Deep neural networks for aberration compensation in digital holographic imaging of the retina

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Introduction

- Project: holographic imaging of the retina in real-time
- Problem: aberrations created by cornea disturb holographic imaging
- Fast estimation and correction of aberrations are necessary

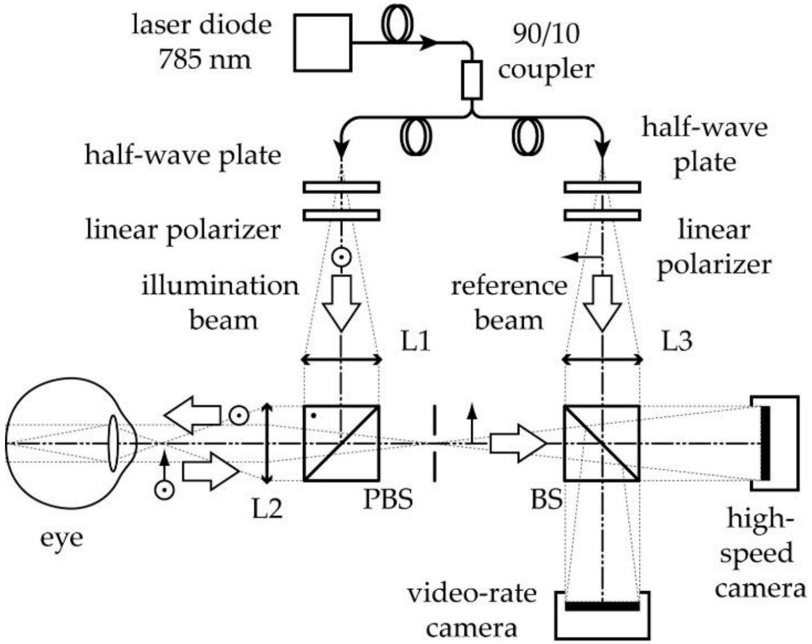
Outline

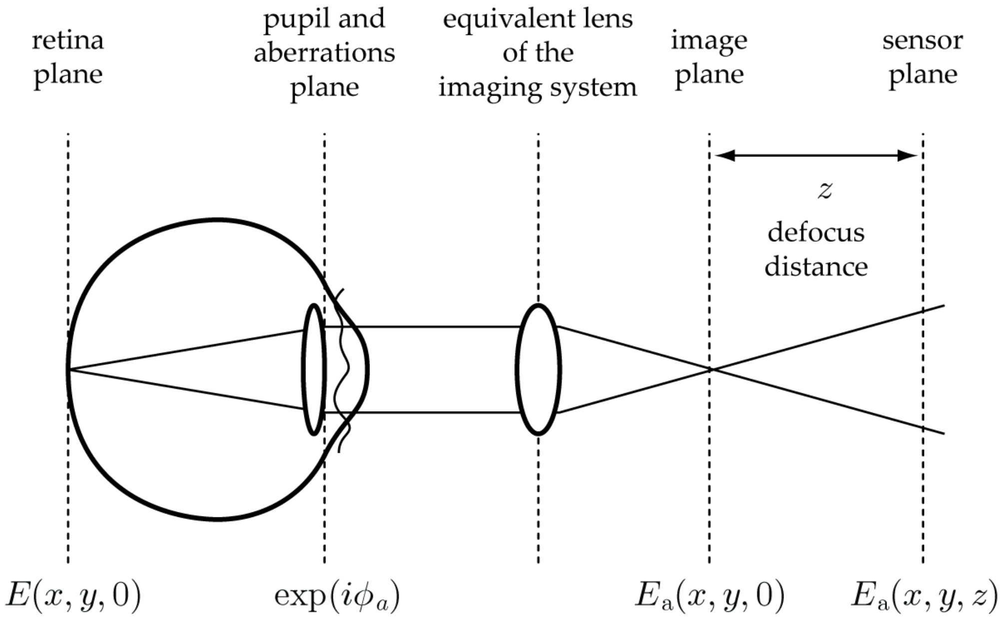
I. Digital holographic imaging

II. Aberration estimation

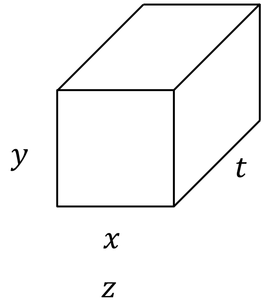
III. Prospects

Setup and image formation





Block of interferograms



Sensor plane

Angular spectrum propagation

Block of holograms

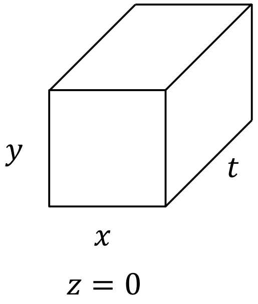


Image plane

Time Fourier transform

Block of spectrograms

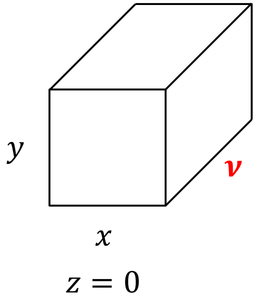
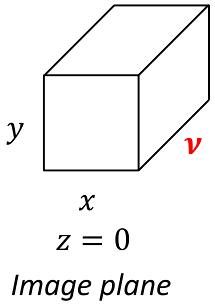


