PHYSICS-DRIVEN LEARNING THROUGH DEEP DIGITAL HOLOGRAPHIC MICROSCOPY

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F-25000 Besancon, France



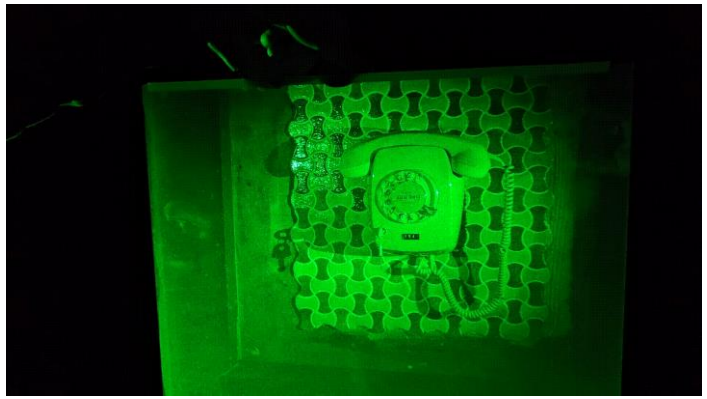
HOLO-CONTROL project

TABLE OF CONTENTS

- Holography overview
- State-of-the-art
- Context
- Methods and preliminary results
- Conclusion

HOLOGRAPHY OVERVIEW

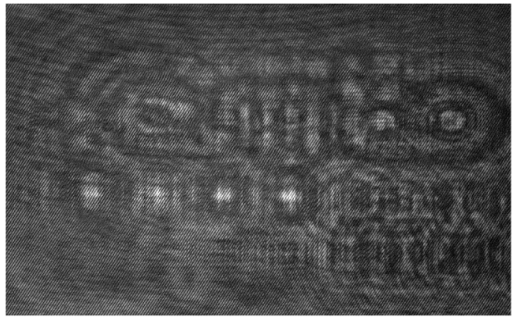
Holography in the 80s:

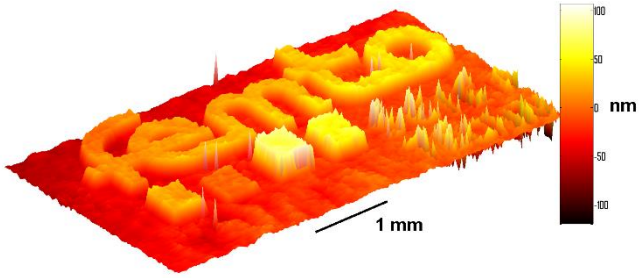


Recorded in the optical laboratory of Besançon (LOBE)/FEMTO-ST

Digital holography in the 2000s:

Numerical reconstruction

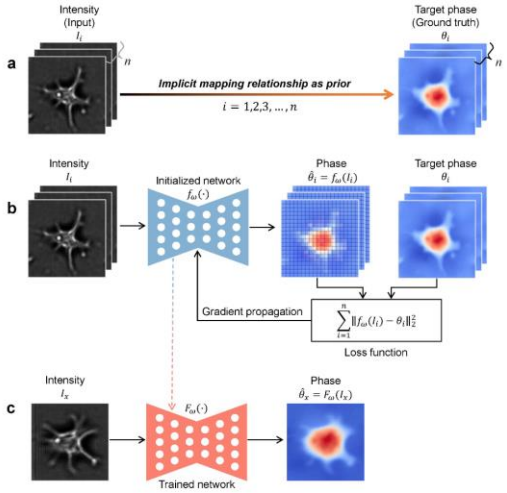




Jacquot, M., *et al.*, *Optics communications*, *190*(1-6), 87-94 (2001)

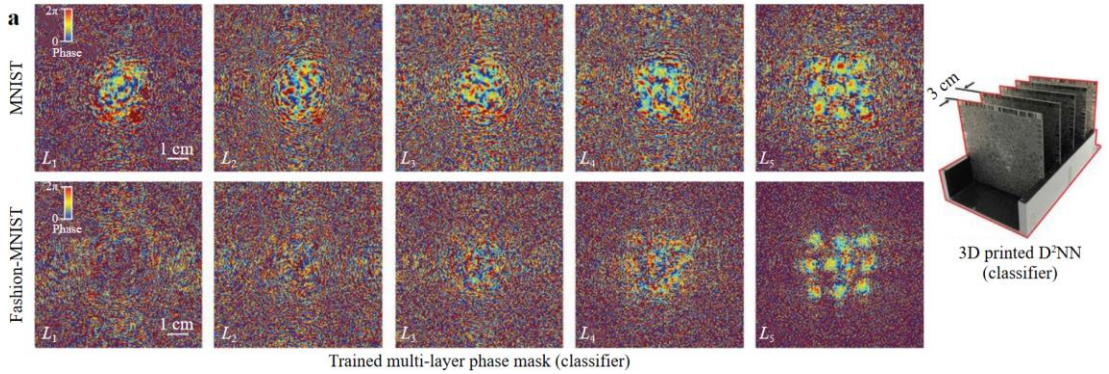
Holography nowadays:

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)

STATE-OF-THE-ART

Wang et al. *Light: Science & Applications* (2020)9:77
https://doi.org/10.1038/s41377-020-0302-3

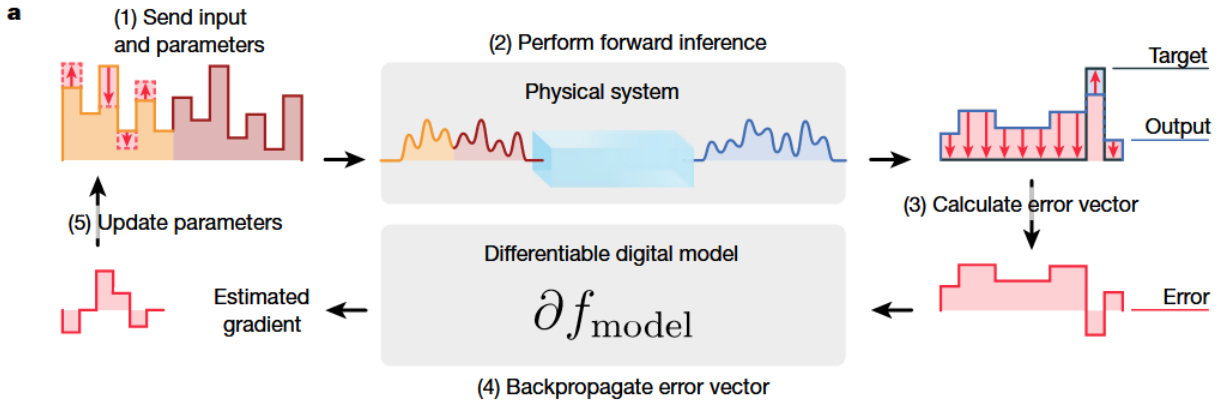
Official journal of the CIOMP 2047-7538
www.nature.com/lsa

Article

Deep physical neural networks trained with backpropagation

https://doi.org/10.1038/s41586-021-04223-6
Received: 19 May 2021
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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]

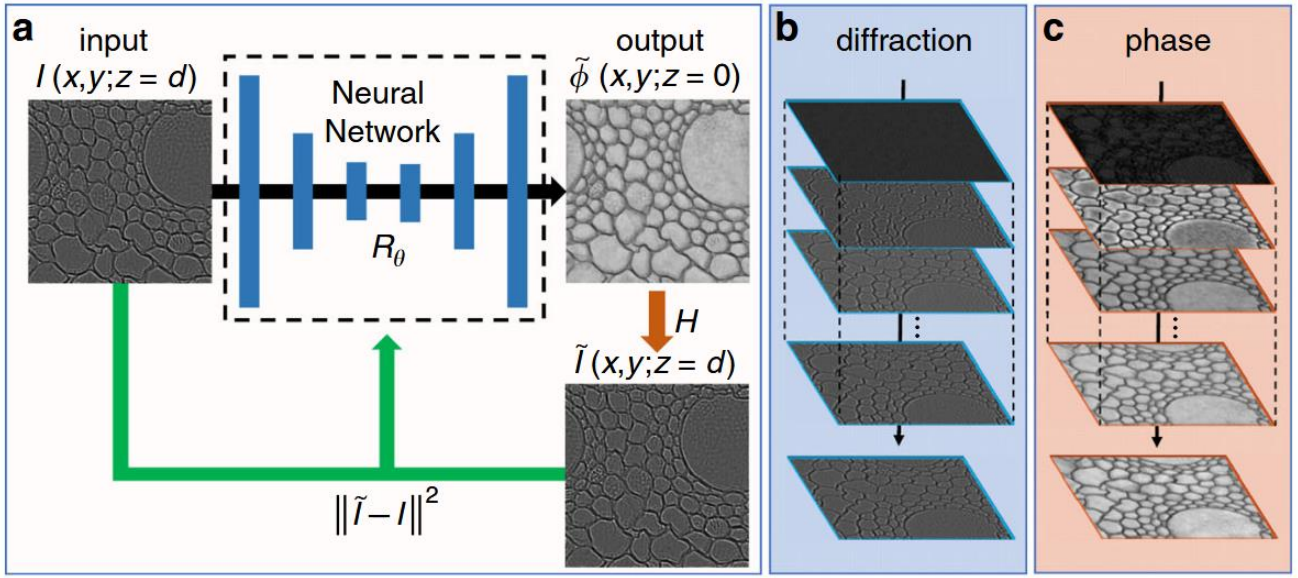


- Learning on a physical system
- Need a differentiable digital model

LETTER Open Access

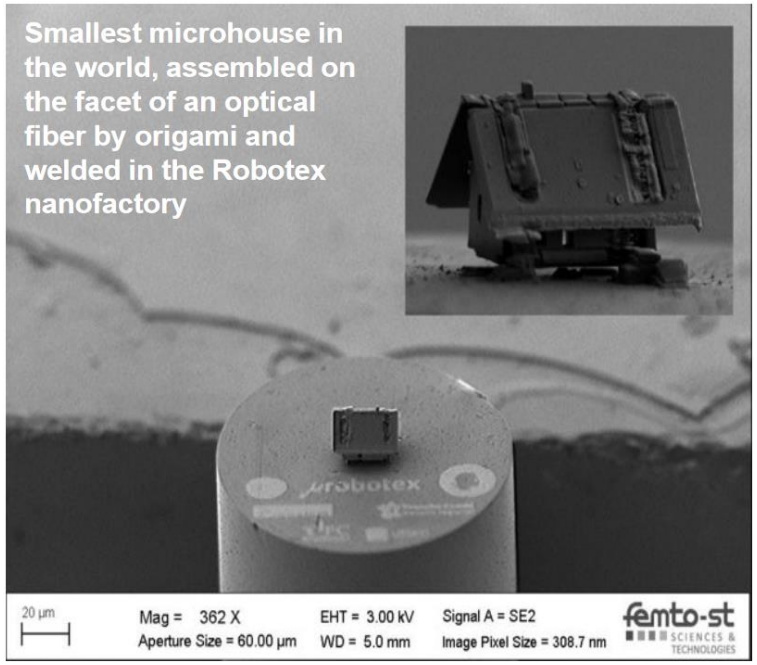
Phase imaging with an untrained neural network

