PHYSICS-DRIVEN LEARNING FOR DIGITAL HOLOGRAPHIC MICROSCOPY

Rémi Kieber, Maxime Jacquot

Université Marie et Louis Pasteur, CNRS, institut FEMTO-ST, F-25000 Besancon, France



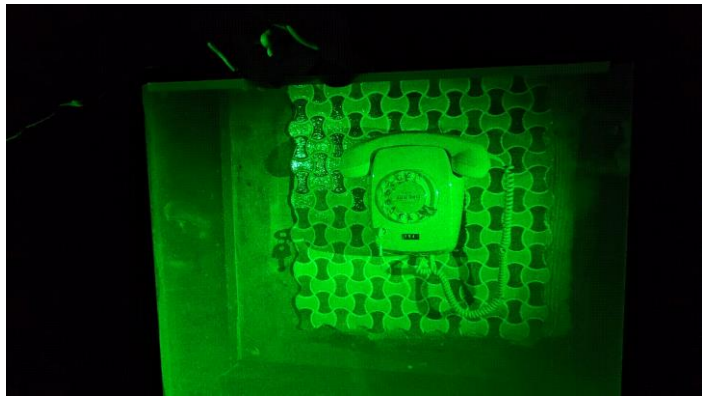
HOLO-CONTROL project

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- Holography overview
- Motivation and objectives
- Context
- Methods and preliminary results
- Conclusion

HOLOGRAPHY OVERVIEW

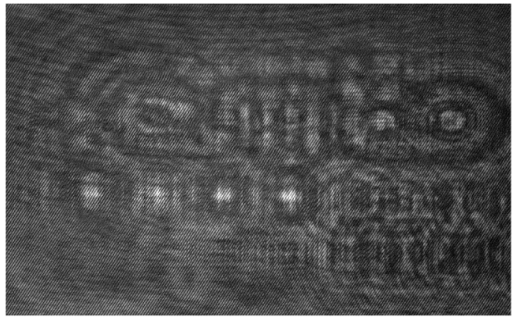
Holography in the 80s:

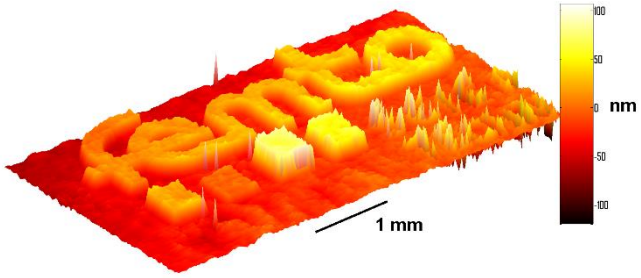


Recorded in the optical laboratory of Besançon (LOBE)/FEMTO-ST

Digital holography in the 2000s:

Numerical reconstruction

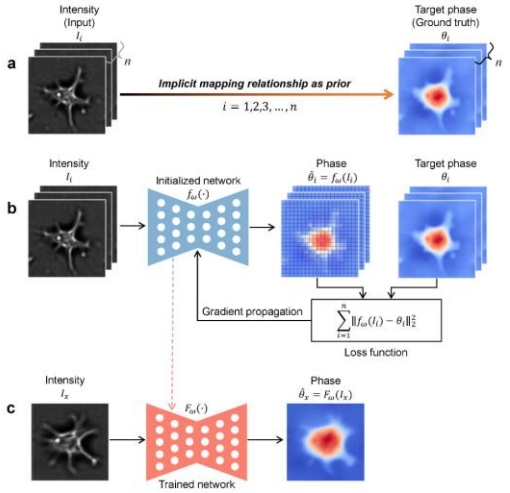




Jacquot, M., *et al.*, *Optics communications*, *190*(1-6), 87-94 (2001)

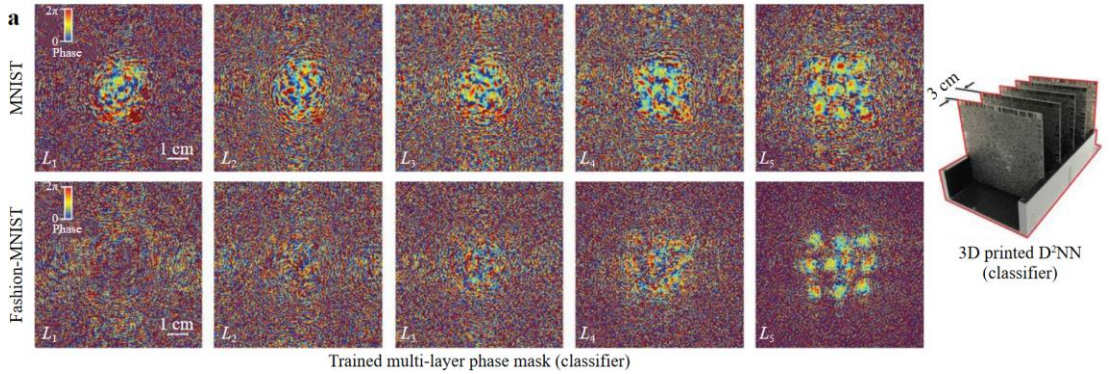
Holography nowadays:

Data-driven neural network for phase recovery



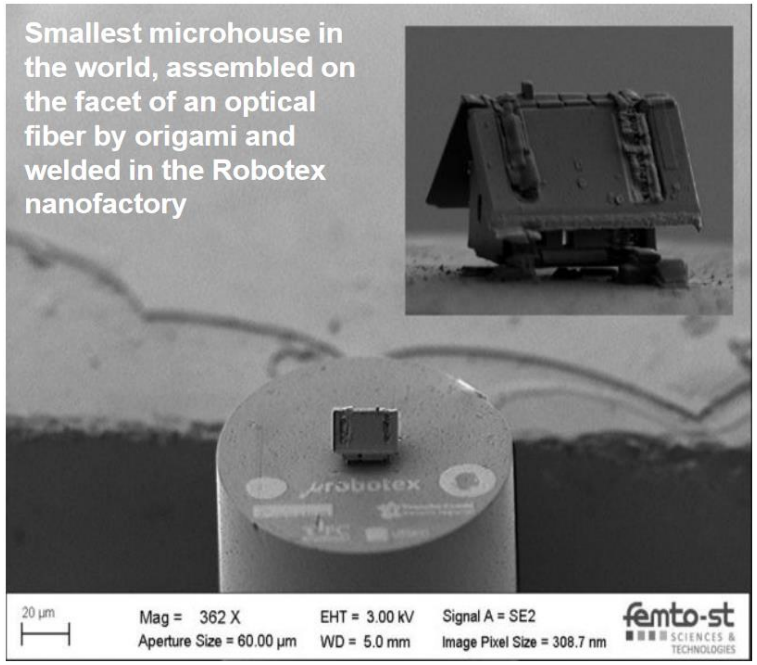
Wang, K., *et al.*, *Light: Science & Applications*, *13*(1), 4. (2024)

Digital classifier with phase mask



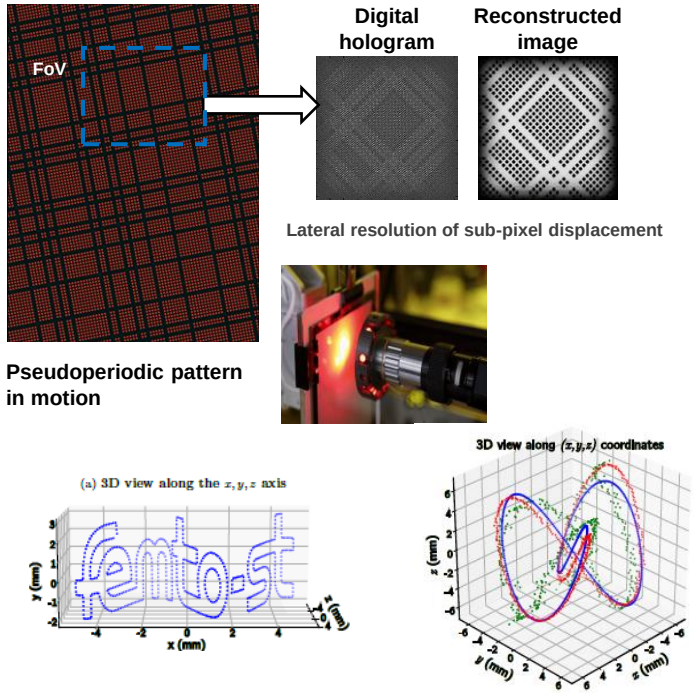
Situ, G., *Light: Advanced Manufacturing*, *3*(2), 278-300. (2022)