Image plane

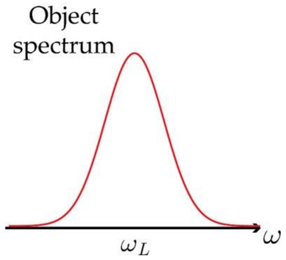
Real-time processing with Holovibes

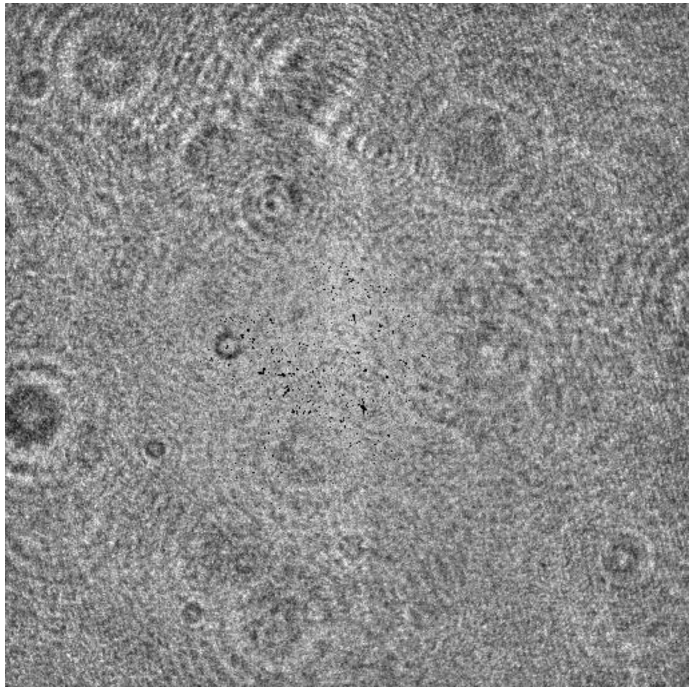
Doppler images

Block of spectrograms