Fei Wang[1,2], Yaoming Bian[1,2], Haichao Wang[1,2], Meng Lyu[1,2], Giancarlo Pedrini[3], Wolfgang Osten[3], George Barbastathis[4] and Guohai Situ[1,2,5]



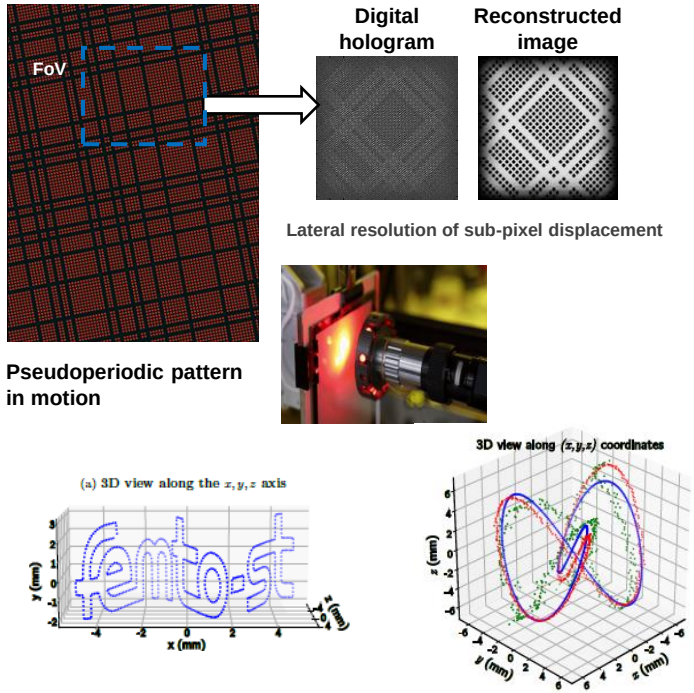
- Phase retrieval based on physics-driven learning
- Training without ground truth

CONTEXT



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

3D computer micro-vision

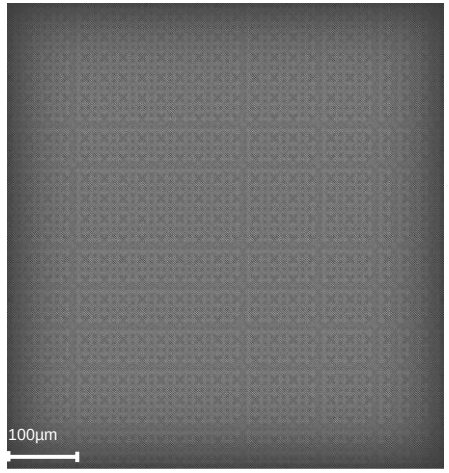


André, A. N., *et al.*, International Journal of Computer Vision, 1-17, (2022)

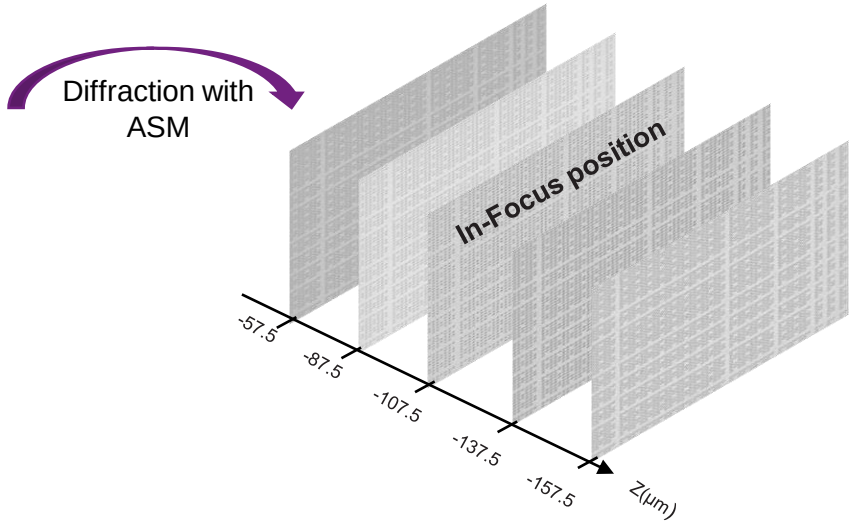
CLASSICAL AUTOFOCUSING BY USING DIGITAL HOLOGRAPHY

But… computation time request & focusing distance?

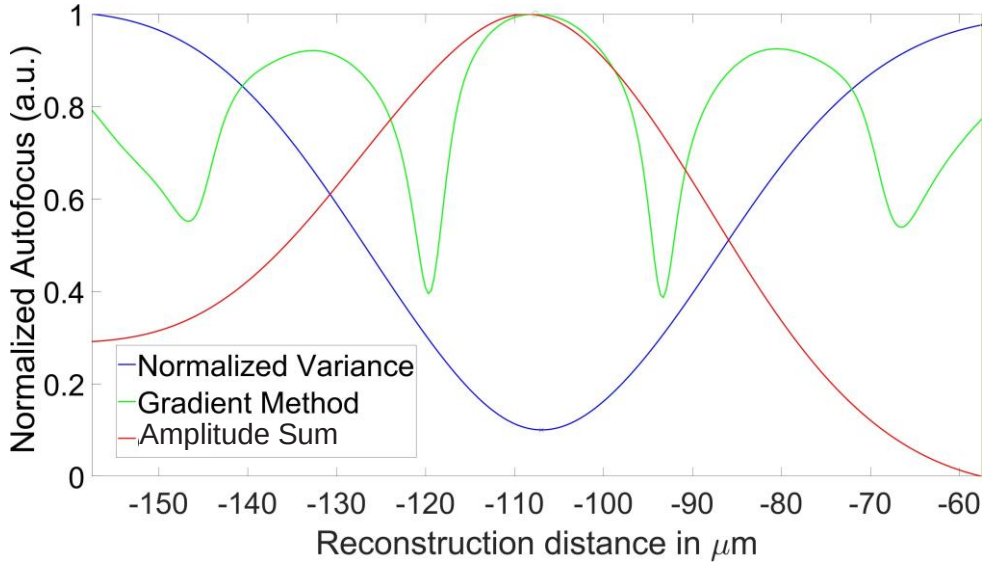
- Reconstruction in each plane
- A single reconstruction → multi-plane propagation with Angular Spectrum Method (ASM)
- Need a focusing metrics (Amplitude sum, Normalized variance, Gradient method…) (minutes scale)



Simulated Digital Hologram



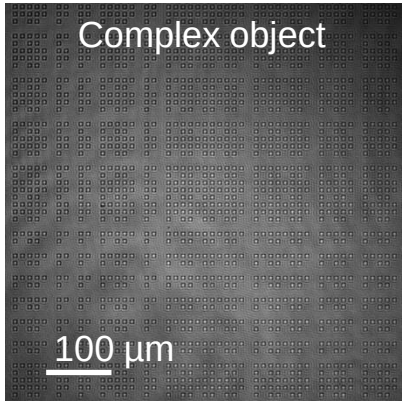
In-focus distance reconstruction

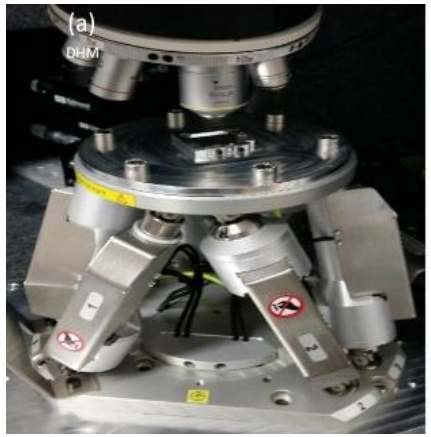


Autofocusing Methods

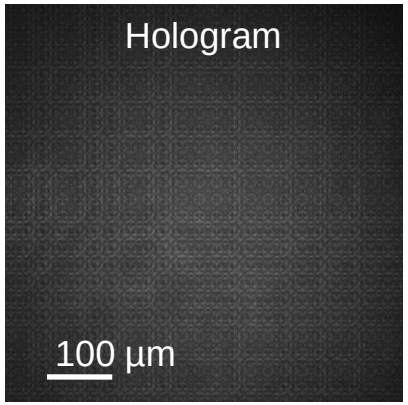
Cuenat, S., et al., Optics Express, 30(14), (2022)