CONTEXT



J.-Y. Rauch, *et al.*, J. Vacuum Sci. Technol. A Am. Vacuum Soc. 36, 041601 (2018)

3D computer micro-vision

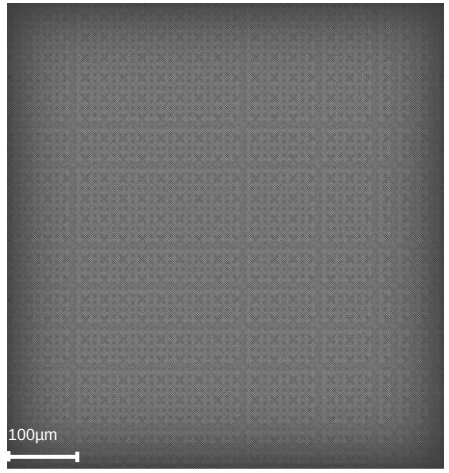


André, A. N., *et al.*, International Journal of Computer Vision, 1-17, (2022)

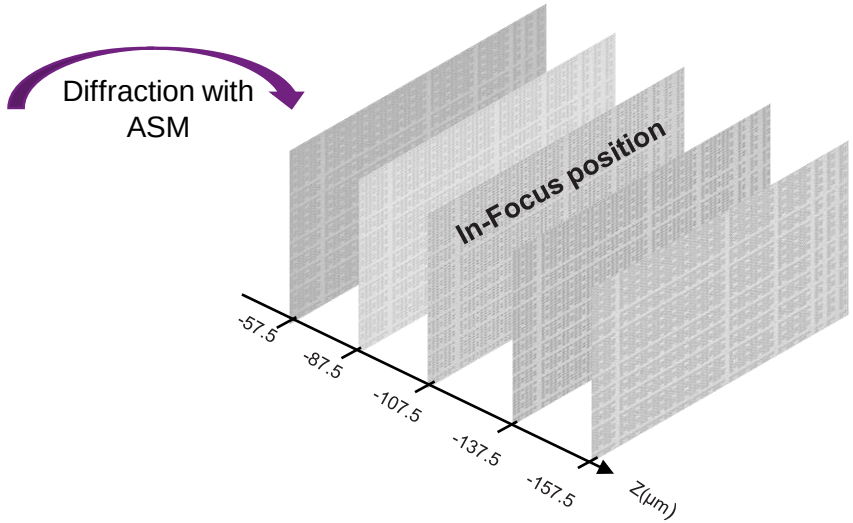
CLASSICAL AUTOFOCUSING BY USING DIGITAL HOLOGRAPHY

But… computation time request & focusing distance?

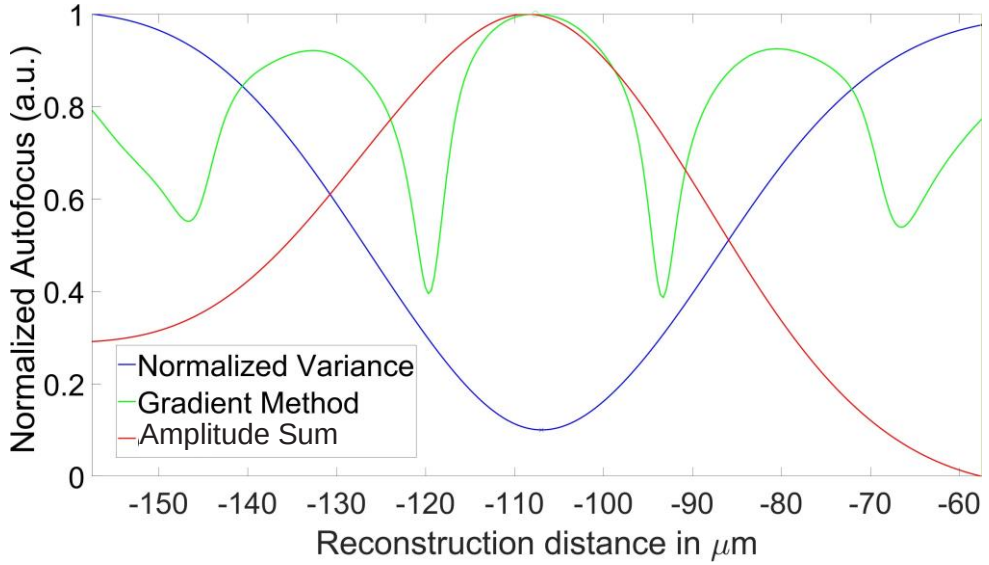
- Reconstruction in each plane
- A single reconstruction → multi-plane propagation with Angular Spectrum Method (ASM)
- Need a focusing metrics (Amplitude sum, Normalized variance, Gradient method…) (minutes scale)



Simulated Digital Hologram



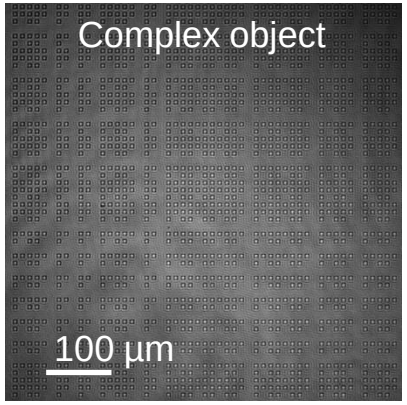
In-focus distance reconstruction

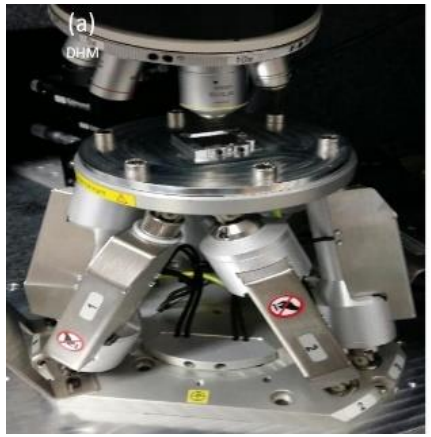


Autofocusing Methods

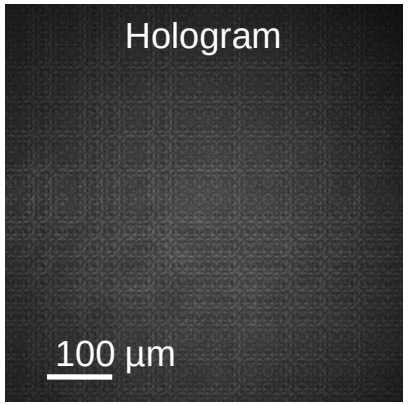
Cuenat, S., et al., Optics Express, 30(14), (2022)

DATA-DRIVEN LEARNING FOR AUTO-FOCUSING IN DHM EXPERIMENT





DHM + Hexapode



Deep learning models

Tiny Vision Transformers ou Tiny VGG

Training on GPU

Regression model

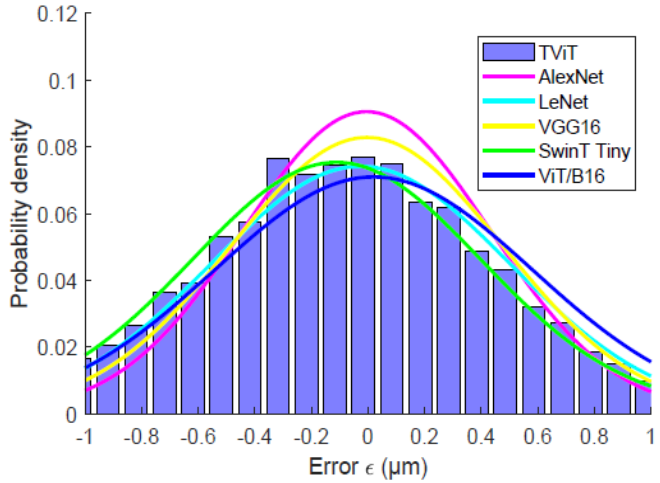
Inference on the CPU

Predicted focusing distance Z

DHM of Lyncee Tec:
MO 10x, NA 0.3,
SLED: λ = 675 nm, δλ = 6 nm
→ Measurement range: 100 µm
→ Axial resolution = 15 µm

Database:
40,000 registered holograms
92 µm range / 1 µm steps

→ images 128x128



Test: 4,040 holograms

Typical focusing error: 1 µm over a range of 92 µm

Cuenat, S., *et al.*, Optics Express, 30(14), (2022)