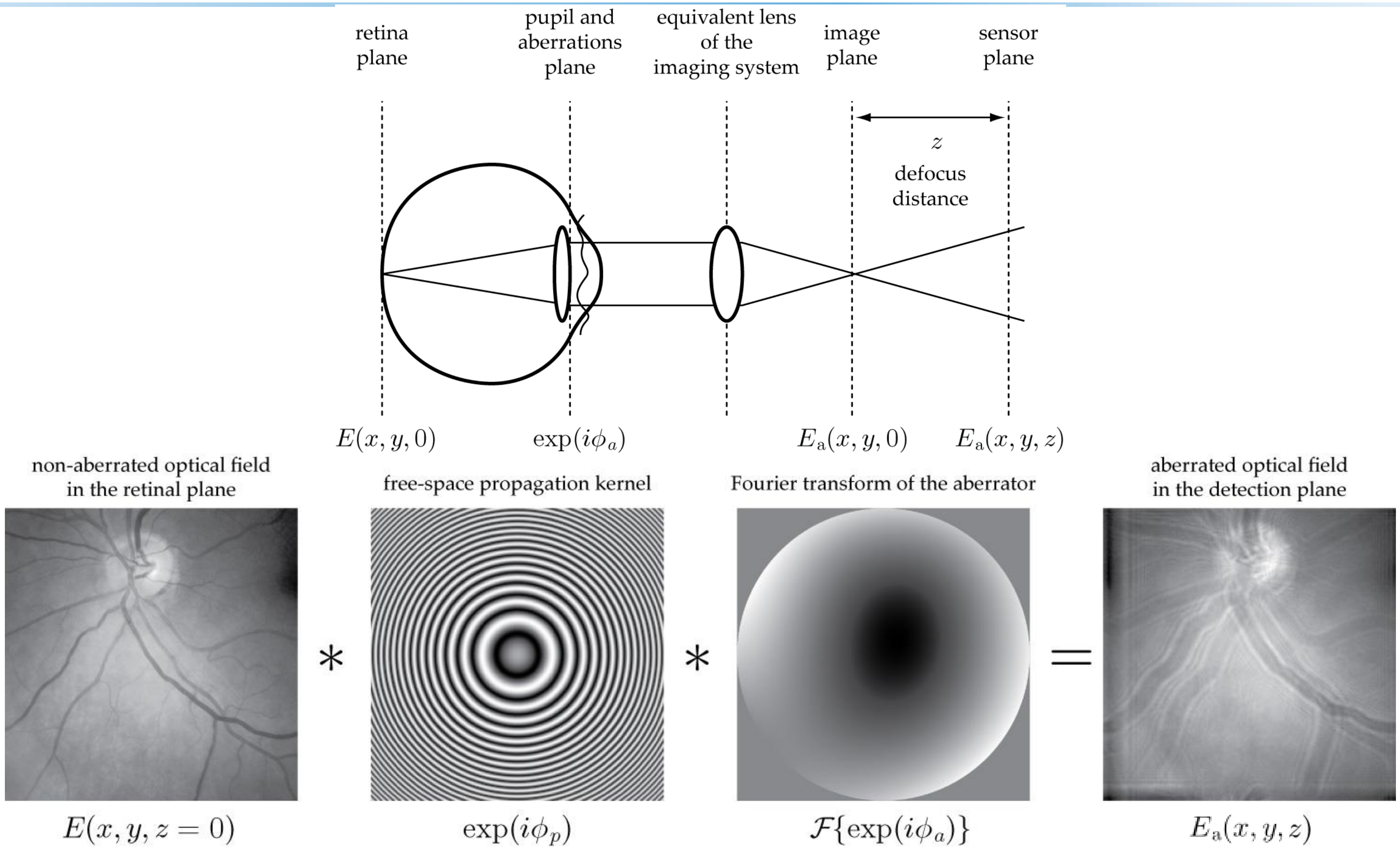
Fluctuation spectrum calculation





Holography Doppler images taken and processed by ***Léo Puyo*** *from Institut Langevin*

