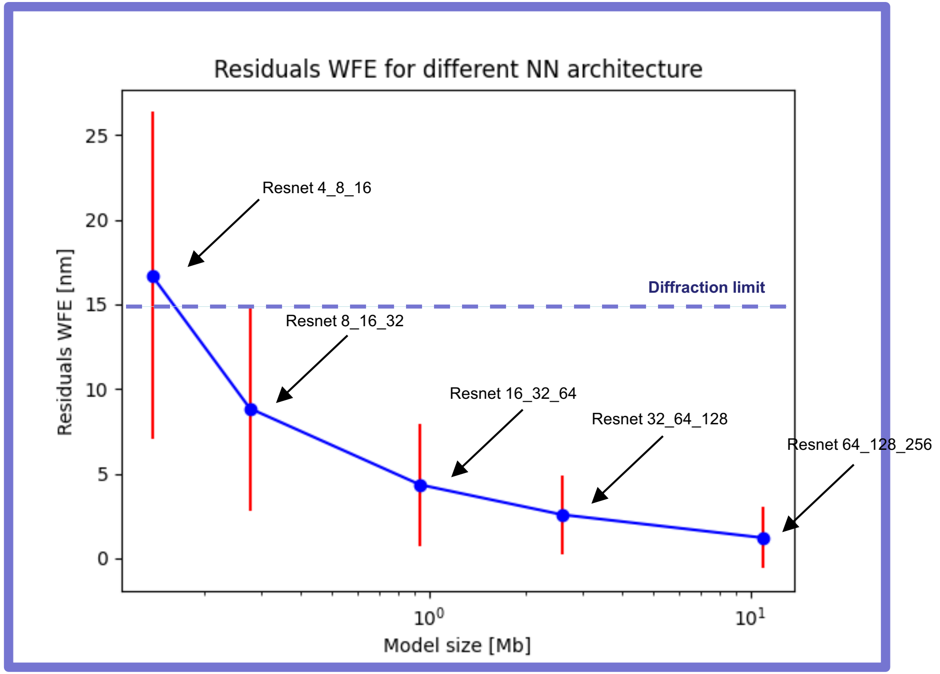


Baseline performance, impact of NN complexity



Label	N1	N2	N3	# parameters	Model size [MB]
NN1	4	8	16	13.10^3	0.134
NN2	8	16	32	31.10^3	0.278
NN3	16	32	64	94.10^3	0.94
NN4	32	64	128	326.10^3	2.6
NN5	64	128	256	$1.2.10^6$	11

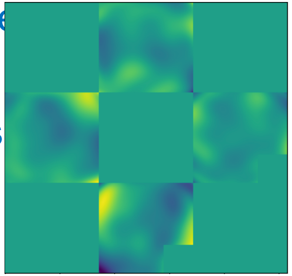
10x smaller than Resnet18



- Performance depends on the number of internal parameters
- Suitable performance for a model size > 0.2Mb

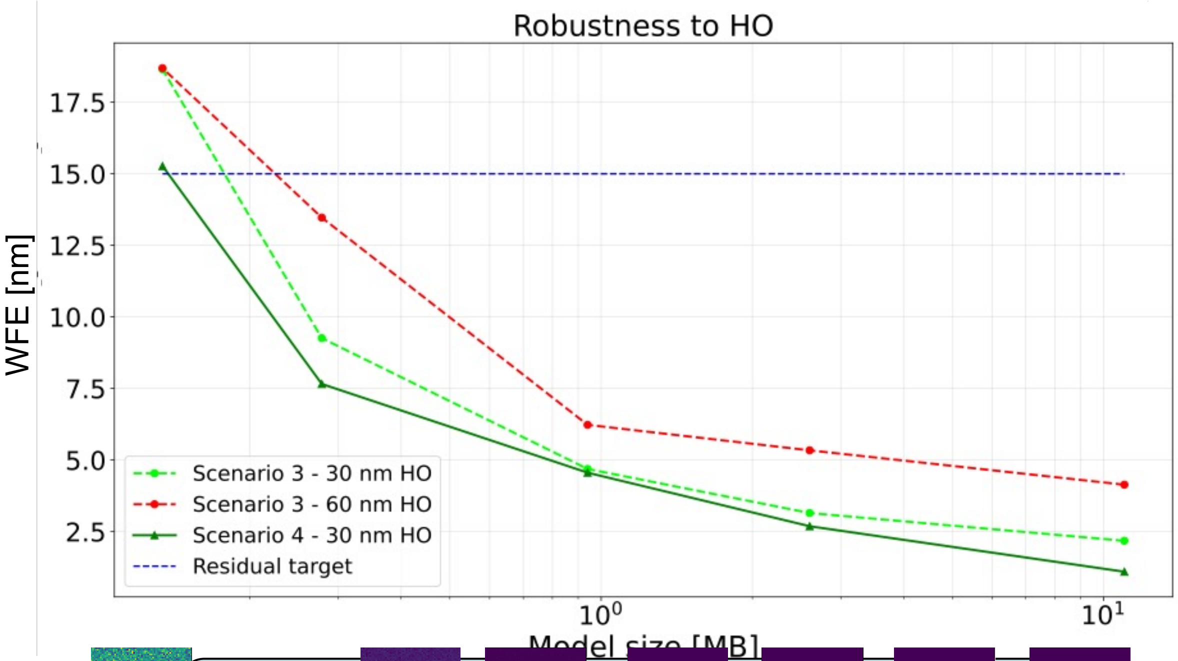
What about noise and high orders ?