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

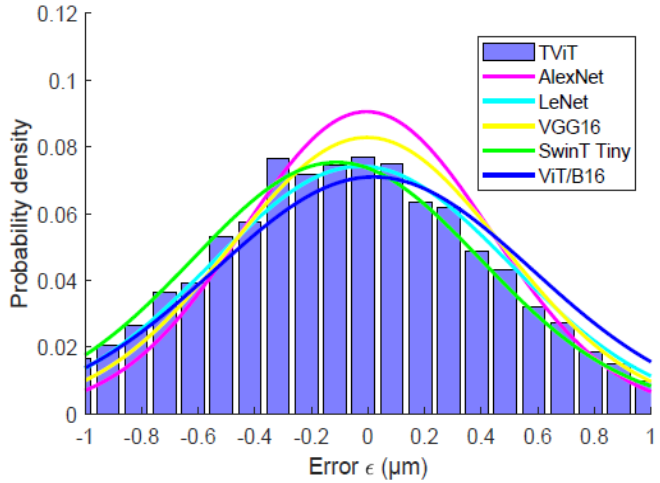
Inference on the CPU

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

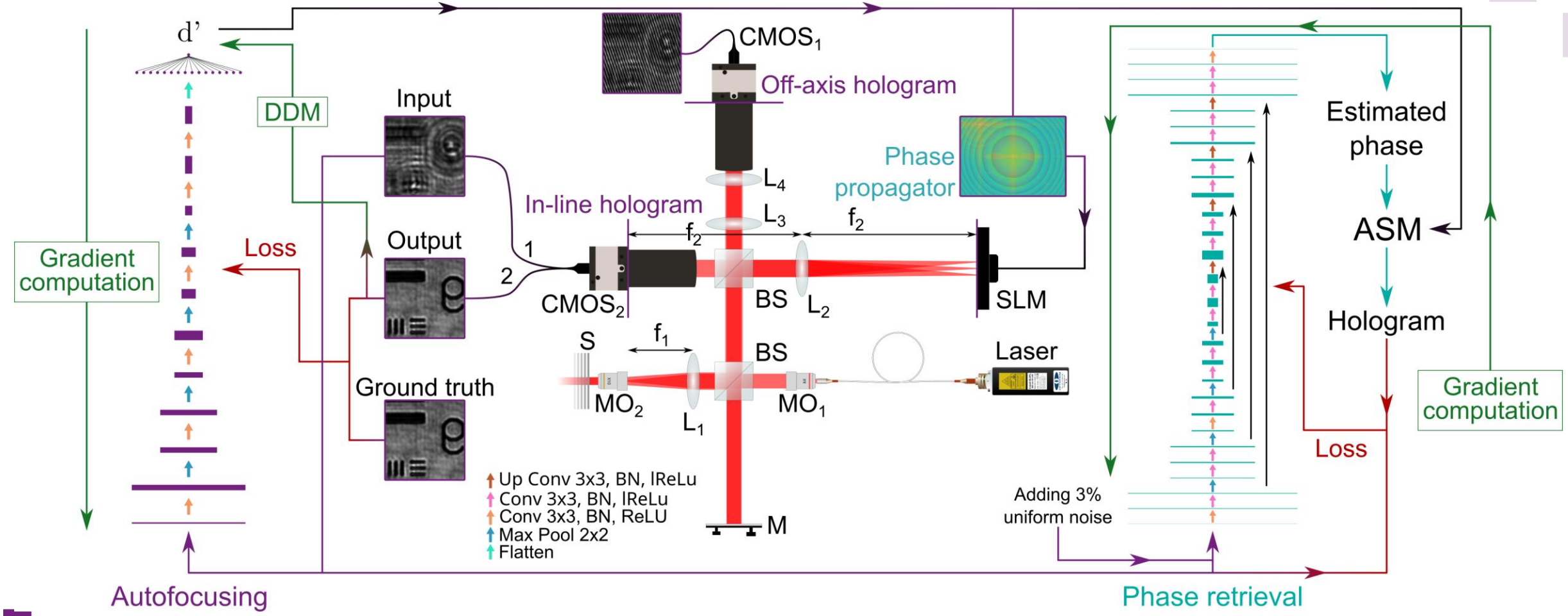


Test: 4,040 holograms

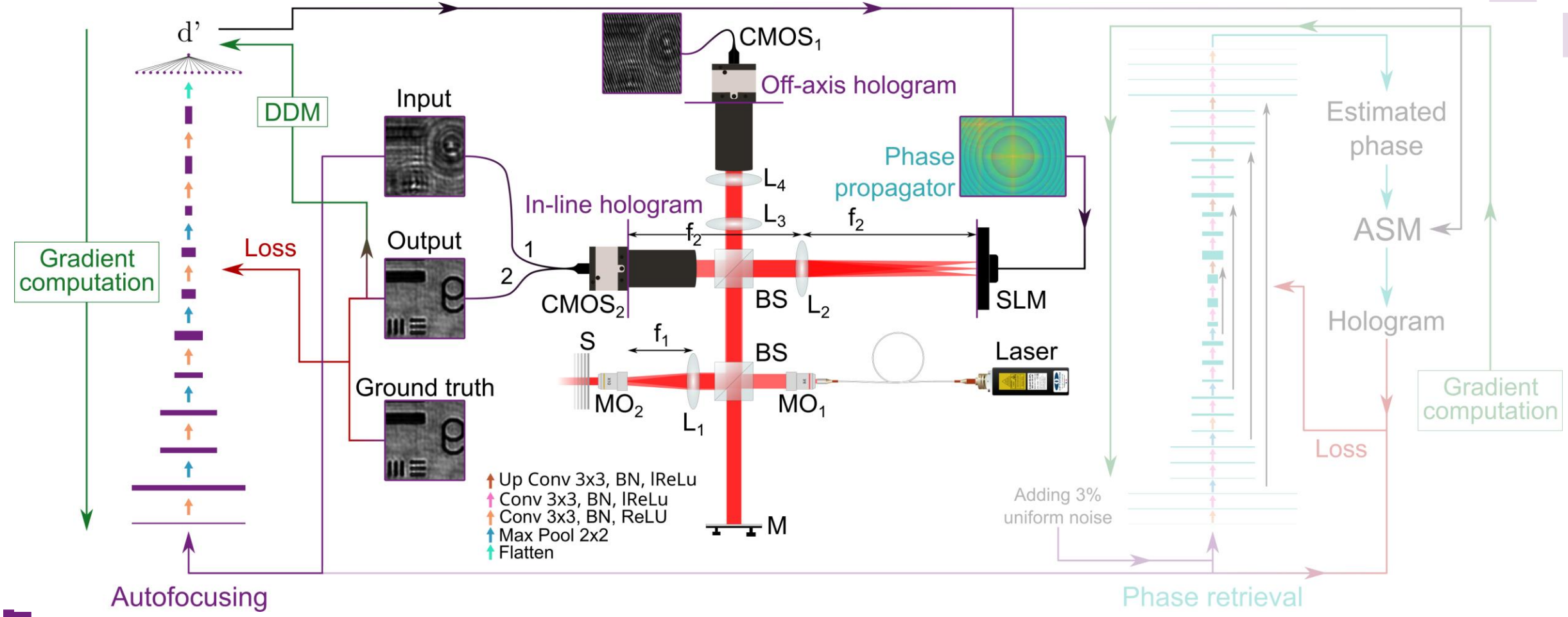
Typical focusing error: 1 µm over a range of 92 µm

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

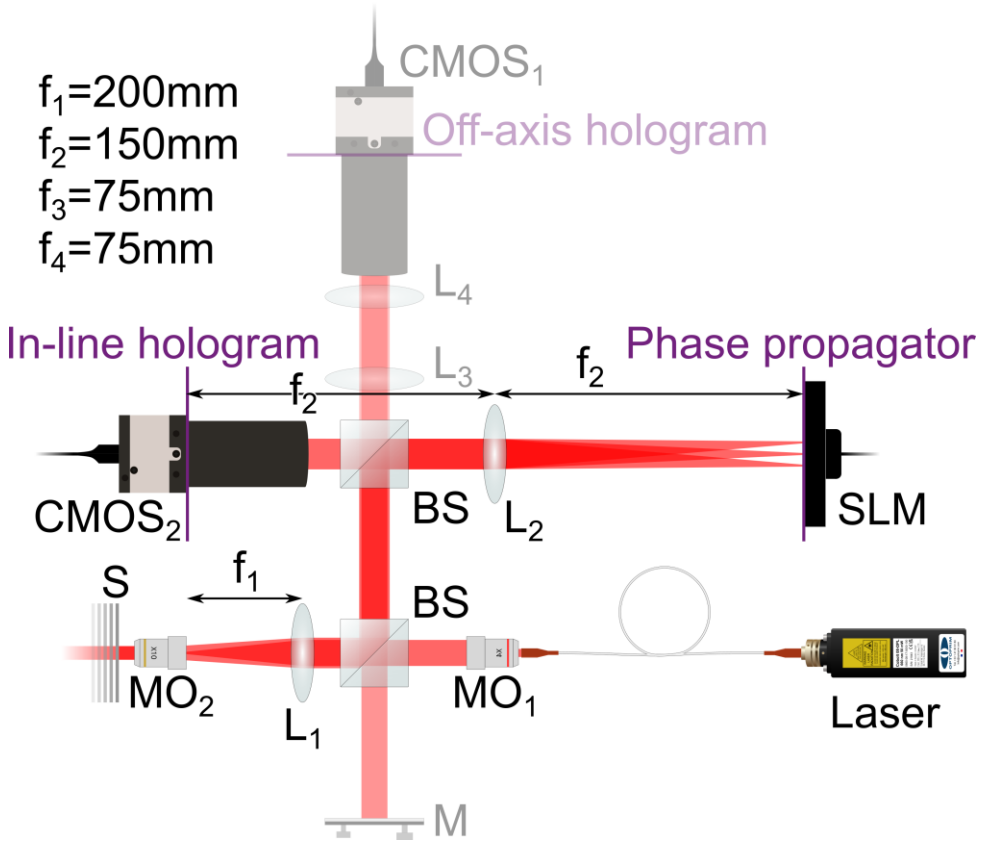
OVERVIEW OF THE NETWORK WITH THE AUTOFOCUSING AND PHASE RETRIEVAL



OVERVIEW OF THE NETWORK FOR THE AUTOFOCUSING



AUTO-FOCUSING SETUP

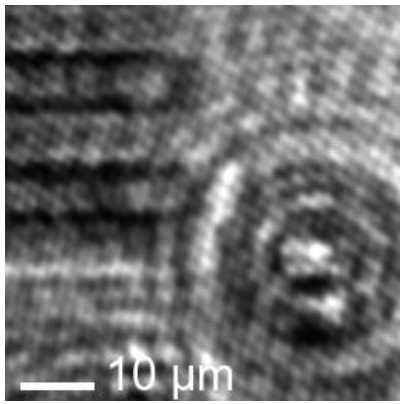


S: Sample
MO: Microscope objective
L: Lens
Laser (λ = 659,6nm, $\Delta\nu$(FWHM) < 1MHz)

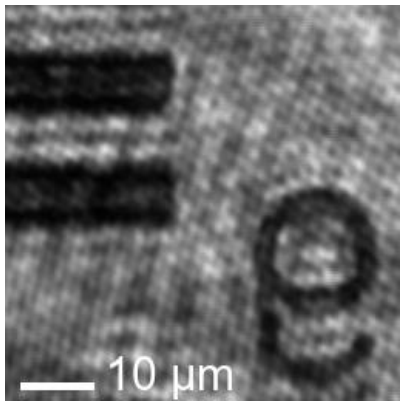
BS: Beam splitter 50:50
M: Mirror
CMOS: CMOS camera
SLM: Spatial light modulator.