Impact of aberrations from cornea



Goal: aberration correction in real-time

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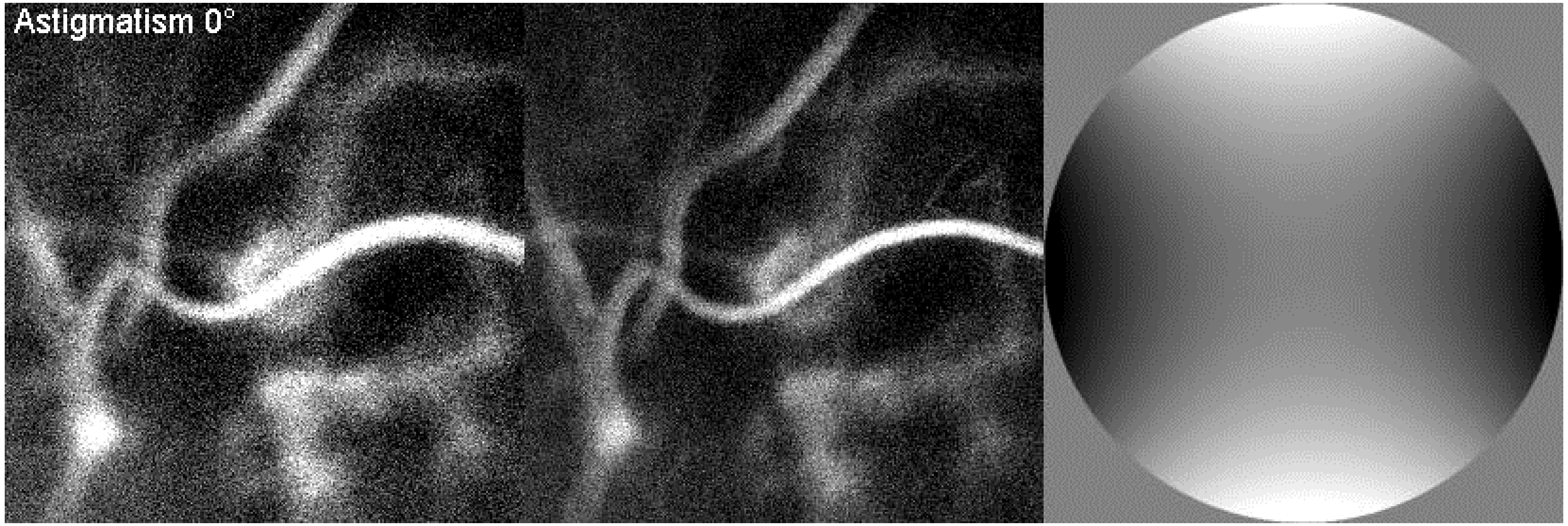
Astigmatism estimation by image-based optimization

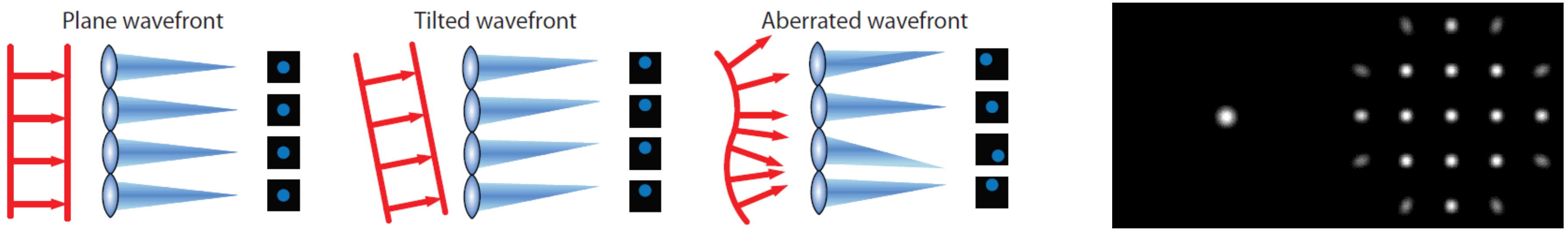
Minimization of $J(c) = \dfrac{\text{entropy}}{\text{Spatial variance}}$