- … e for te …
  … noise …
  … r nois …



- … NR = $\sqrt{f+\sigma_{RON}^2}$

- 2 scenarios :
  - Model error (Noise / HO unknown)
  - Noise / HO prior quantification (pre-calibrated)
- High orders are due to mirror polishing errors, thermal gradients, vibrations etc…

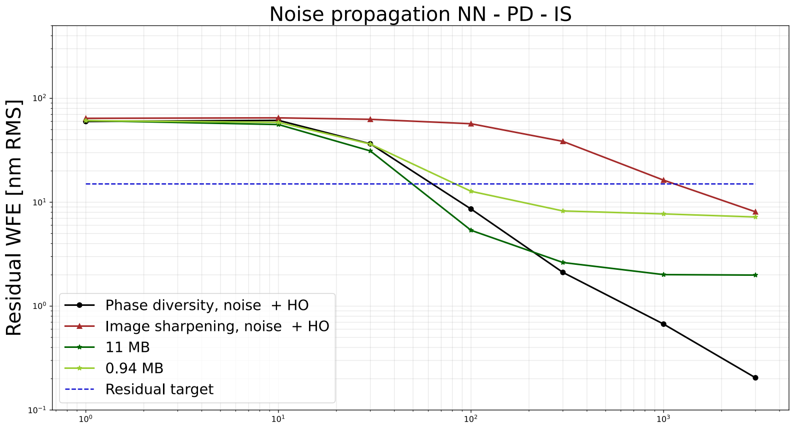


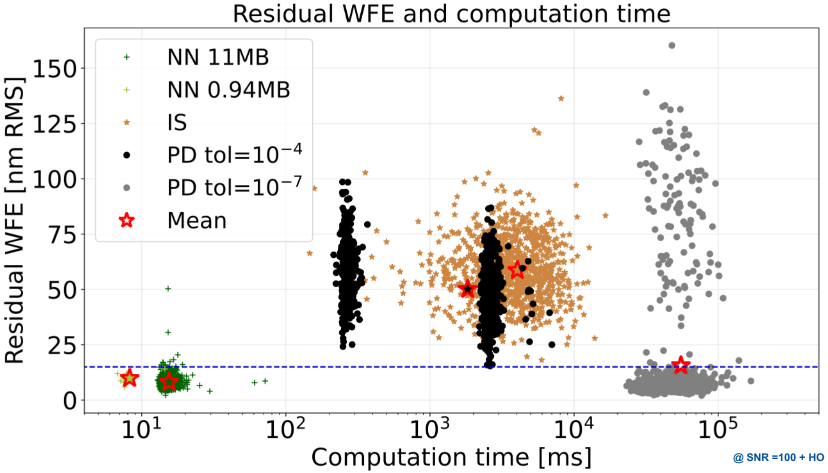
- Neural ne… fi… /FE… em… cas… gh orders ar… e
- Requires a larger architecture than the nominal case

Comparison to SoTA methods

- Phase diversity
  - Fit a PSF model $\hat{h}$ to the current PSF
  - Numerical optimization – Powell method
  - $\underset{\{c_k^i\}}{\arg\min} \left|PSF - \widehat{h(\{c_k^i\})}\right|^2 + \beta * \sum_{i,k} {c_k^i}^2$

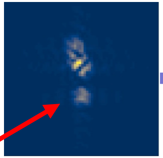
- Image sharpening
  - Optimize image centered intensity
  - Active iterative correction of the mirror position
  - $\underset{\{c_k^i\}}{\arg\max} \sum_{x=xc-2W}^{xc+2W} \sum_{y=xc-2W}^{yc+2W} I(x,y)$





- NN demonstrates a level at SoTA for performance, and better for computing time.
- At SNR = 100, NN methods shows a great performances both in computation time and performances.

AZIMOV Coarse and fine phasing

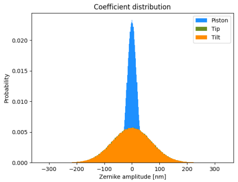


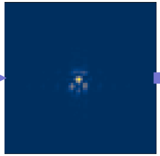
No piston sensing !