In-line digital holographic microscopy

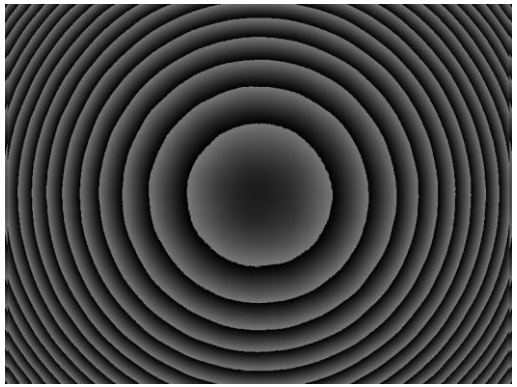
In-line hologram



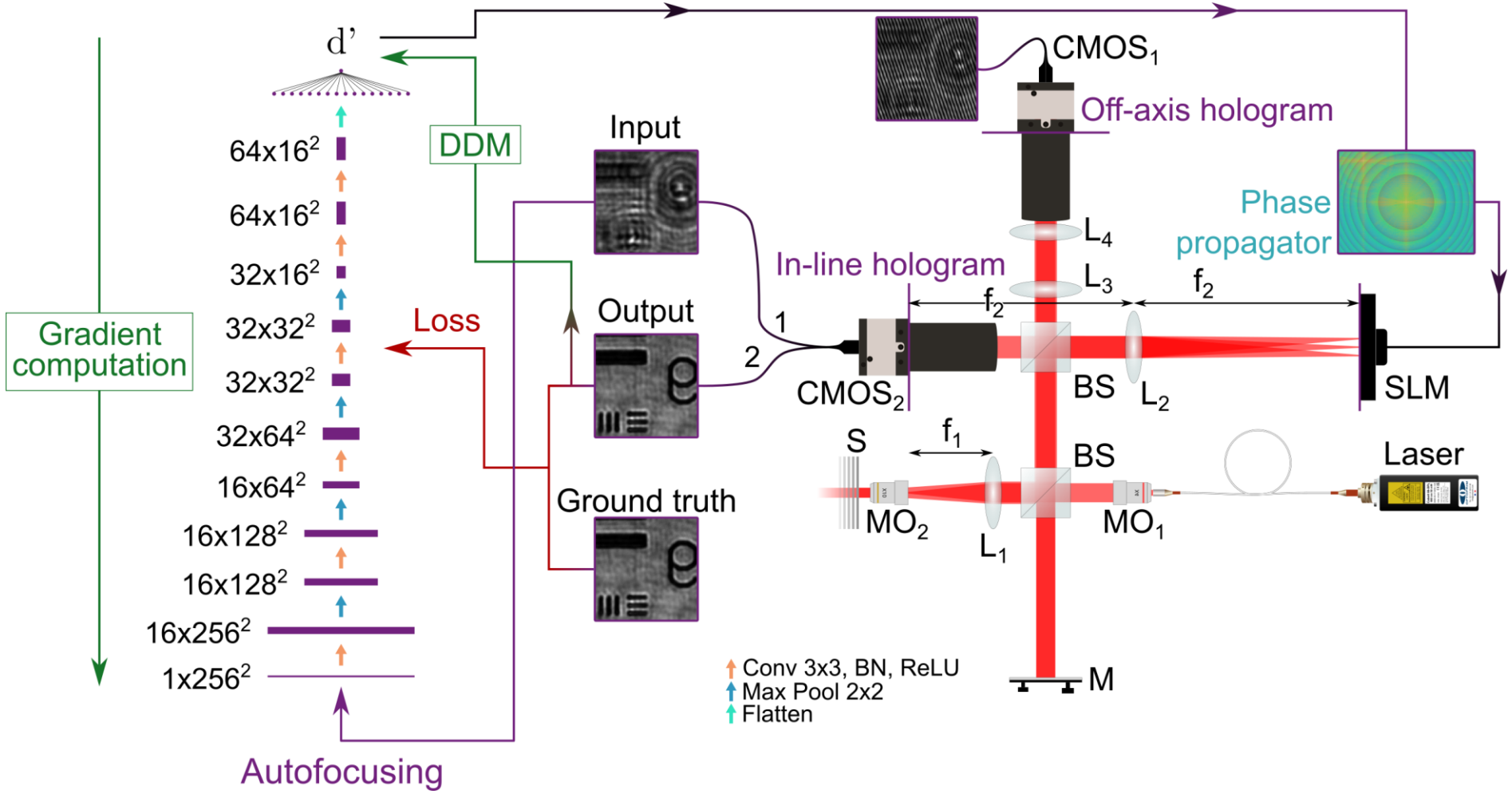
In-line hologram with auto-focusing



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



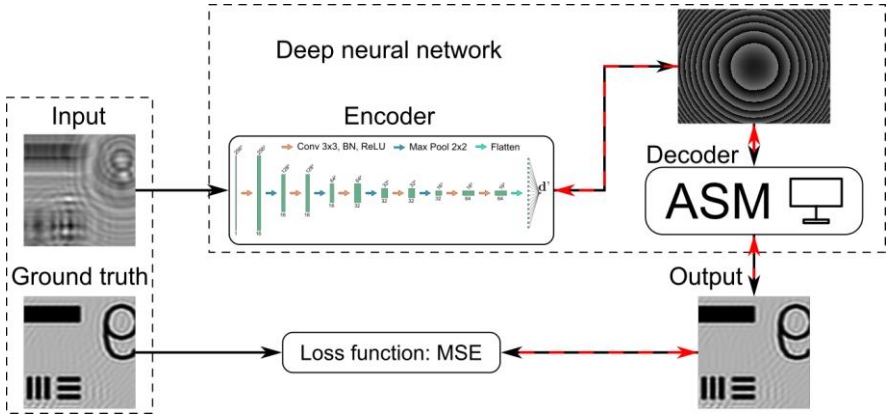
PHYSICS-ENHANCED NETWORK TRAINING OVERVIEW



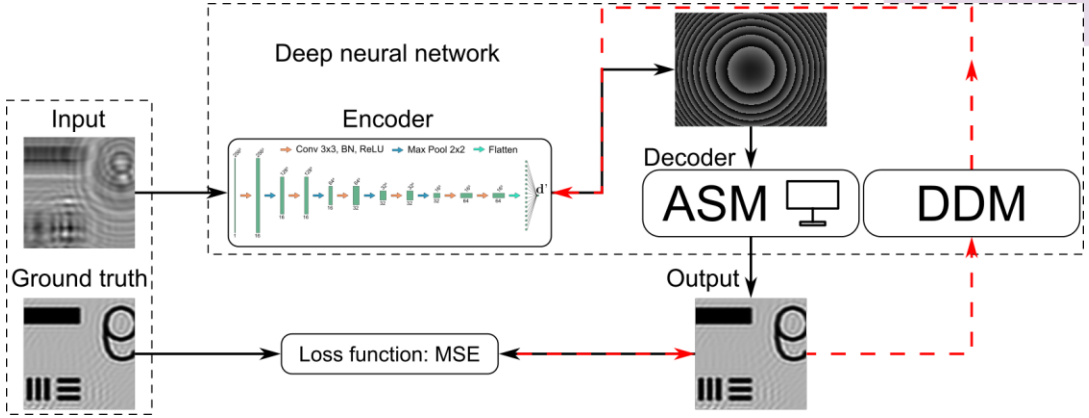
Reconstruction distance randomised over a range from 0 to 100 µm

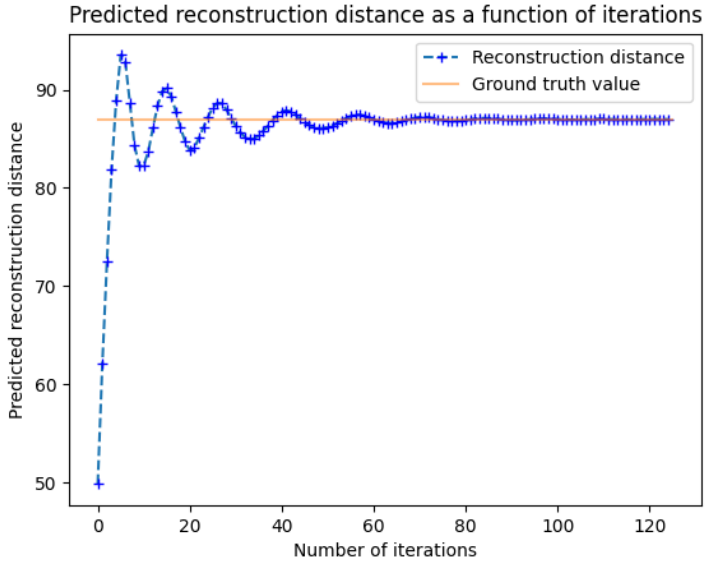
UNTRAINED NEURAL NETWORK TRAINING IN SIMULATION