STATE-OF-THE-ART

nature machine intelligence

Article

https://doi.org/10.1038/s42256-022-00584-3

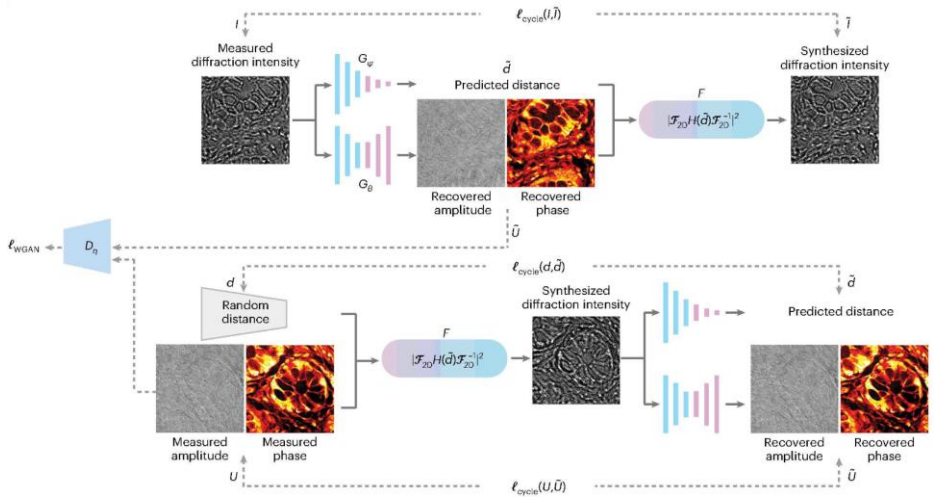
Deep learning based on parameterized physical forward model for adaptive holographic imaging with unpaired data

Received: 31 March 2022

Accepted: 3 November 2022

Published online: 16 January 2023

Chanseok Lee[1,2], Gookho Song[1,2], Hyeonggeon Kim[1,2], Jong Chul Ye[3] & Mooseok Jang[1,2]



- Metrology measurements
- Amplitude, phase and distance prediction

Article

Deep physical neural networks trained with backpropagation

https://doi.org/10.1038/s41586-021-04223-6

Received: 19 May 2021

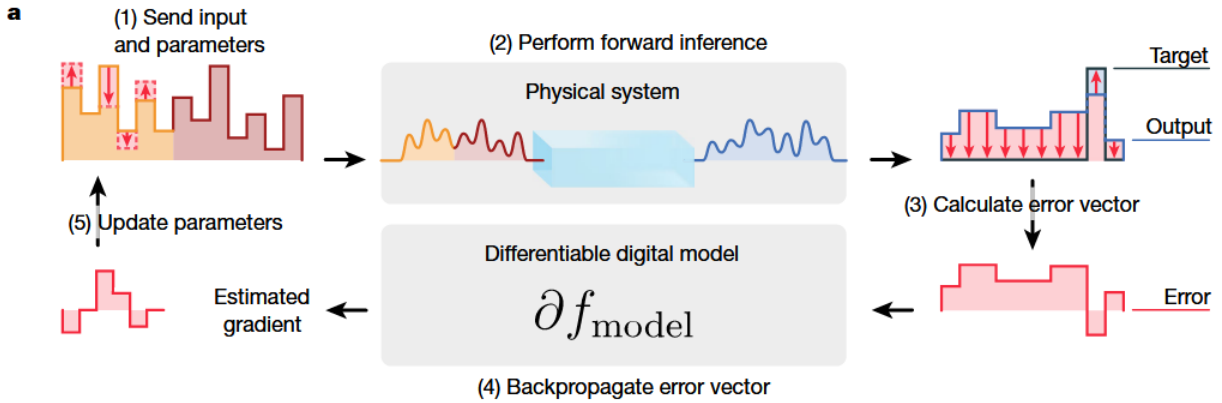
Accepted: 9 November 2021

Published online: 26 January 2022

Open access

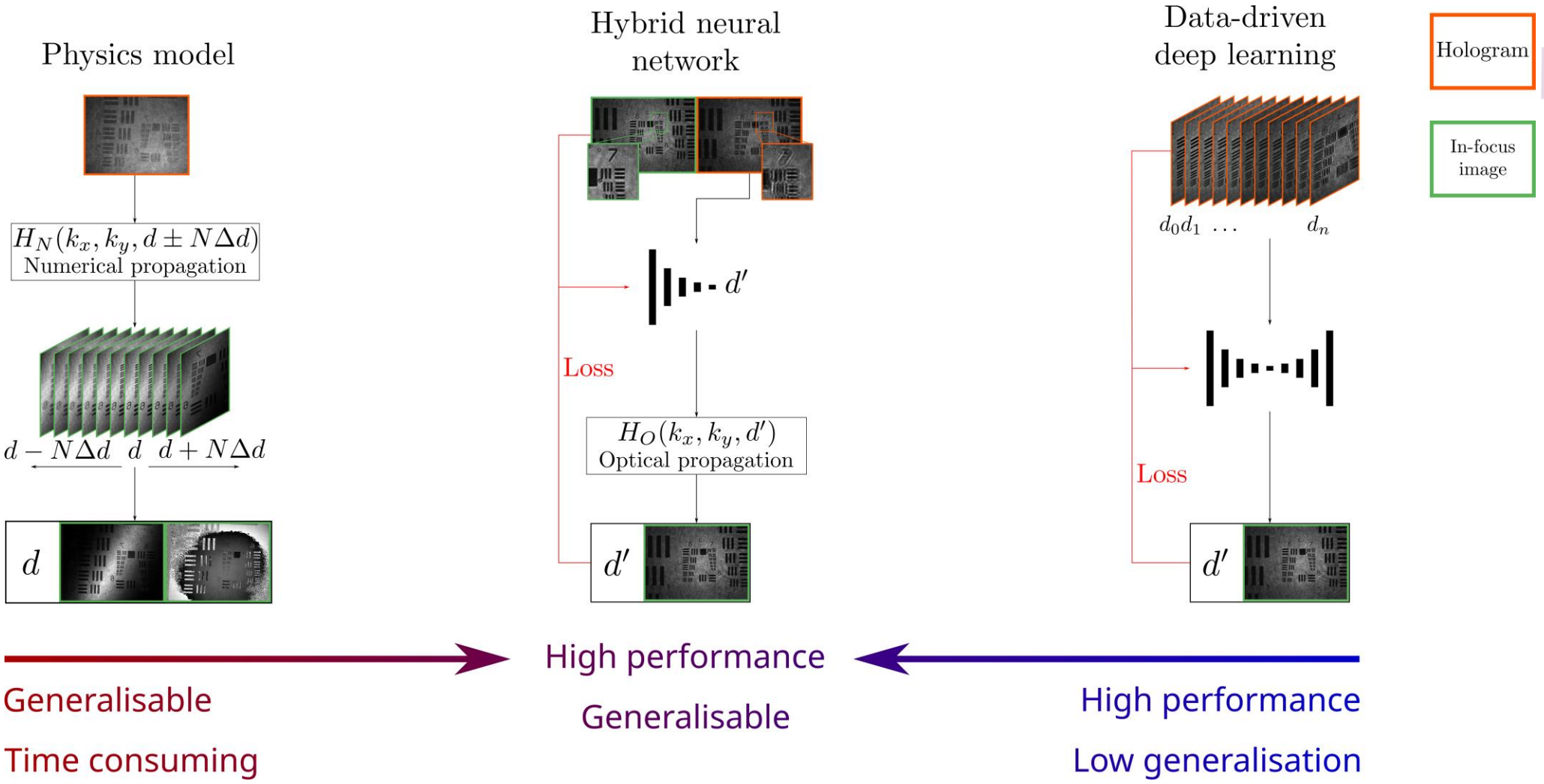
Check for updates

Logan G. Wright[1,2,4], Tatsuhiro Onodera[1,2,4], Martin M. Stein[1], Tianyu Wang[1], Darren T. Schachter[3], Zoey Hu[1] & Peter L. McMahon[1]