Recenter the 4 PSFs

Tip – Tilt correction

NN 1

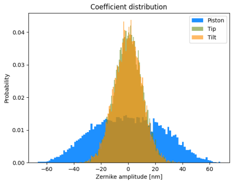


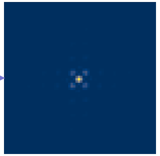


Fine phasing

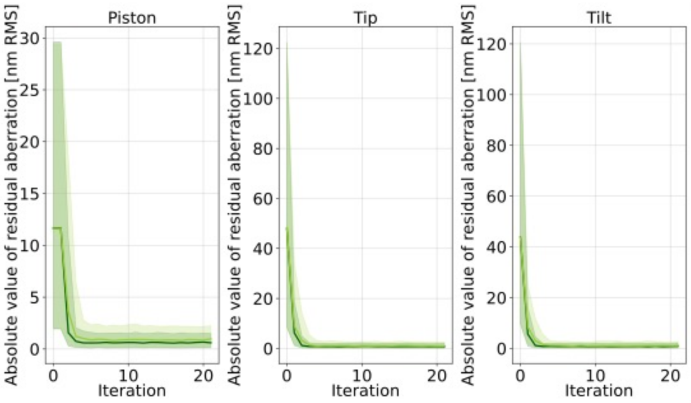
Low PTT correction

NN 2

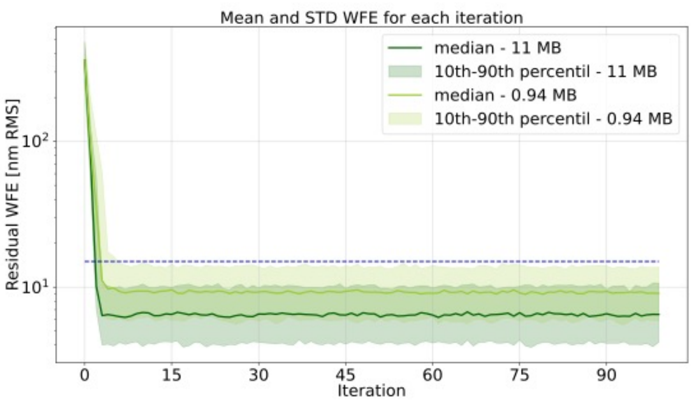




Coefficient to coefficient residuals

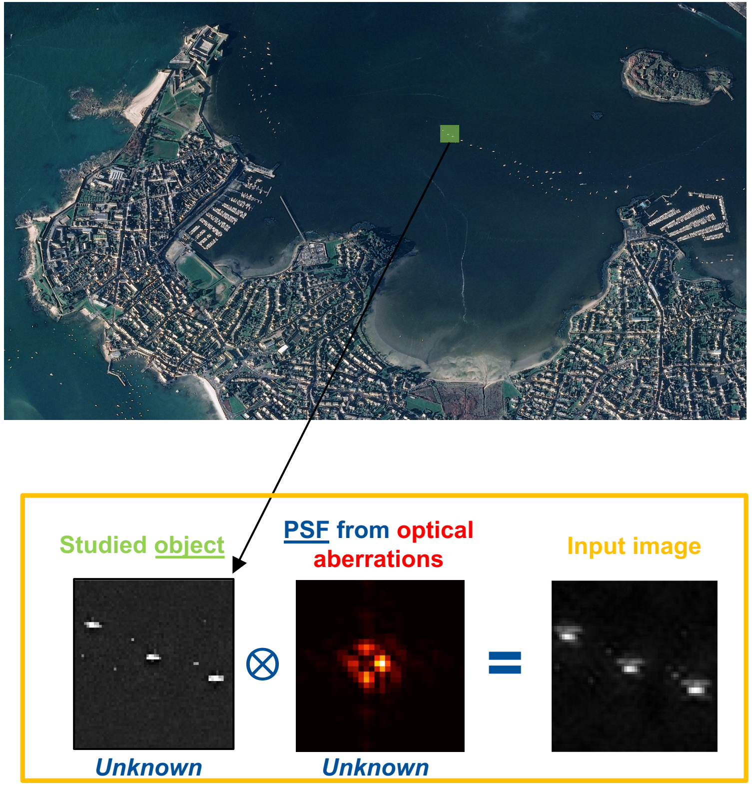


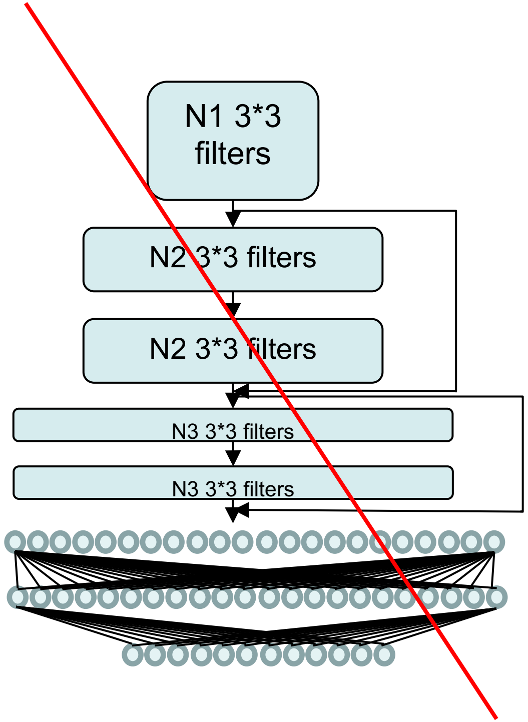
Full pupil validation

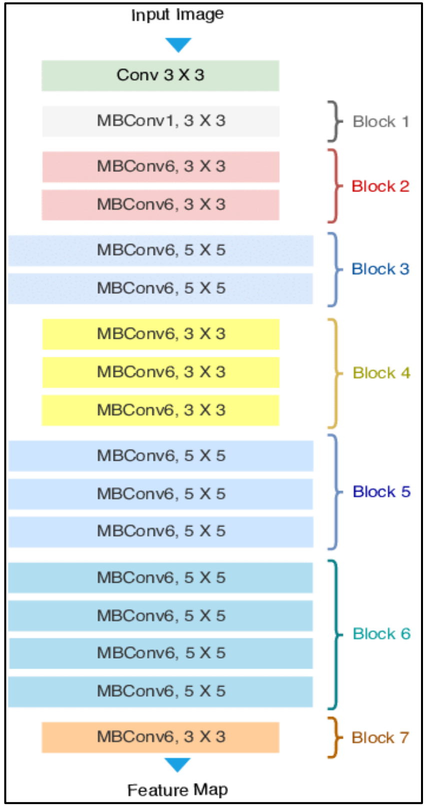


In a full phasing scenario, the 2 steps NN reaches diffraction limit requirement and remains stable at SNR = 100

Outlook : Extended scenes – Earth Observation







EfficientNet−B0 [4]

RÉPUBLIQUE FRANÇAISE
Liberté Égalité Fraternité

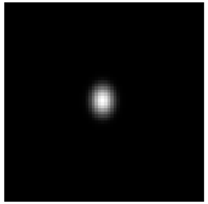