Pytorch Autograd calculation



Physics-aware training



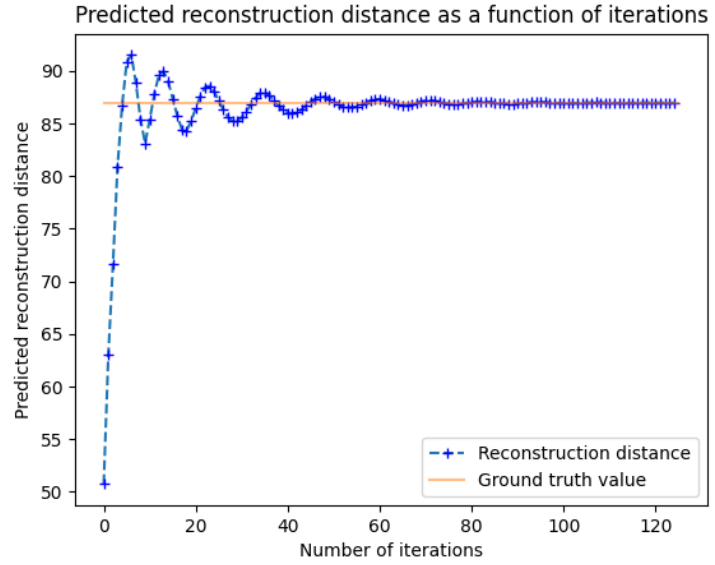


Forward path

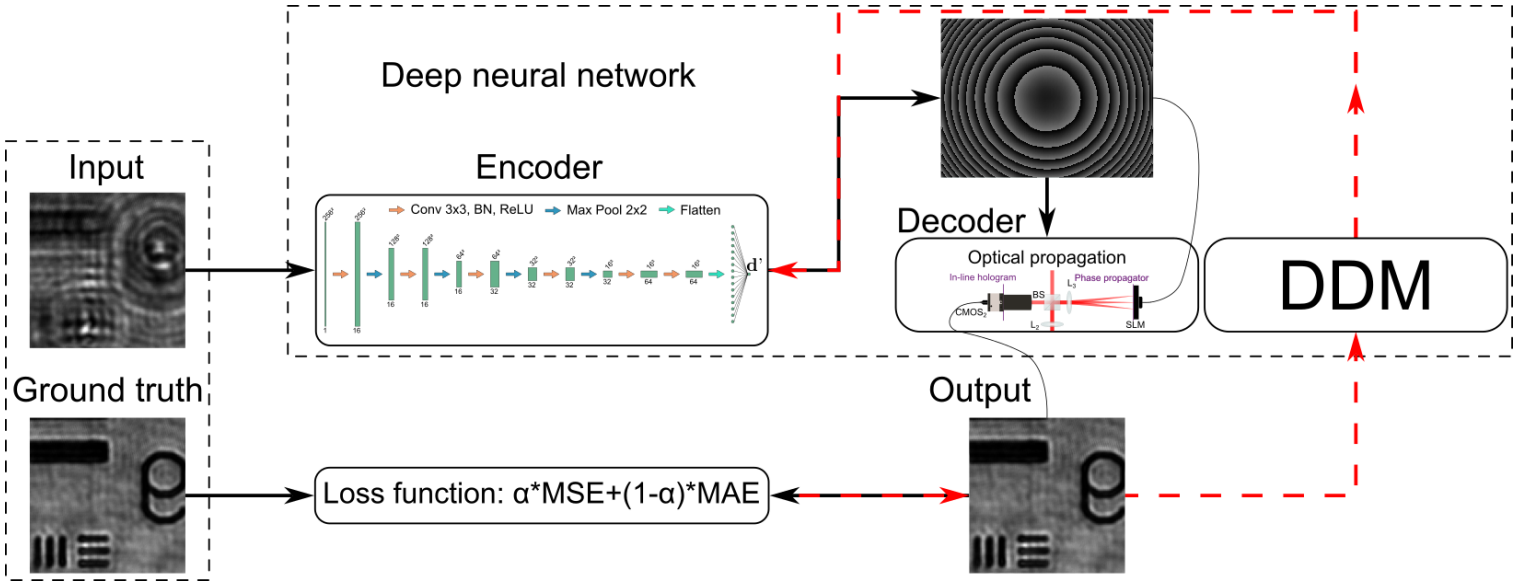
Gradient flow

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

ASM: Angular spectrum method
DDM: Differentiable digital model



UNTRAINED NEURAL NETWORK IN EXPERIMENT

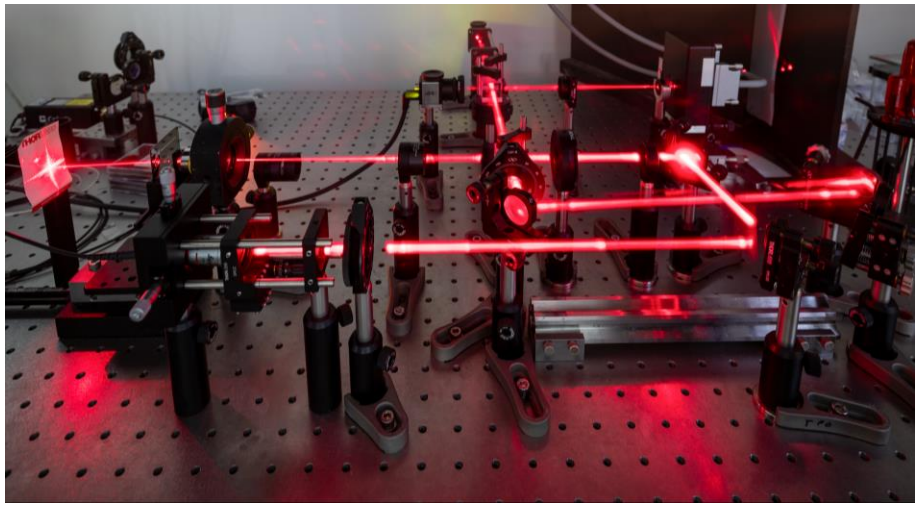


Forward path

Gradient flow

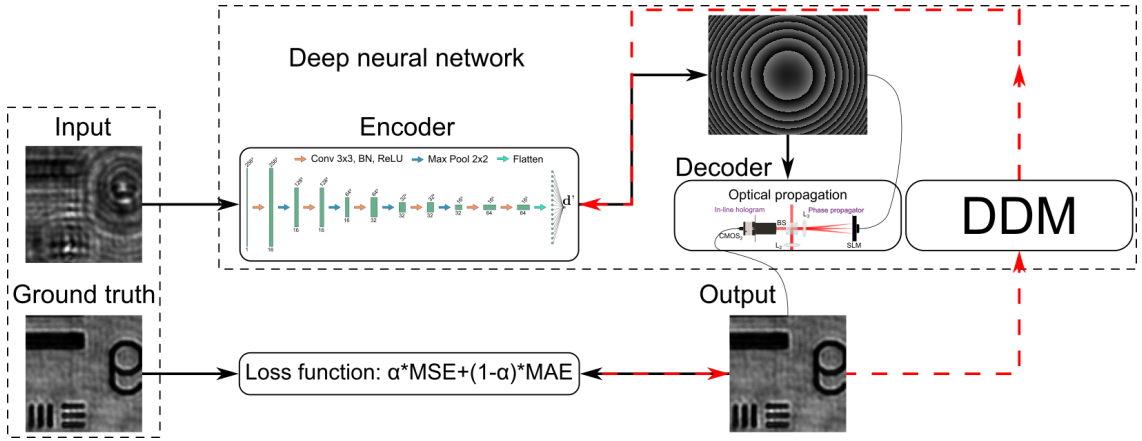
DDM: Differentiable digital model

Experimental setup



- Untrained network (1 input hologram)
- Averaging on 10 images.
- Learning rate: 1,205e-3
- Loss function: $\alpha \times \mathrm{MSE} + (1-\alpha) \times \mathrm{MAE}$

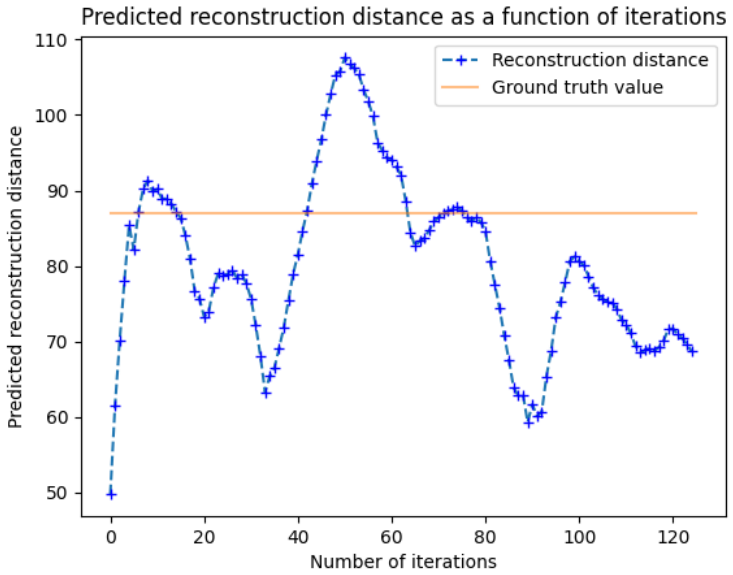
FIRST ATTEMPT, TRAINING ON PHYSICAL LAYER

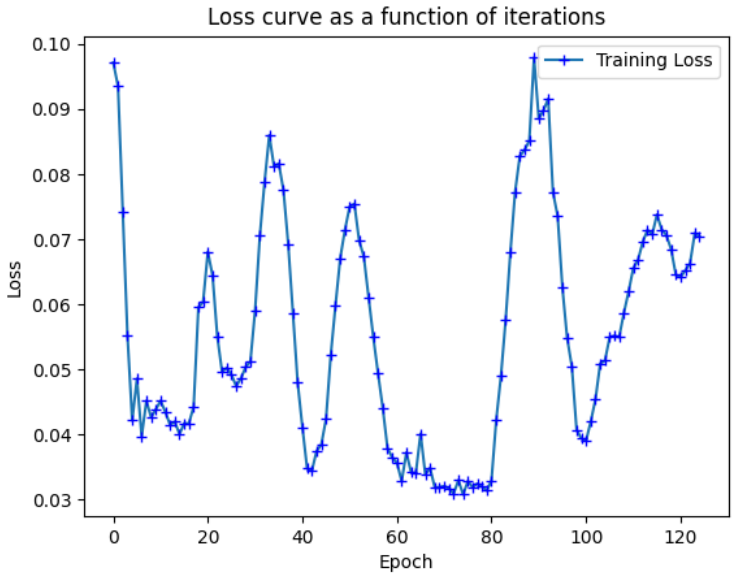


- Untrained network (1 input hologram)
- Loss function: $\alpha \times \mathrm{MSE} + (1-\alpha) \times \mathrm{MAE}$
- Reconstruction distance set at 87 µm
- Learning rate: 1,205e-3