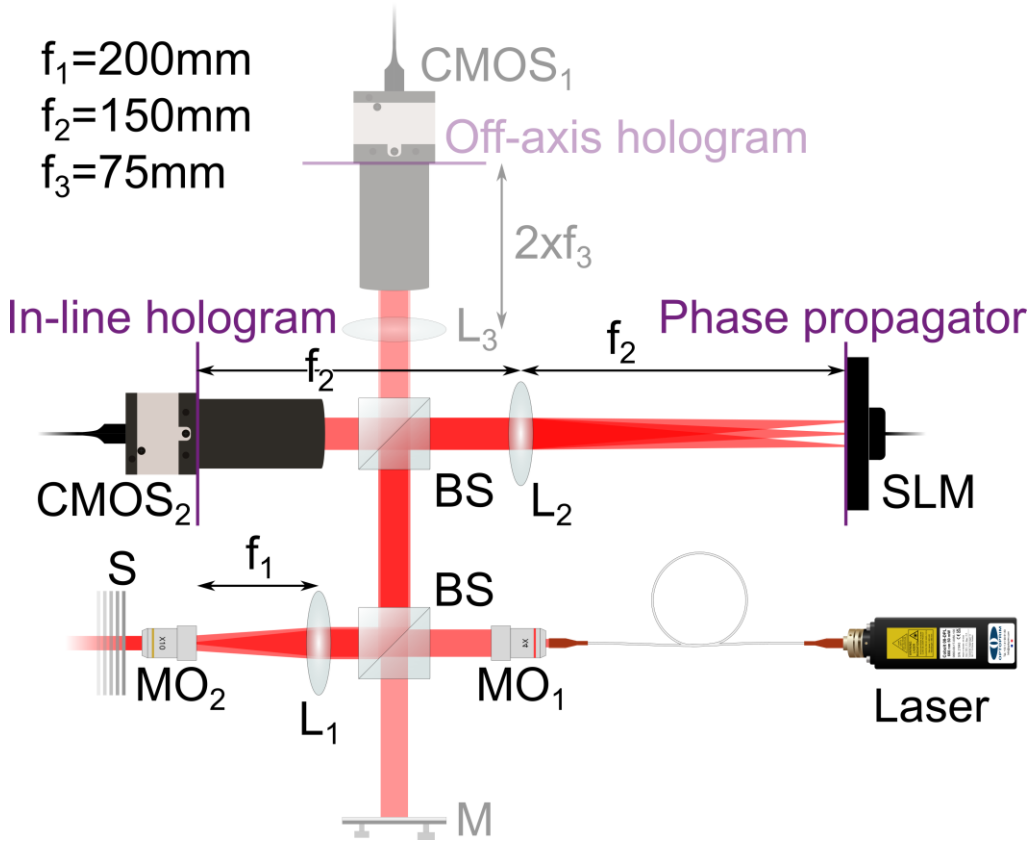


- Learning on a physical system
- Need a differentiable physical model

HYBRID NEURAL NETWORK FOR AUTOFOCUSING



AUTO-FOCUSING SETUP

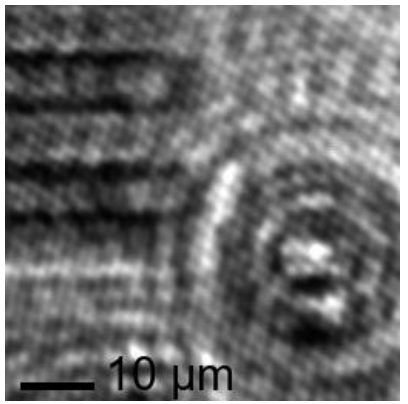


S: Sample
MO: Microscope objective
L: Lens
Laser (λ = 659,6nm, $\Delta\nu$(FWHM) < 1MHz)

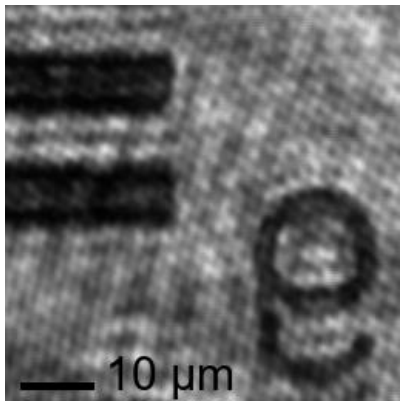
BS: Beam splitter 50:50
M: Mirror
CMOS: CMOS camera
SLM: Spatial light modulator.