ONERA THE FRENCH AEROSPACE LAB

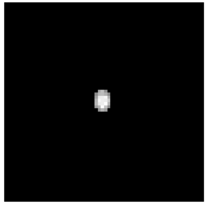
U.PORTO FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

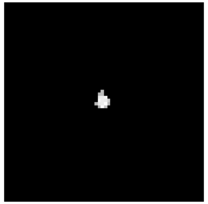
LAM LABORATOIRE D'ASTROPHYSIQUE DE MARSEILLE

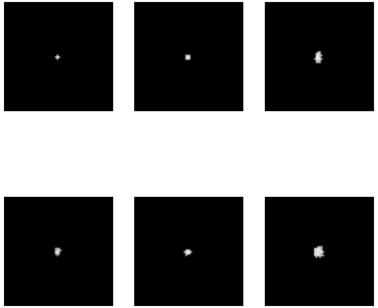
(4)Tan, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks " 2020

Outlook : Extended scenes – Earth Observation
Data generation

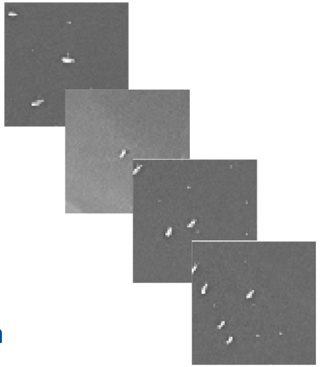

Parametrized gaussian

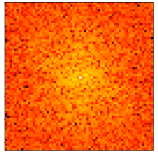

Poisson noise

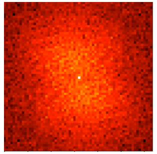

Threshold

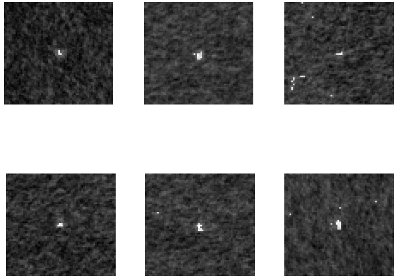


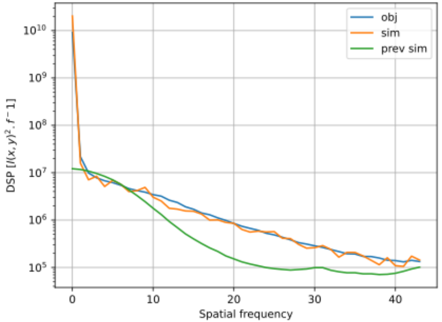
From real data




mean(|FFT(im)|)

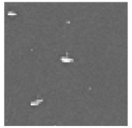

std(|FFT(im)|)