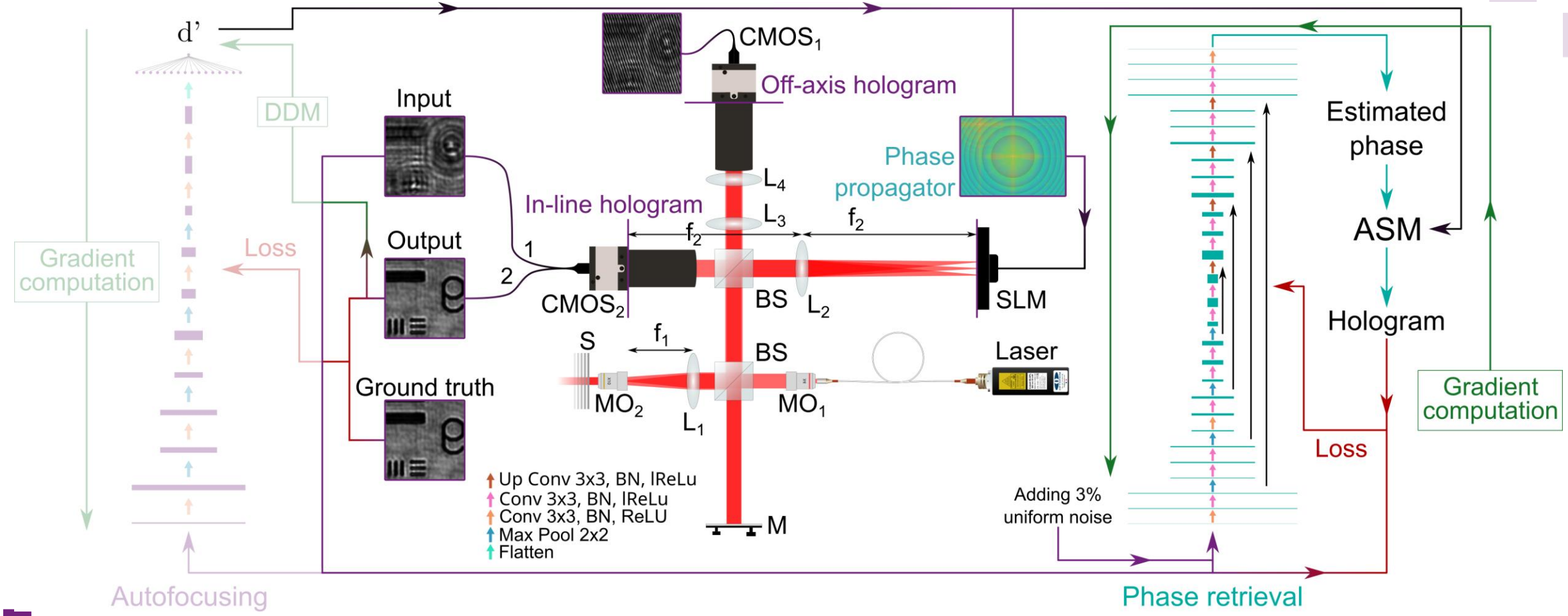
⟶ Forward path ⟶ Gradient flow

ASM: Angular spectrum method
DDM: Differentiable digital model





OVERVIEW OF THE NETWORK FOR THE PHASE RETRIEVAL

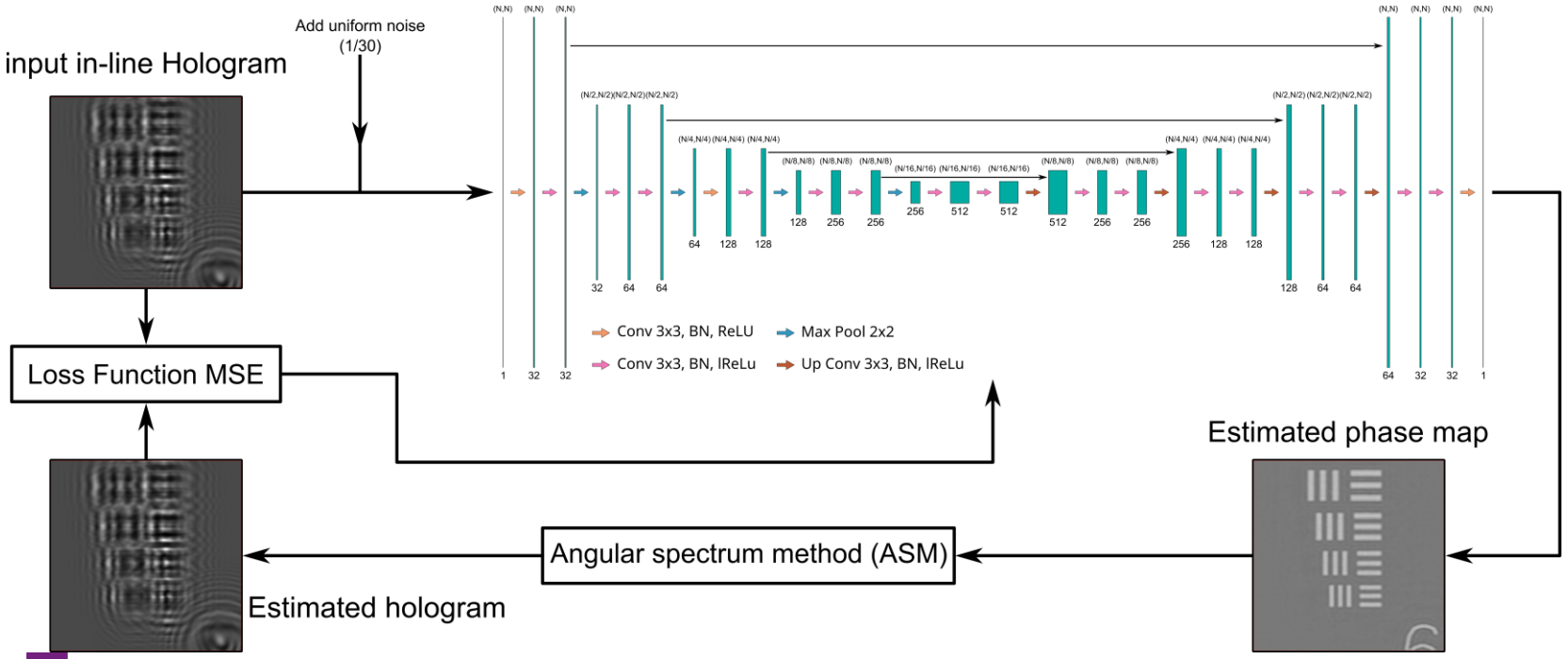


PHASE RETRIEVAL BASE ON PHYSENNET ALGORITHM[1]

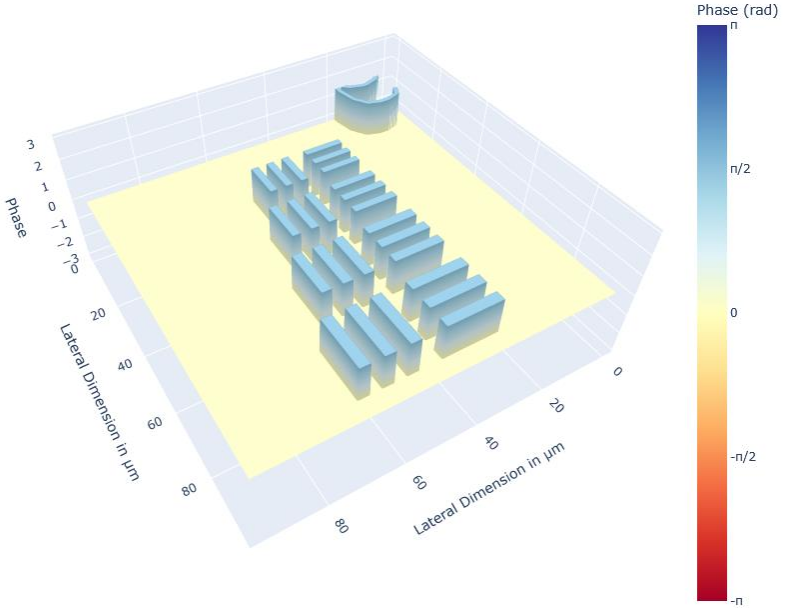
Phase retrieval using **simulated** data
Untrain network, only **one input** hologram
Learning rate : 0.001
Stop training at 10000 iterations or loss ≤ 0.00045

Simulated microscopic object:

- Wavelength: 659,6nm
- Magnification: 11X
- Pixel size: 0,2181 µm
- Object size: 96µm
- Phase height: $\pi/2$