In-line digital holographic microscopy

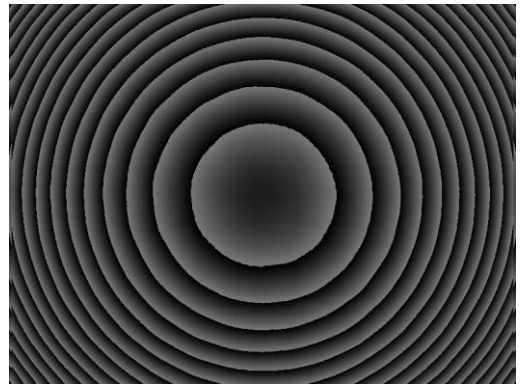
In-line hologram



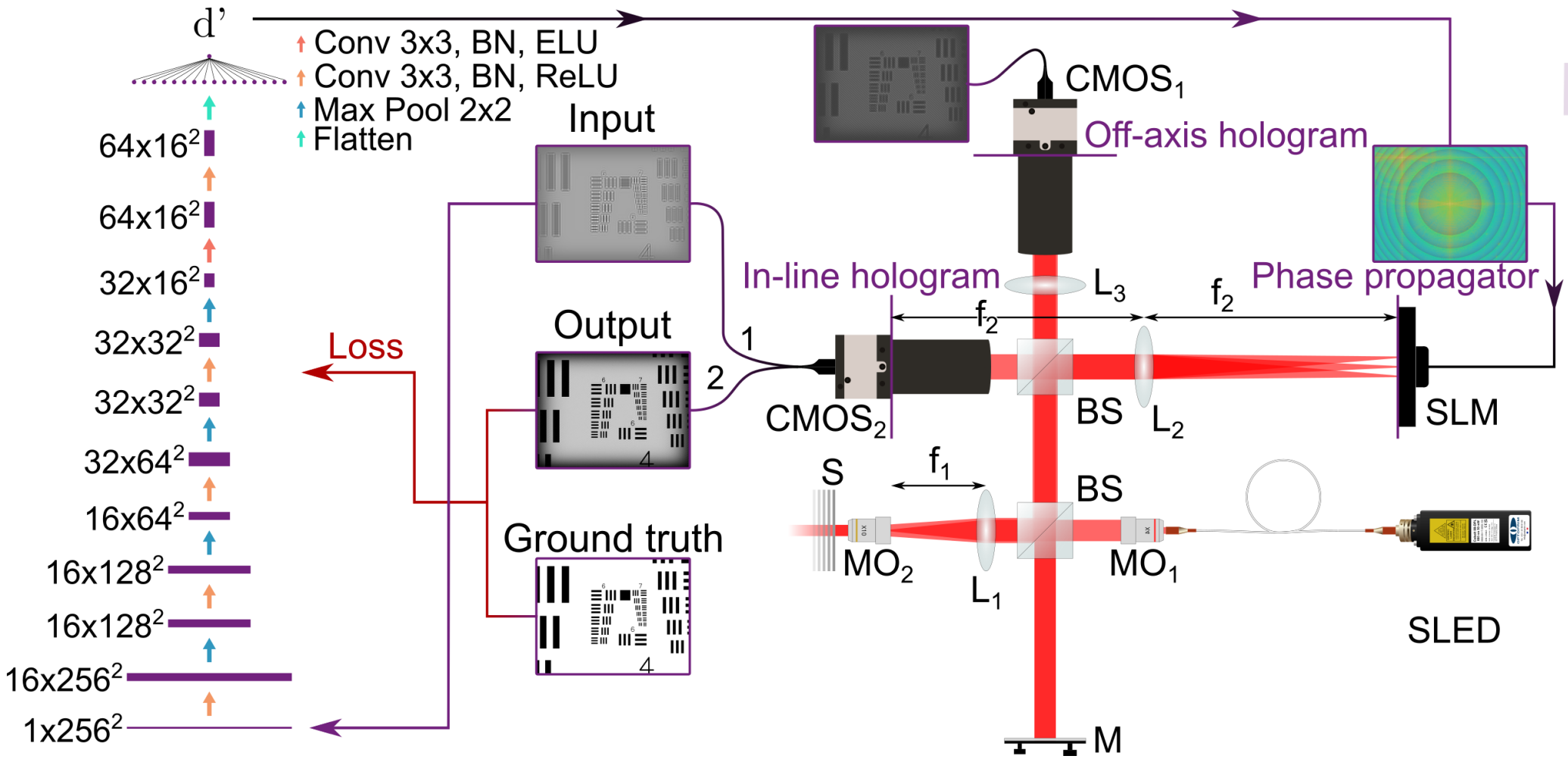
In-line hologram with auto-focusing



SLM: phase propagator over a range of 0 to 100 µm



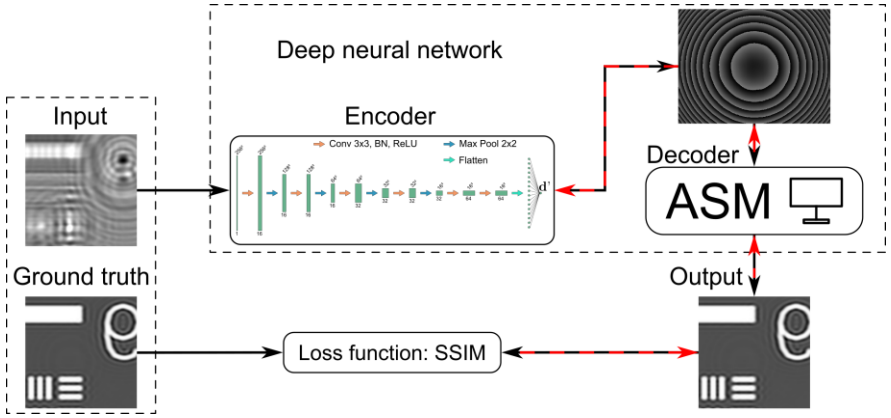
PHYSICS-ENHANCED NETWORK TRAINING OVERVIEW



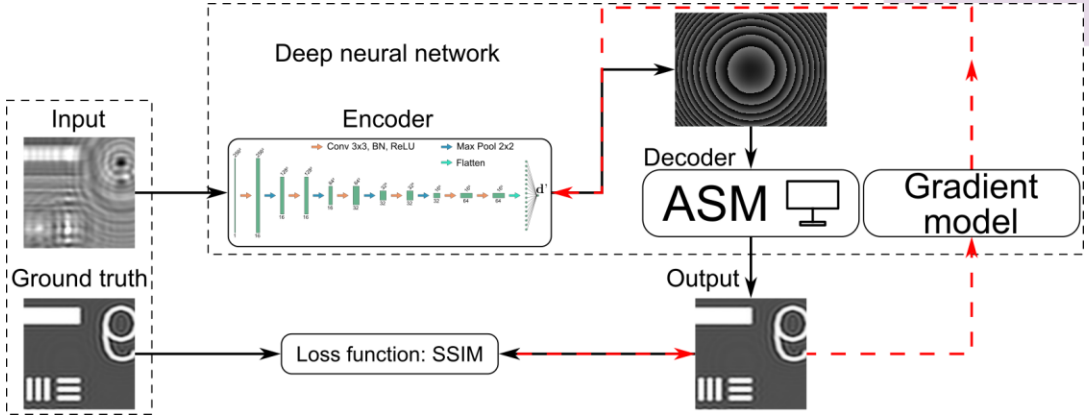
Reconstruction distance randomised over a range from 0 to 100 µm

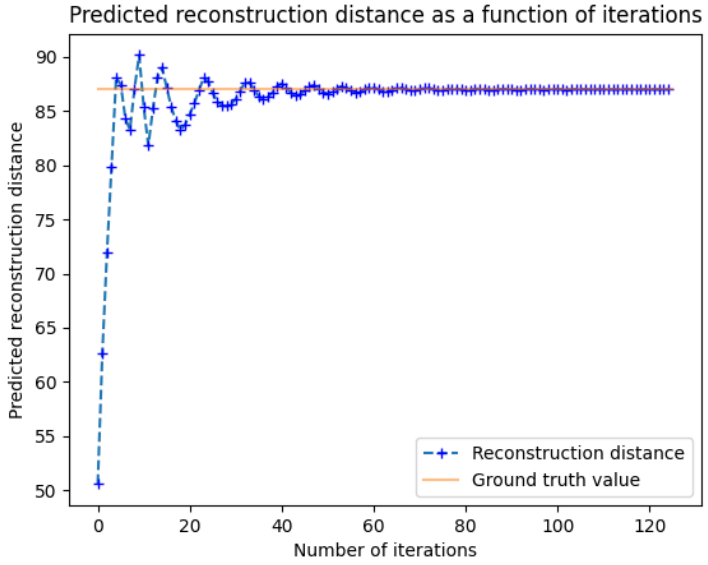
UNTRAINED NEURAL NETWORK TRAINING IN SIMULATION

Pytorch Autograd calculation



Physics-aware training

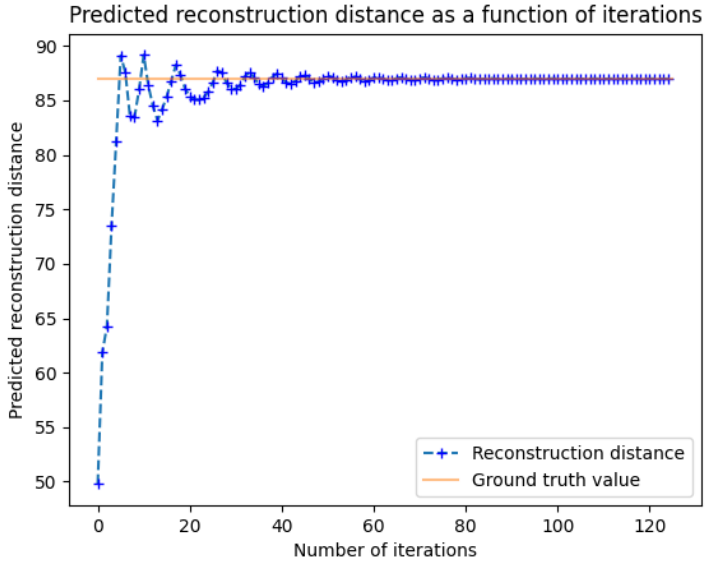




→ Forward path

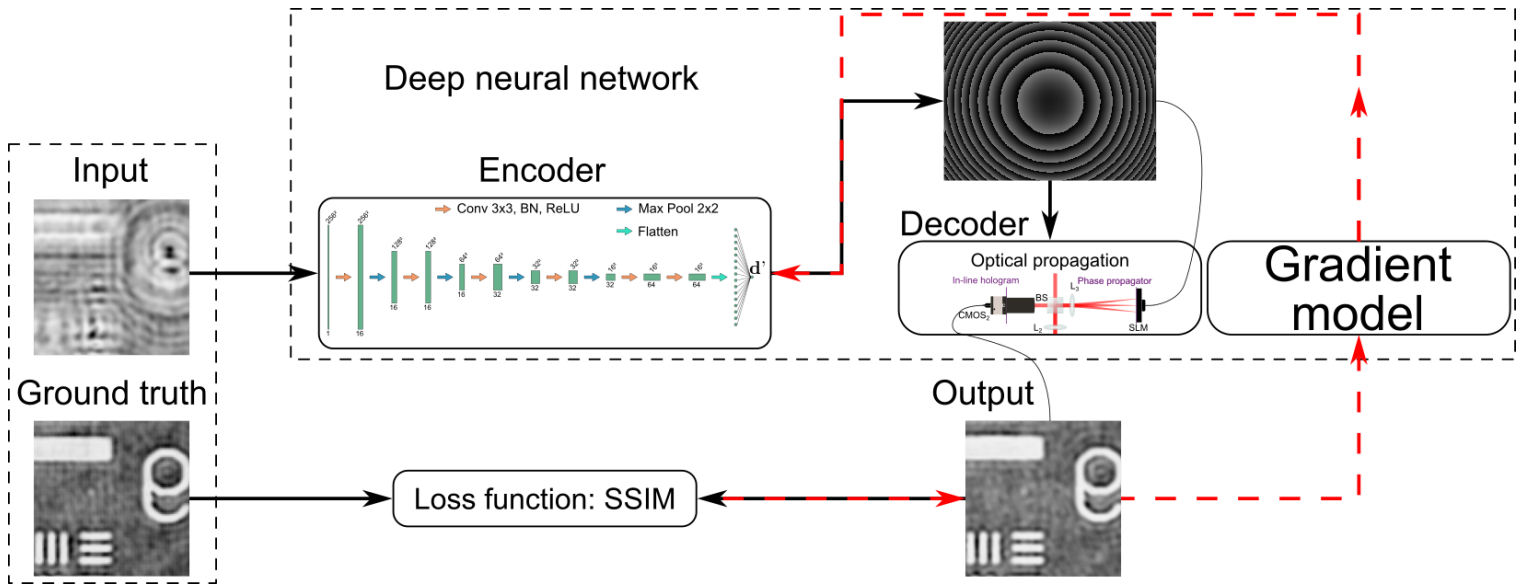
→ Gradient flow

- Untrained network (1 input hologram)
- Loss function: SSIM
- Reconstruction distance set at 87 µm
- Learning rate: 1,205e-3