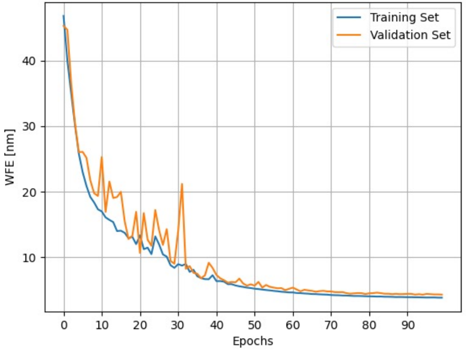


Outlook : Extended scenes – Earth Observation

Real data

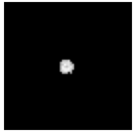


5 Objects – 20k PSFs

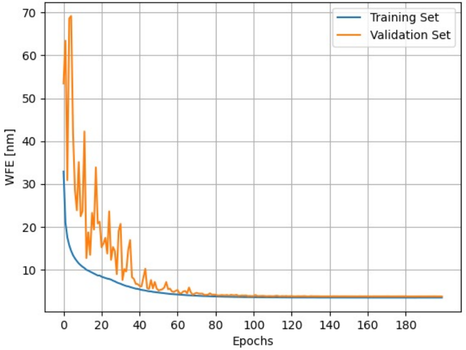


Diffraction limit
Generalize over other object
Generalize over real data

Simple simulation

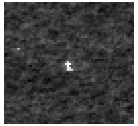


100k Objects –1 PSF

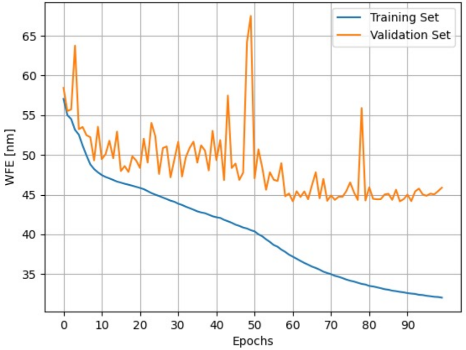


Diffraction limit
Generalize over other object
Generalize over real data

Simulation from spectrum



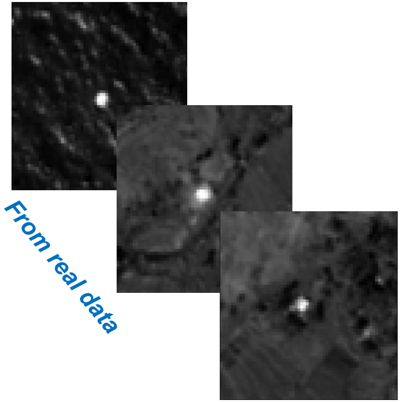
100k Objects –1 PSF

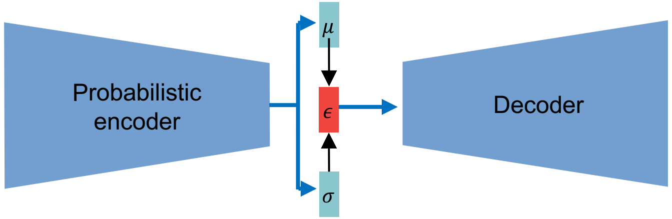


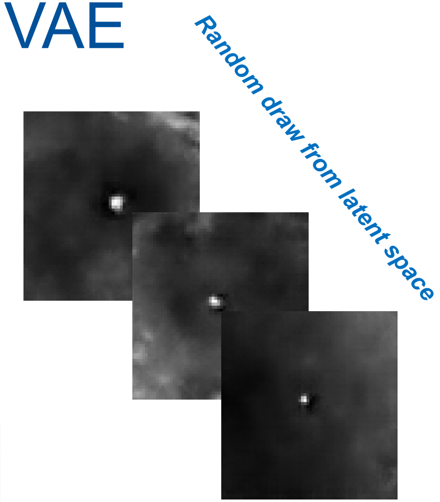
Diffraction limit
Generalize over other object
Generalize over real data