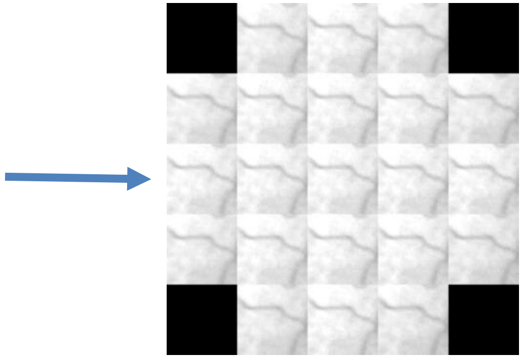


Aberrated image *Corrected image* *Aberrated wavefront*

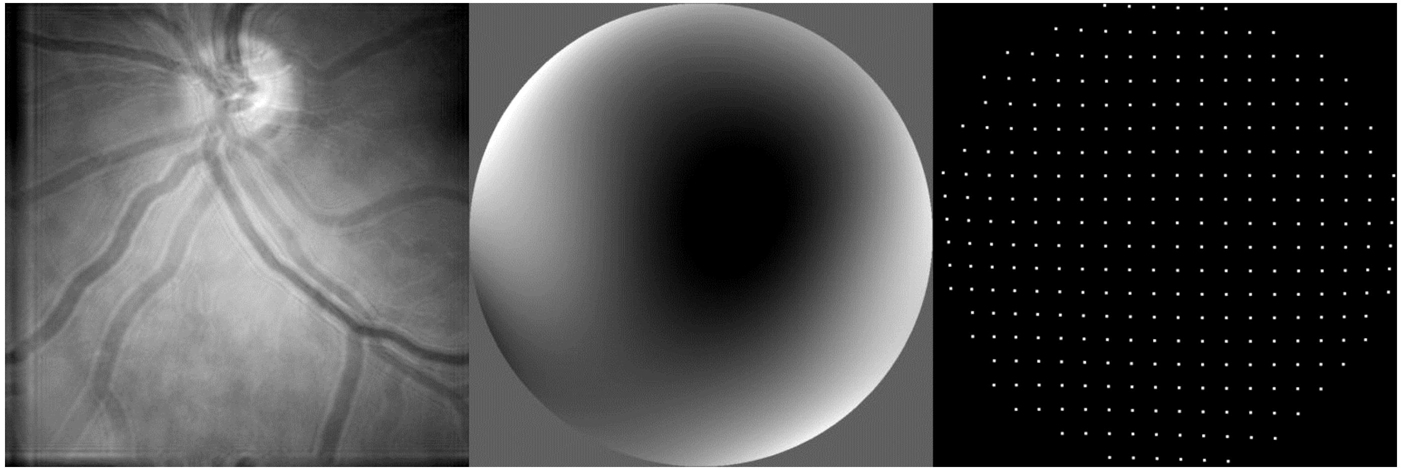
Astigmatism 0°, 45° and 90°

Aberration measurement with digital wavefront sensor





Principle of Shack-Hartmann wavefront sensor

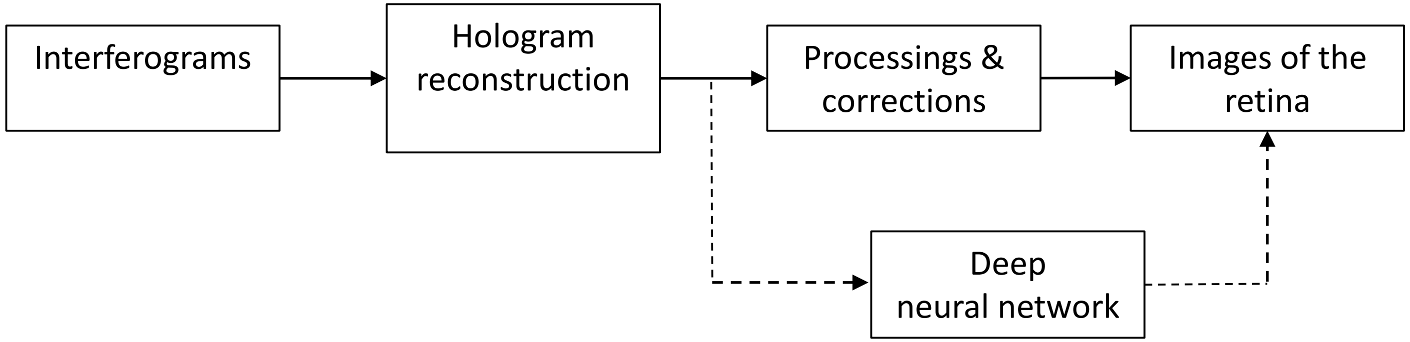


Simulations

- Each aberration corresponds to one degree of Zernike polynomial (one mode).
- M reference matrix of size $n_{subapertures}$ x n_{modes}
- $Y = MA$, where Y is observation vector ($n_{subapertures}$ x 1) and A is amplitude vector (n_{modes} x 1)
- Then M is reversed to find A.