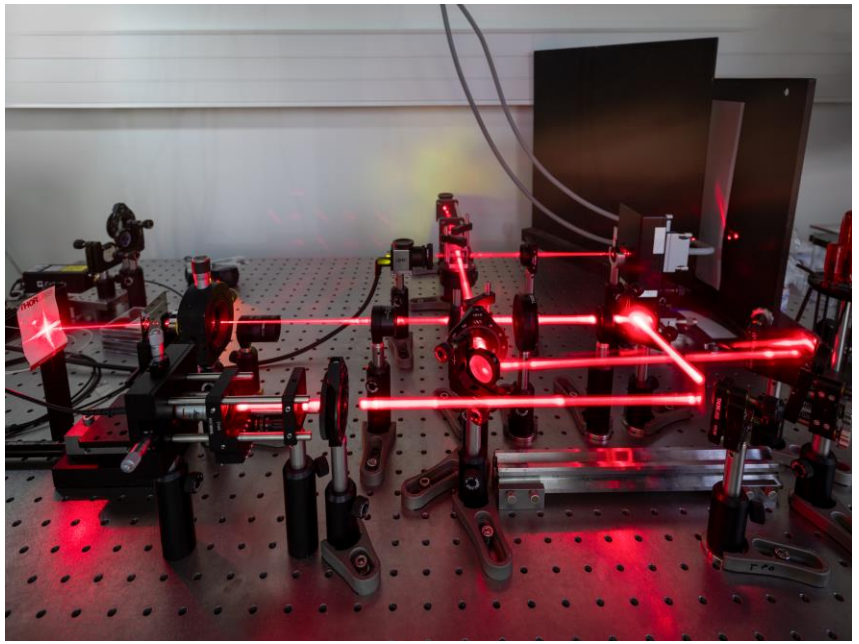
ASM: Angular spectrum method

UNTRAINED NEURAL NETWORK IN EXPERIMENT



Forward path

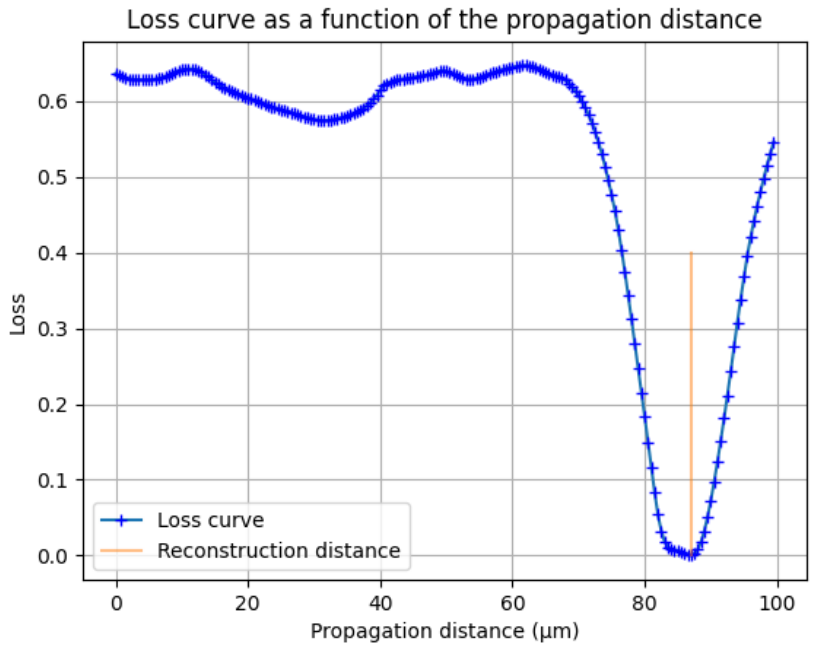
Gradient flow



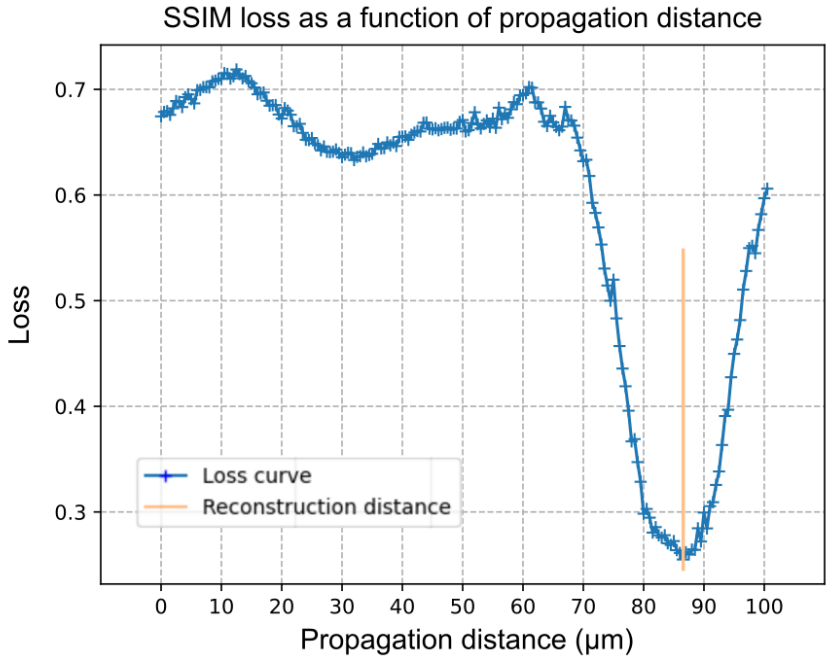
- Untrained network (1 input hologram)
- Averaging on 10 images.
- Learning rate: 1,205e-3
- Loss function: SSIM