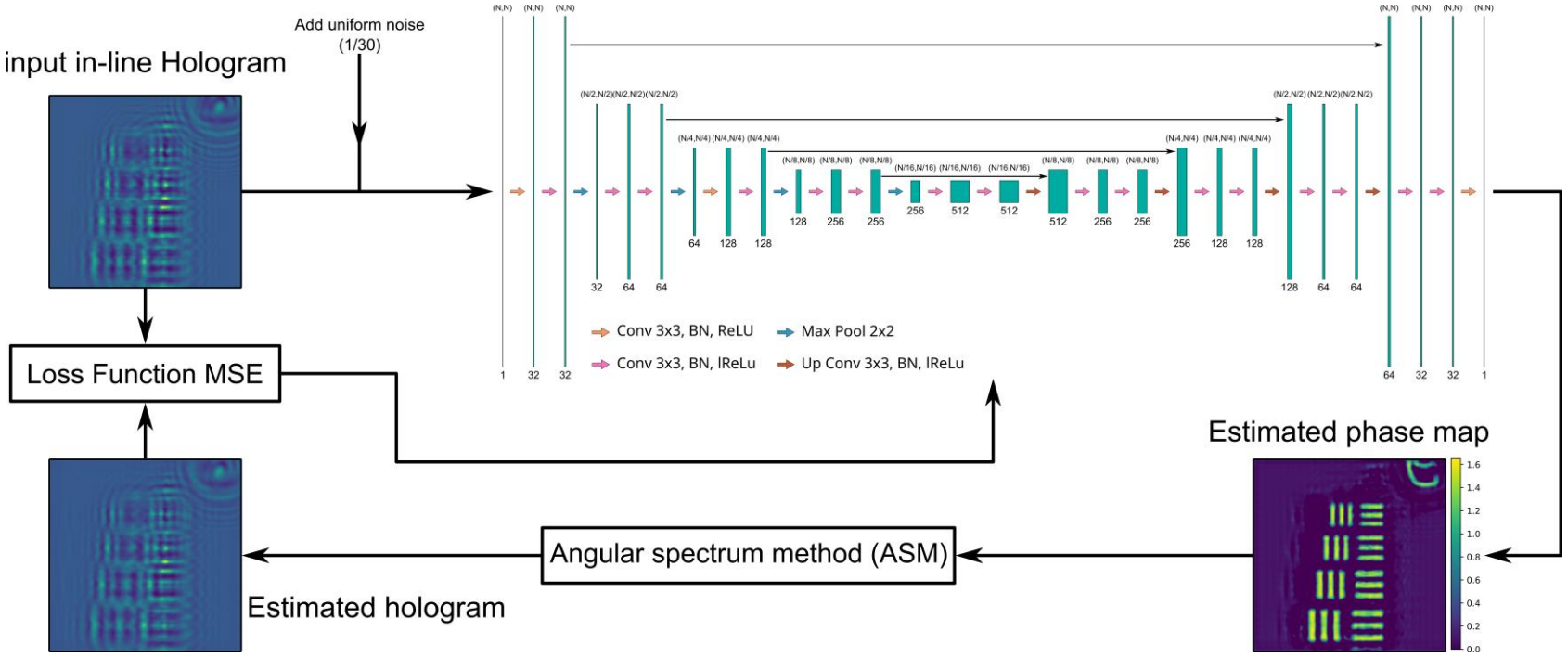


Ground truth

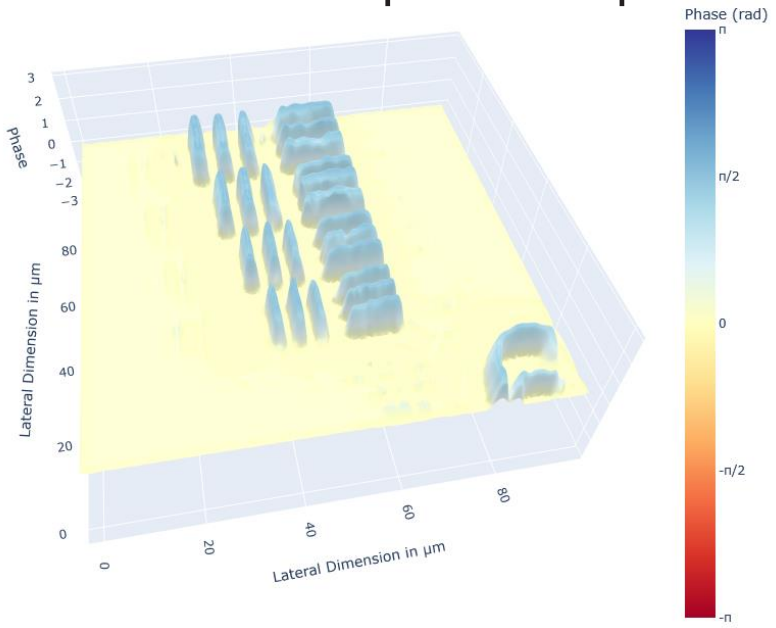


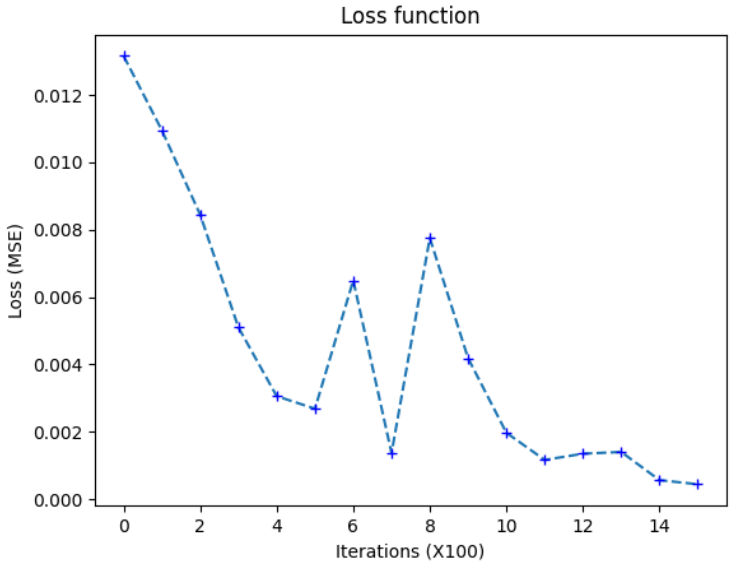
[1] F. WANG, et al. "Phase imaging with an untrained neural network" Light: Science & Applications, 2020

PHASE RETRIEVAL FOR Z=85μm

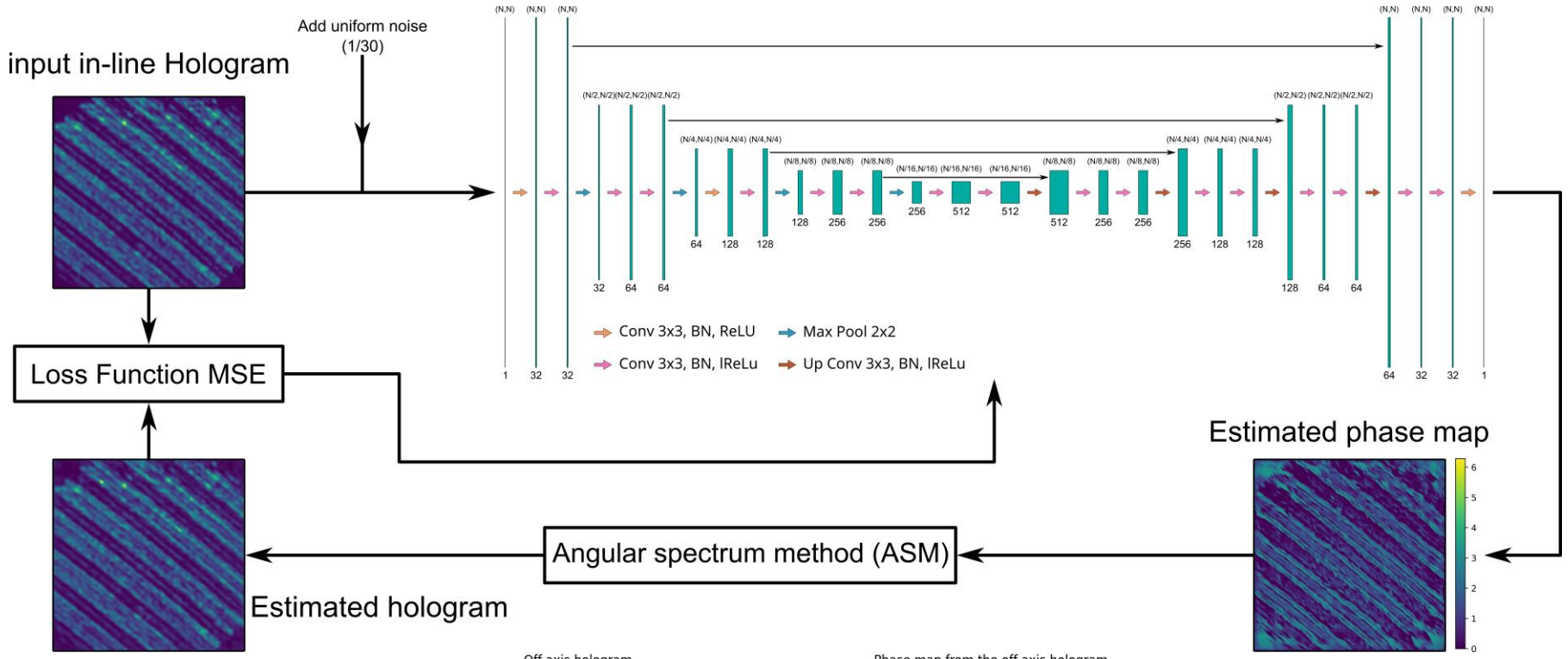


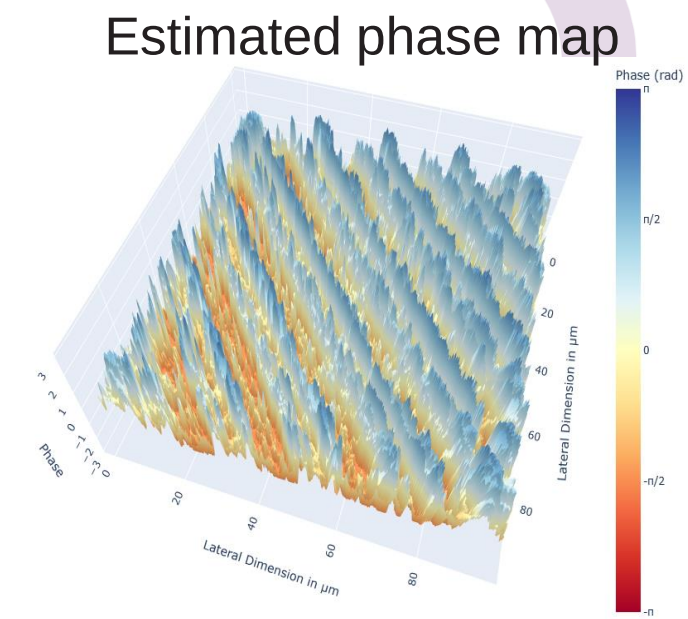
Estimated phase map

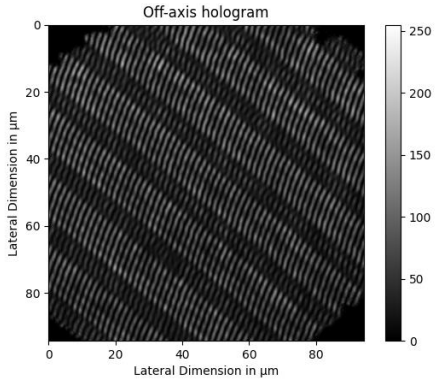


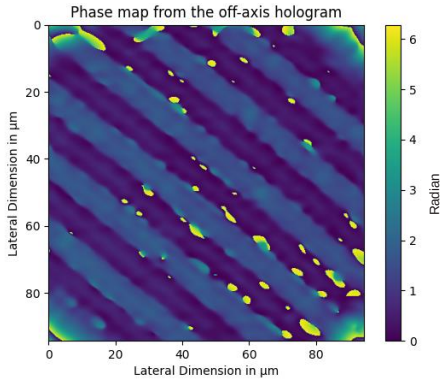


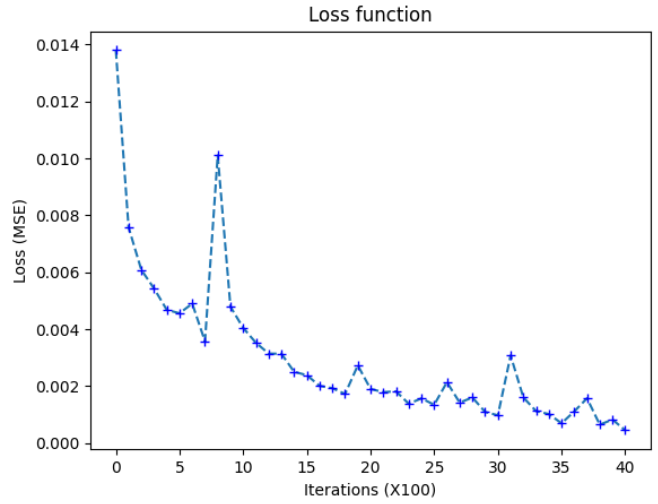
PHASE RETRIEVAL FOR Z=85μm ON EXPERIMENTAL DATA









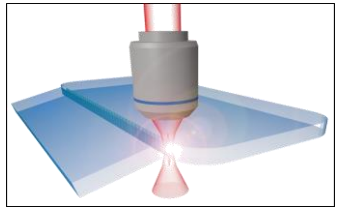


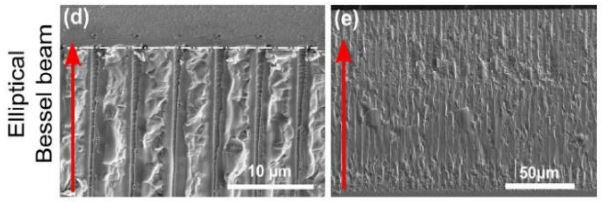
CONCLUSION AND FUTURE WORK

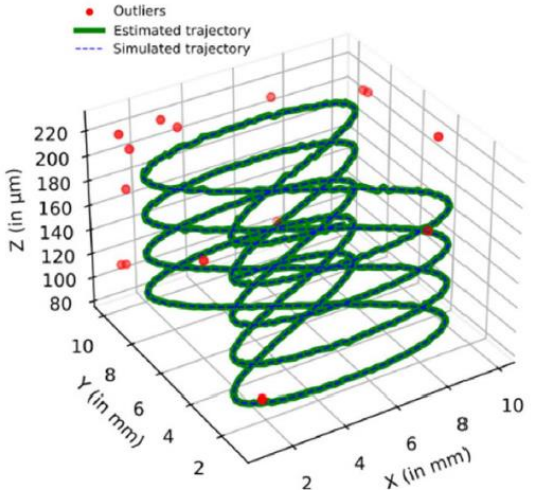
- Preliminary experimental autofocusing results
  - Further investigation is needed to understand why the network did not converge to the ground truth value.