To go further

Realistic objet generation using VAE

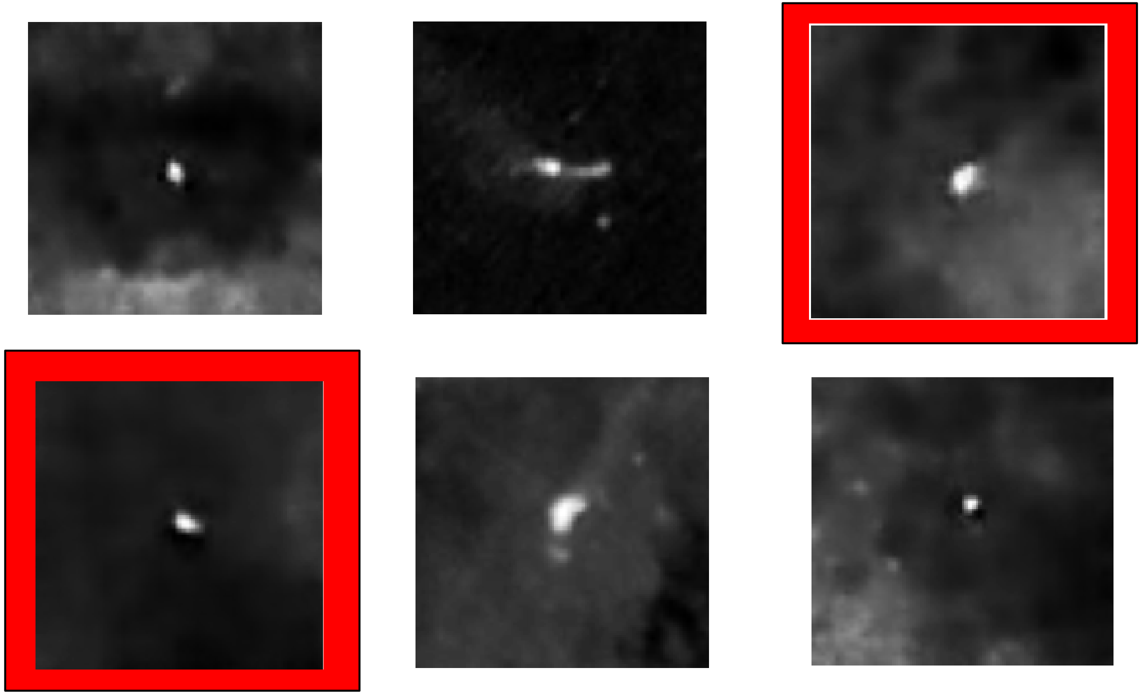






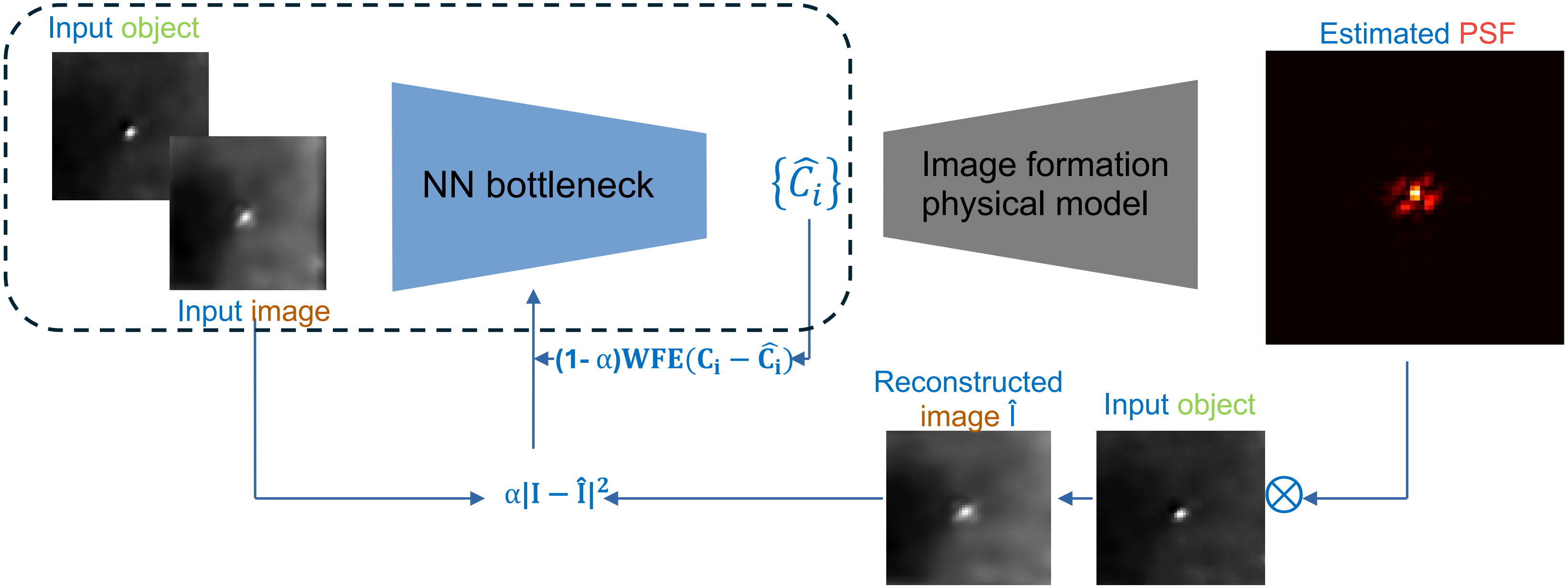
Layer	Type	Parameters
enc1	Conv2d	(1, 32, (3, 3), (1, 1), (1, 1))
enc2	Conv2d	(32, 64, (3, 3), (2, 2), (1, 1))
enc3	Conv2d	(64, 64, (3, 3), (2, 2), (1, 1))
enc4	Conv2d	(64, 64, (3, 3), (1, 1), (1, 1))
linearenc	Linear	(16384, 16)
mu_layer	Linear	(16, 8)
log_var_layer	Linear	(16, 8)
lineardec	Linear	(8, 16384)
dec1	ConvTranspose2d	(64, 64, (3, 3), (1, 1), (1, 1))
dec2	ConvTranspose2d	(64, 64, (3, 3), (2, 2), (1, 1), (1, 1))
dec3	ConvTranspose2d	(64, 32, (3, 3), (2, 2), (1, 1), (1, 1))
dec4	ConvTranspose2d	(32, 1, (3, 3), (1, 1), (1, 1))

Who are the 2 impostors ?