LOSS FUNCTION SCANNING

Simulation with the DPM

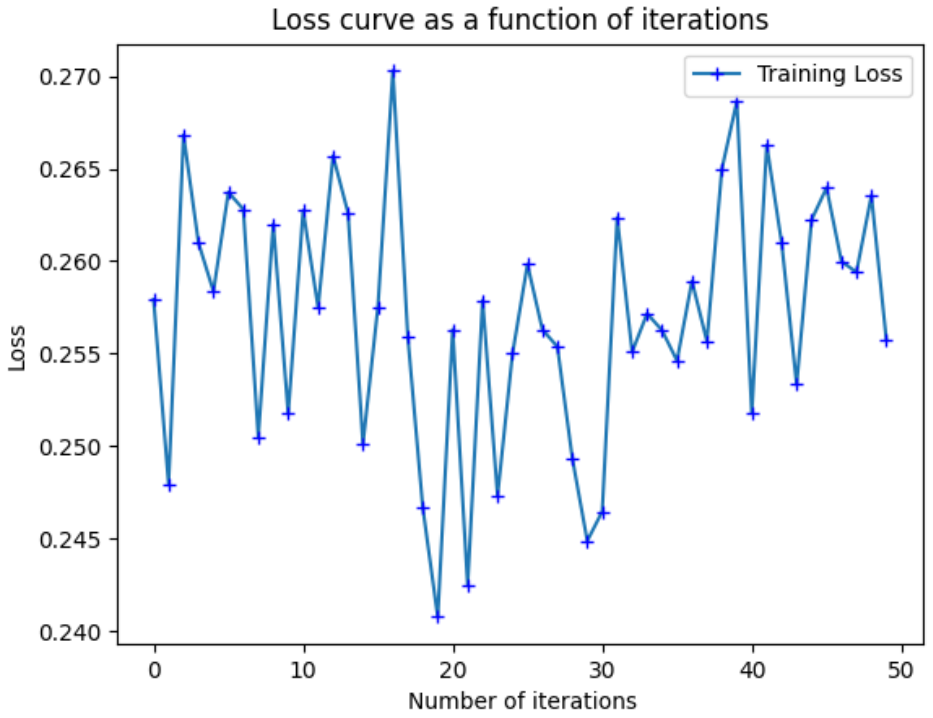


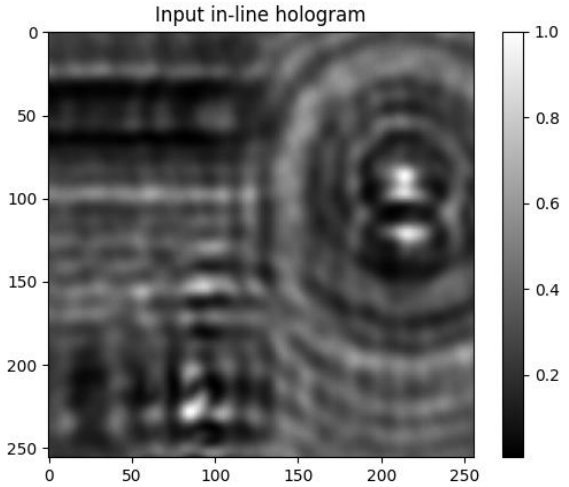
Experimental

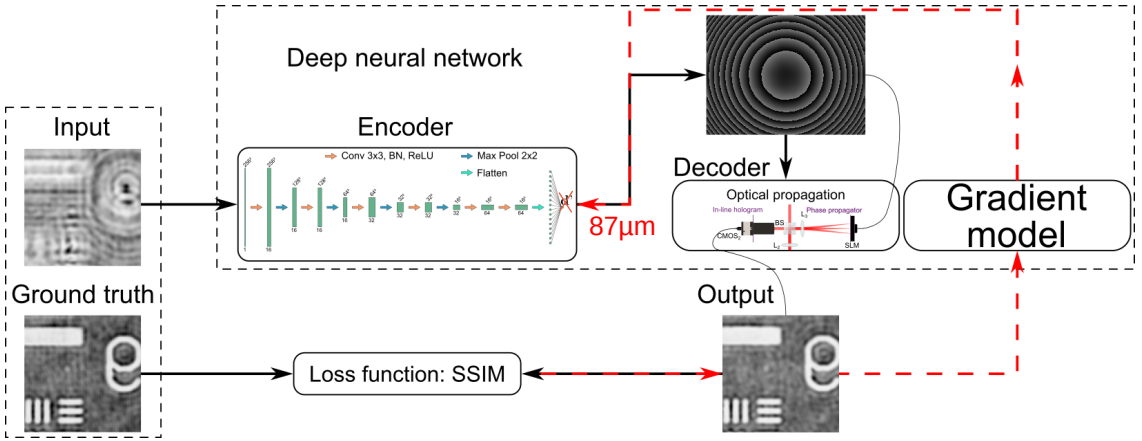


- Loss function : SSIM
- Ground truth reconstruction distance 87µm
- Similar behaviour
- Noise less in simulation

STABILITY OF THE NETWORKS

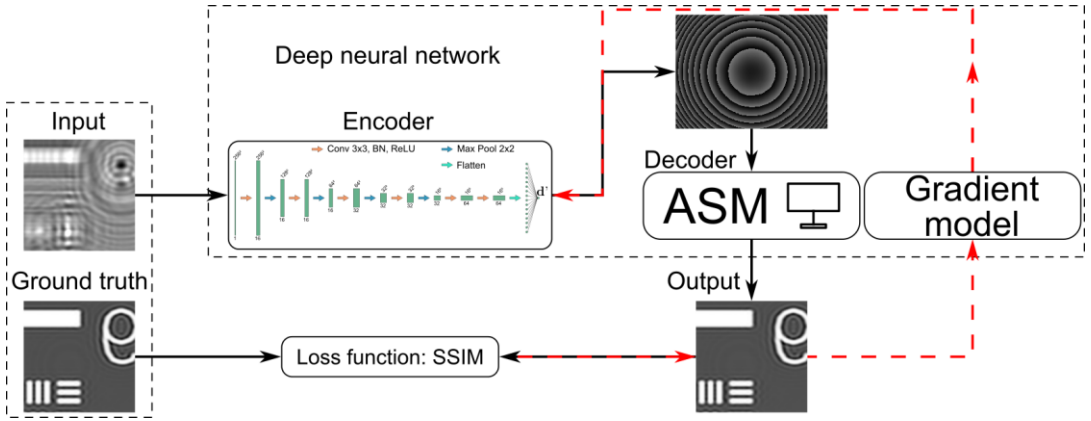


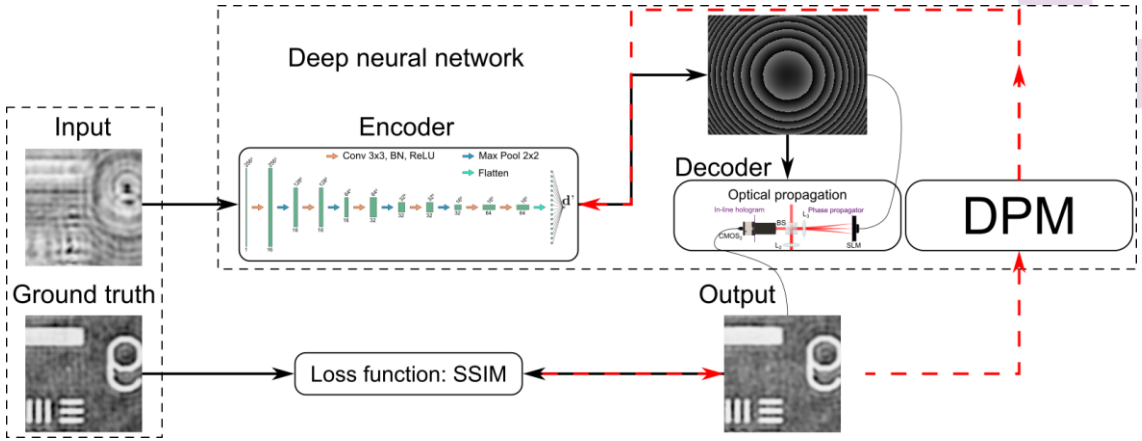


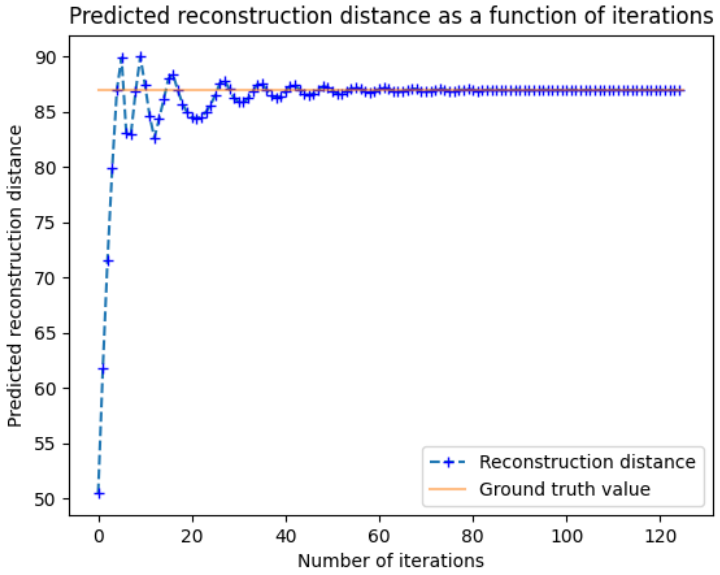


We set the propagation distance to 87 µm and then computed the loss over multiple iterations.

FIRST ATTEMPT, TRAINING ON PHYSICAL LAYER







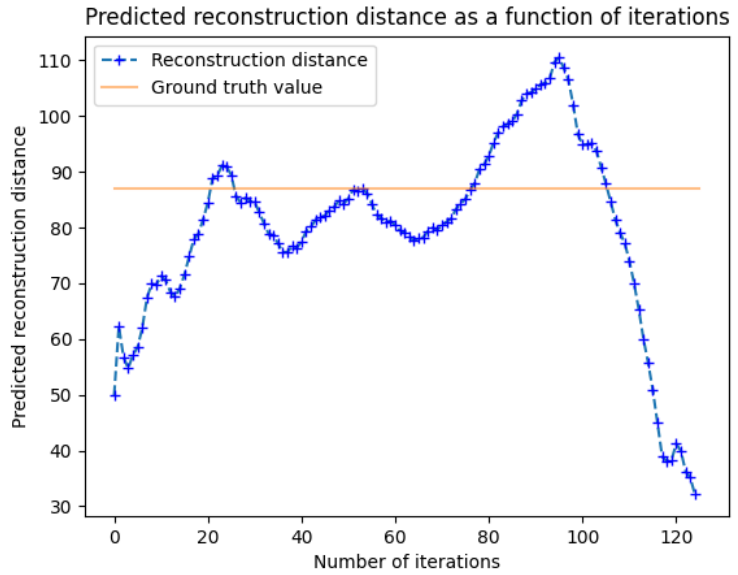
Forward path

Gradient flow

- Untrained network (1 input hologram)
- Loss function: SSIM + Total Variation
- Reconstruction distance set at 87 µm
- Learning rate: 1,205e-3