- Adapt the phase retrieval process for experimental data in order to reduce the noise.

- Target applications: computer micro-vision for Simultaneous Localization & Mapping (SLAM) in microscopy, and imaging femto-second laser fabrication process



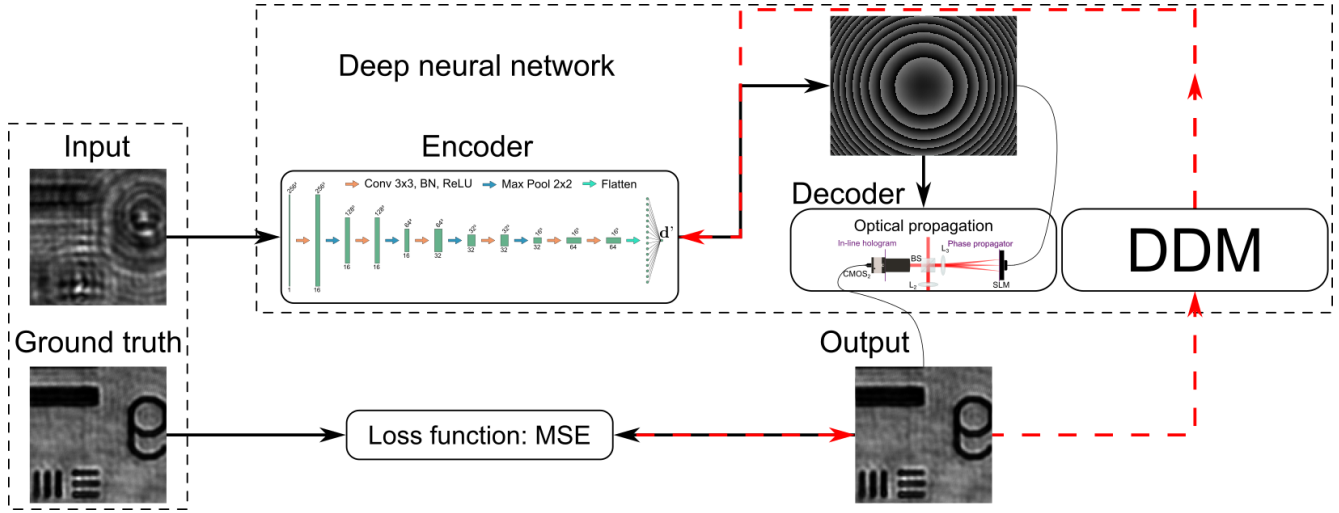


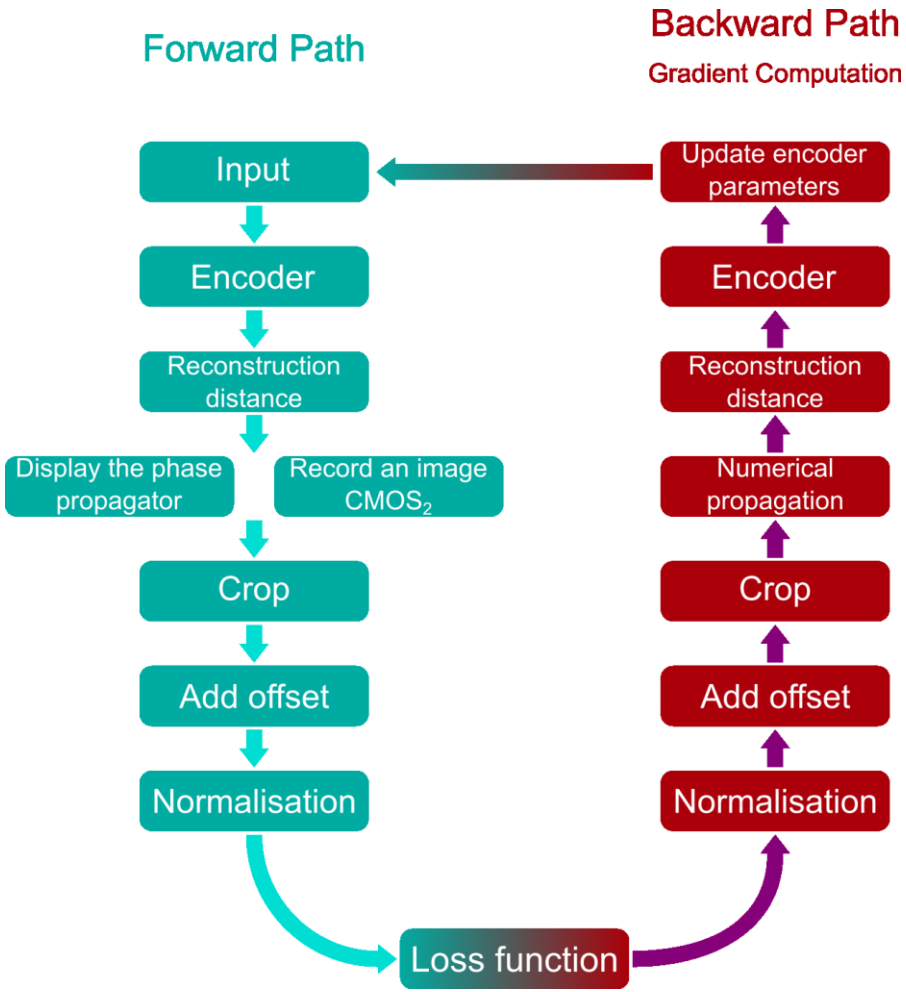


Cuenat, S., *et al.* Journal of the European Optical Society-Rapid Publications, 20(2), 31. (2024)

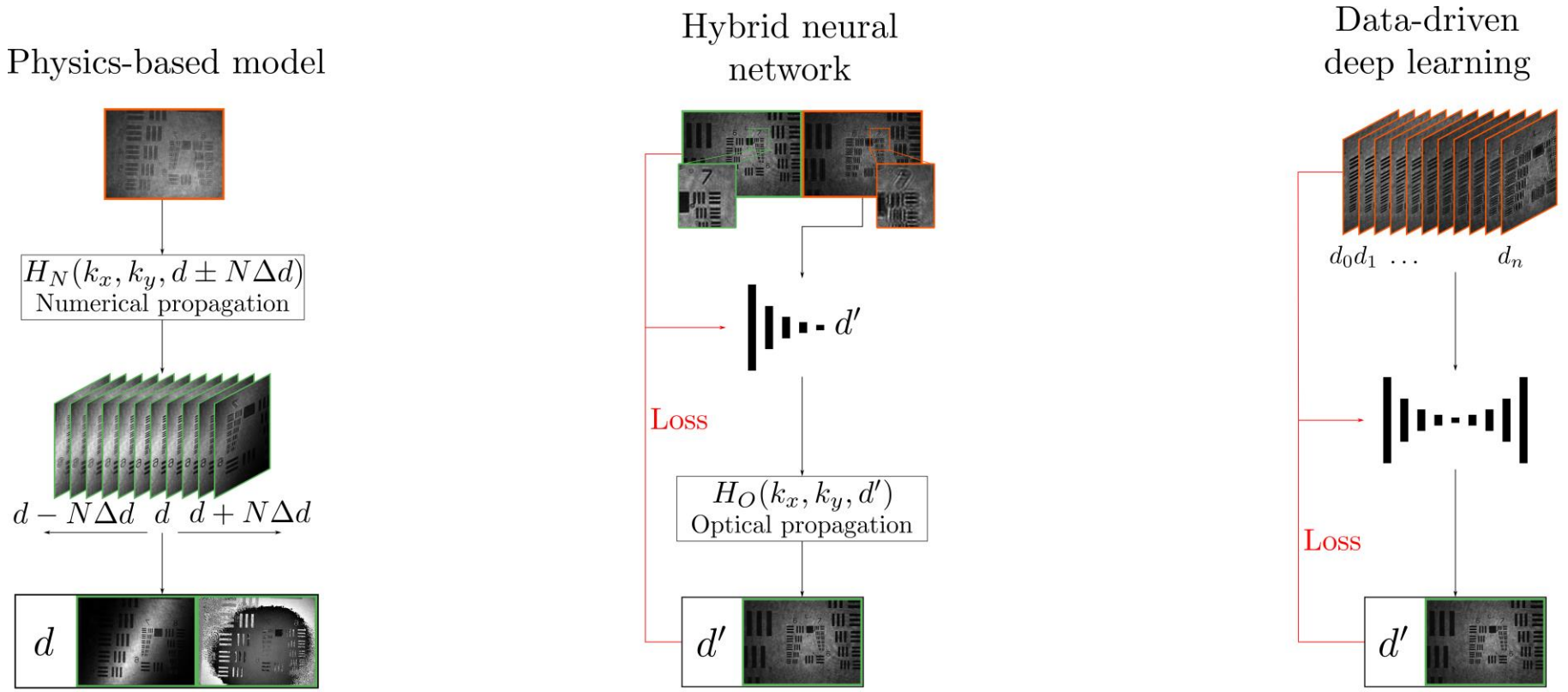
Thanks you for your attention

PHYSICS-ENHANCED NETWORK TRAINING OVERVIEW





HYBRID NEURAL NETWORK FOR AUTOFOCUSING



PHASE RETRIEVAL FOR Z=78μm