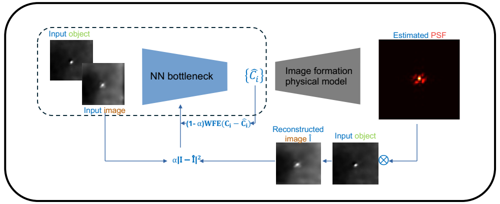


To go further

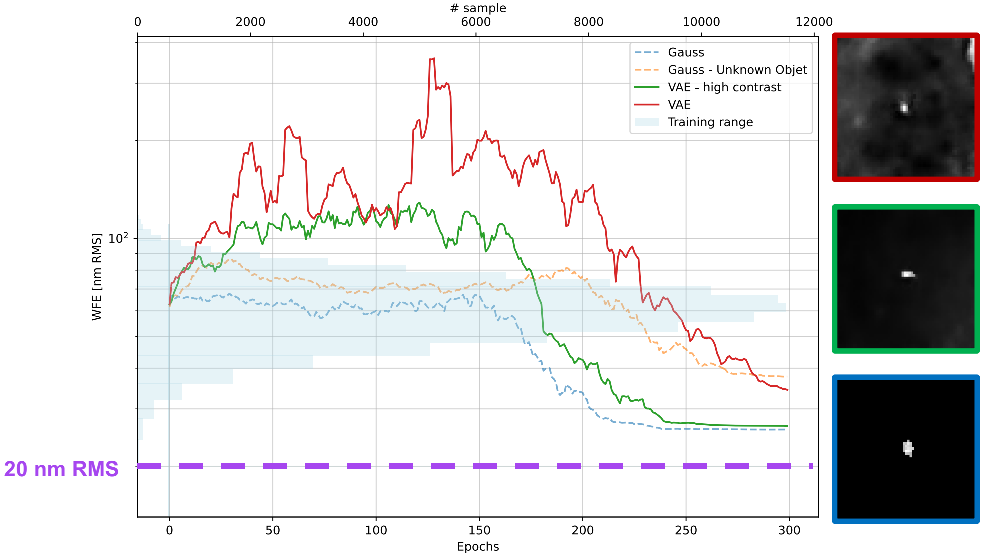
Learning strategy



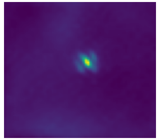
Results



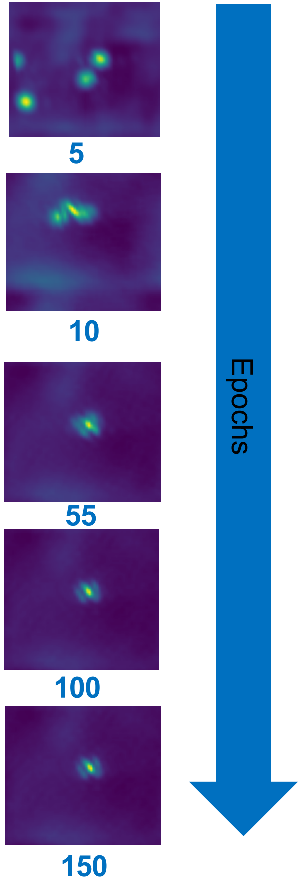
Validation losses



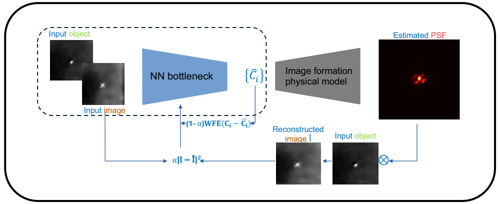
Input image



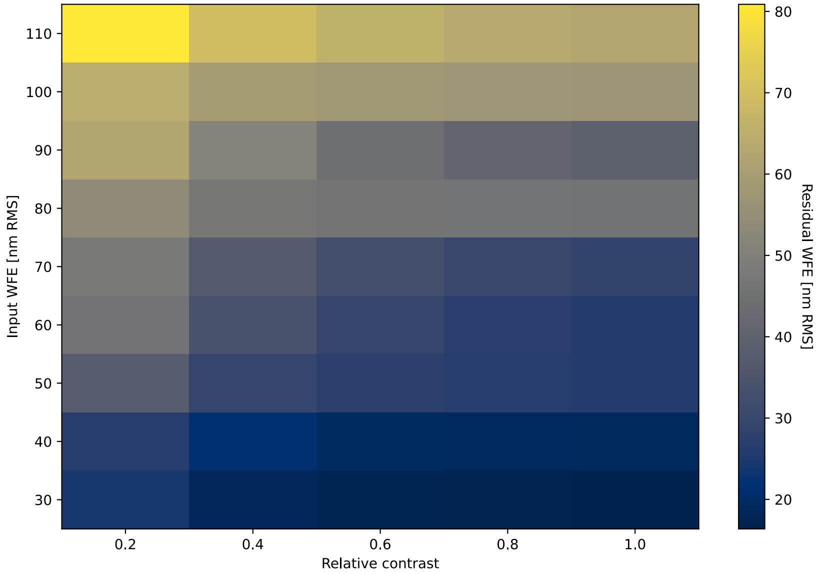
Reconstructed images (from validation dataset)