- The results still diverge using a learning rate much lower (~divided by 2)

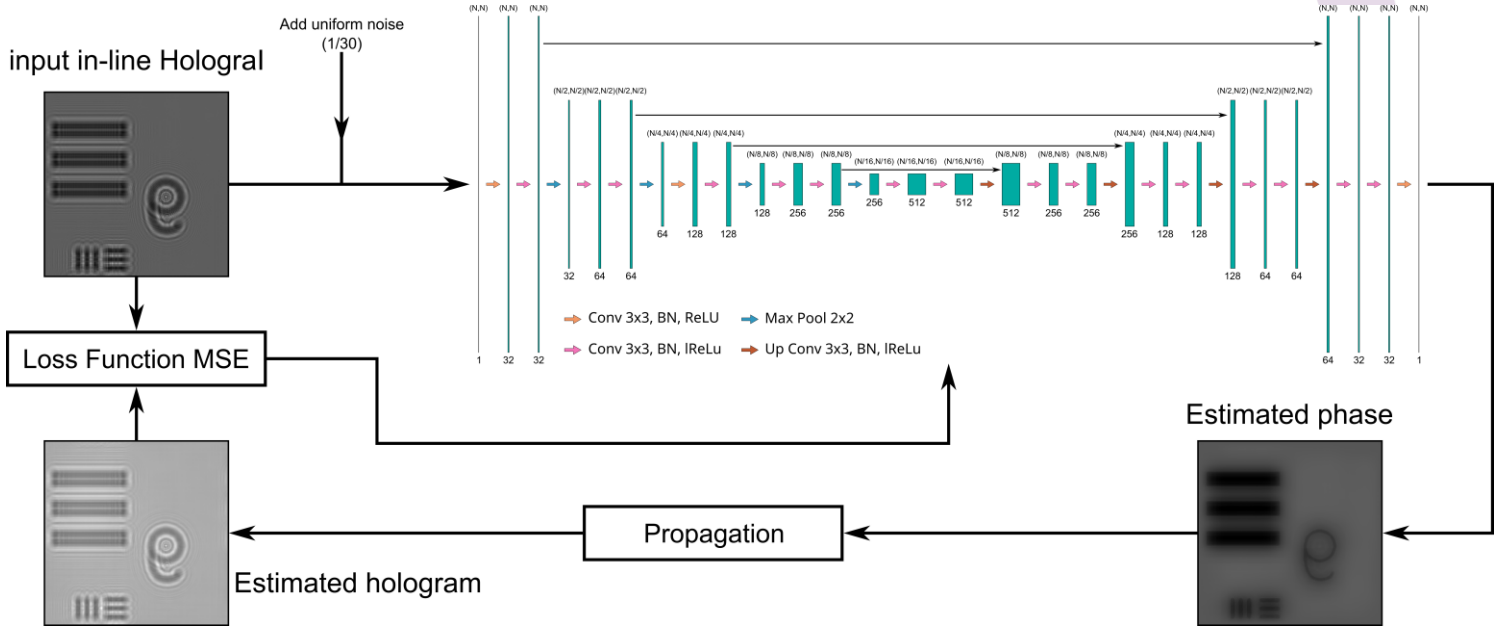
ASM: Angular spectrum method



PHASE PREDICTION BASE ON PHYSENNET ALGORITHM

Transforming our object at the macro scale
(Diffraction distance 22,3mm, λ= 632,8nm, camera pixel size 8µm)

Untrain network, only one input hologram
Learning rate : 0,05
Train on 10000 iteration



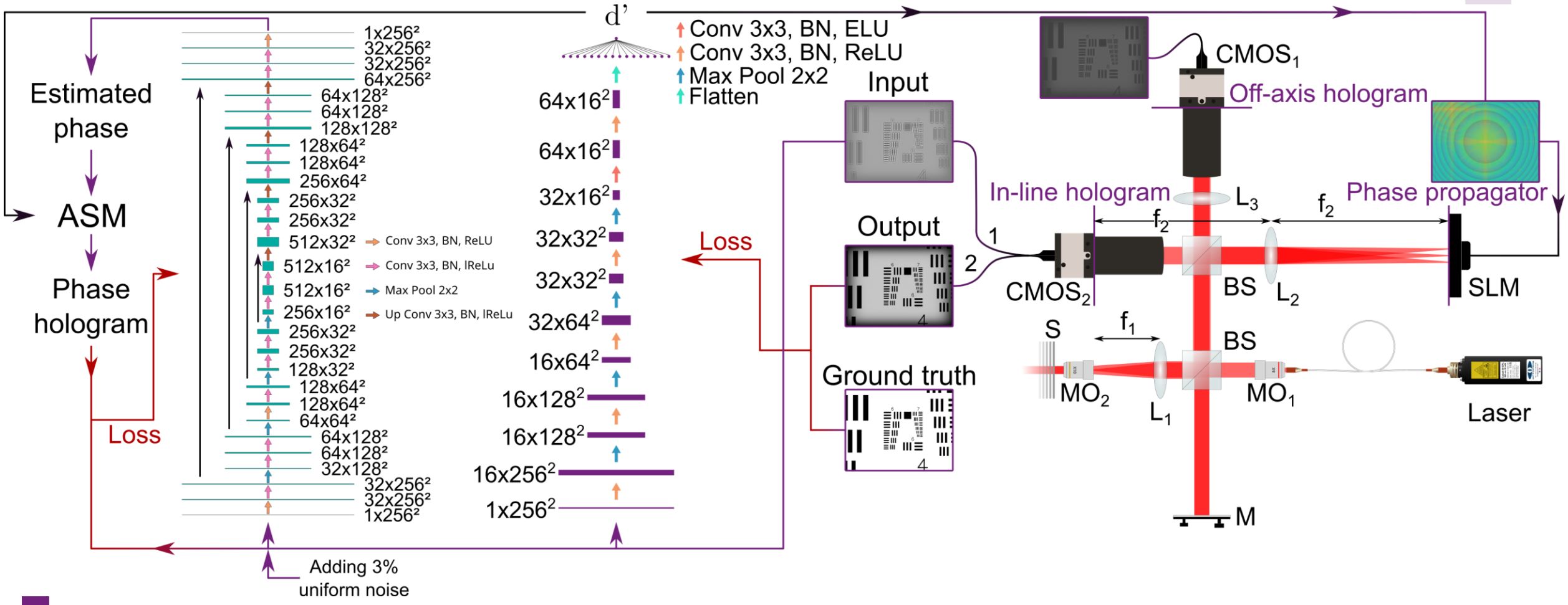
Comparison between the input and estimated hologram:

SSIM: 0,8312

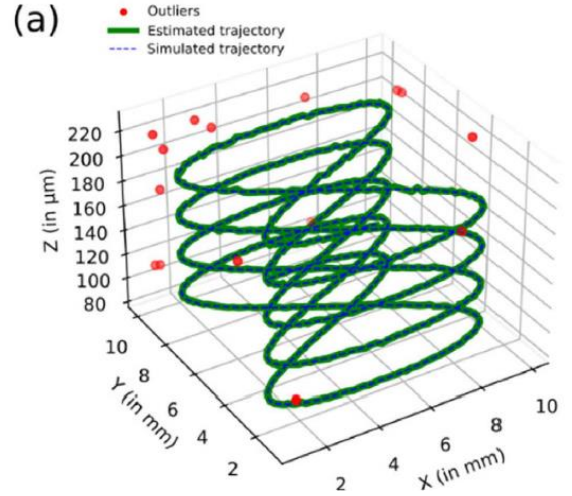
$$PSNR = 10 * \log_{10}\left(\frac{255^2}{mean\left((y0 - y)^2\right)}\right) = 22{,}06$$

The phase jump in phase estimation is not fixed, varying between 0,45π and 0,78π. (GT: π/2).

OVERVIEW OF THE NETWORK WITH THE AUTOFOCUSING AND PHASE PREDICTION



CONCLUSION AND FUTURE WORK



Cuenat, S., *et al.* Journal of the European Optical Society-Rapid Publications, 20(2), 31. (2024)

- Autofocusing preliminary experimental results
  - The simulation and the experiment have a close behaviour, but we didn't achieve a training in experiment.
- The difference between simulation and experiment:
  - we didn't add noise in the simulation
  - we didn't have to deal with physical parameters (exposure time of the cameras)

- A multi-modal approach to the network for parallel auto-focusing, phase image reconstruction, aberration correction, and 3D position (tilt, positioning, etc.).

Thanks you for your attention