Results



Train with low contrast



Train with mid contrast

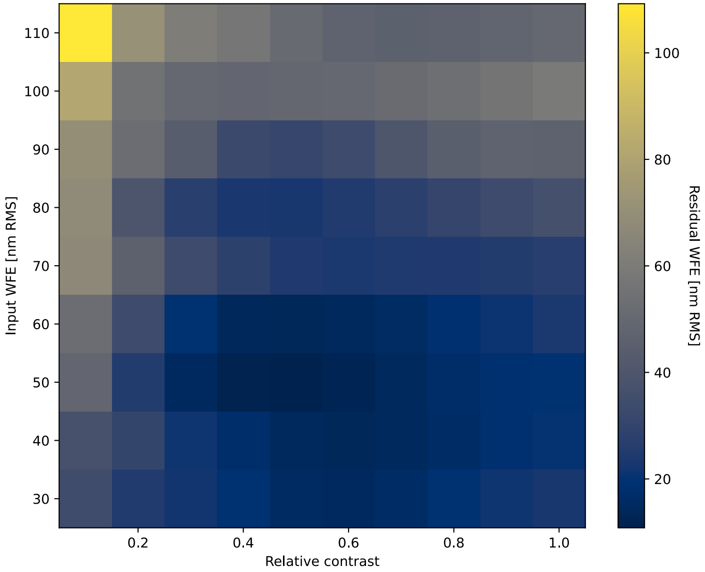
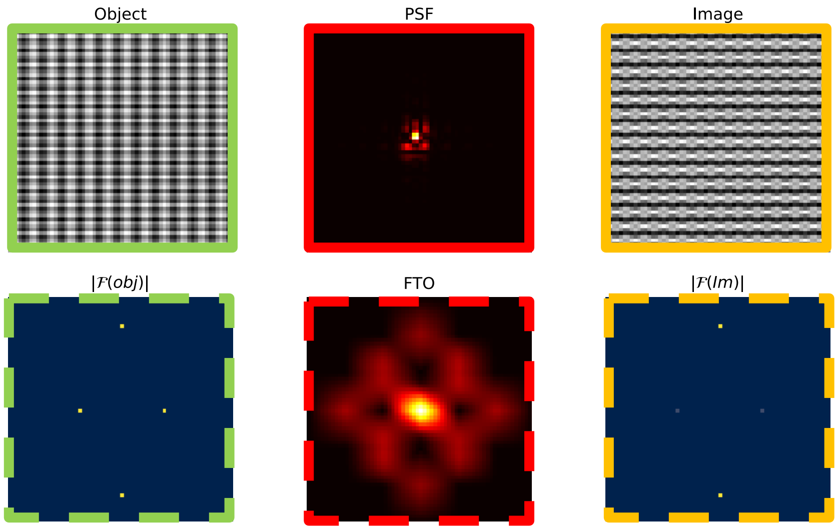


Image formation limit

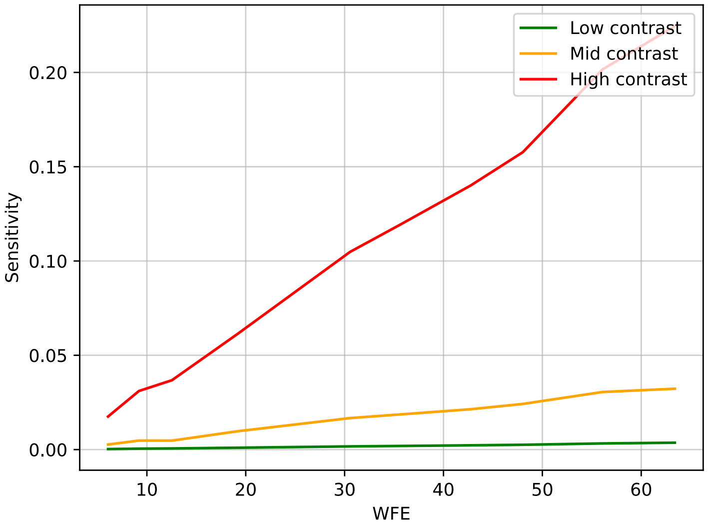
- First limit : Spectral content

$$Im = \mathcal{F}^{-1}(\mathcal{F}(obj) \times \mathcal{F}(PSF))$$



- Second limit : Sensitivity loss from contrast

$$Sensitivity = \sum_{\{i,j\}} \sigma_{i,j}(I_{ref} - I)$$



Conclusion & Outlook

NN reachs performance requirement for WFS on a point source.

Inference improved SoTA in terms of computing time.

Extended scene WF analysis requires high contrast images

Test on optical bench generated PSFs of AZIMOV (UK-ATC).

Work on extended scenes :

- Fight the contrast : pre-processing ?

Communications

Presentations :

- WFSWorkshop – 2022
- COSPAR – 2023

Posters :

- SPIE - 2022
- TAS - 2023
- AO4ELT – 2023

Publications :

- **Proceeding ;** Dumont, Maxime, et al. "Deep learning for space-borne focal-plane wavefront sensing." Space Telescopes and Instrumentation 2022: Optical, Infrared, and Millimeter Wave. Vol. 12180. SPIE, 2022.
- **Proceeding ;** Deep learning for low-order phasing of segmented telescopes, M. Dumont
- **Article :** “Phasing segmented telescopes via deep learning methods: application to a deployable CubeSat” – JOSA-A Published