Tests on real data in progress…

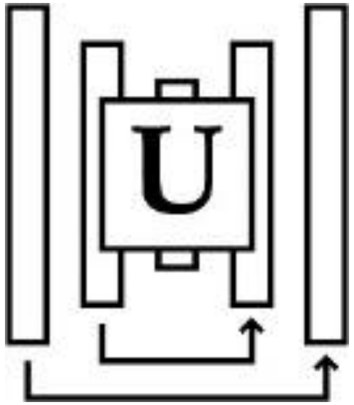
Aberration compensation with deep neural network



U-Net

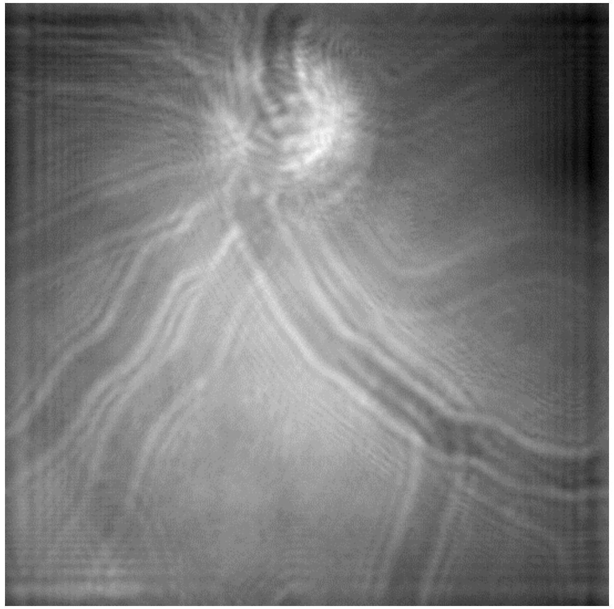
Ronneberger, et al. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

⇨



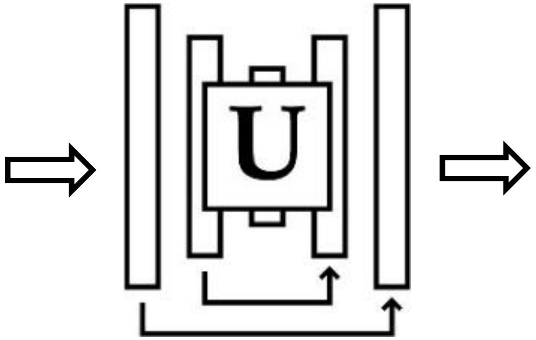
input : image
output : image

Hologram rendering with a U-Net

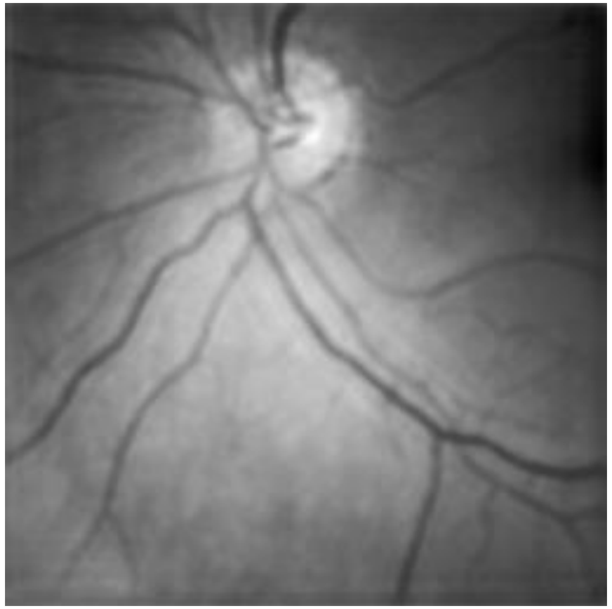


Input: aberrated hologram

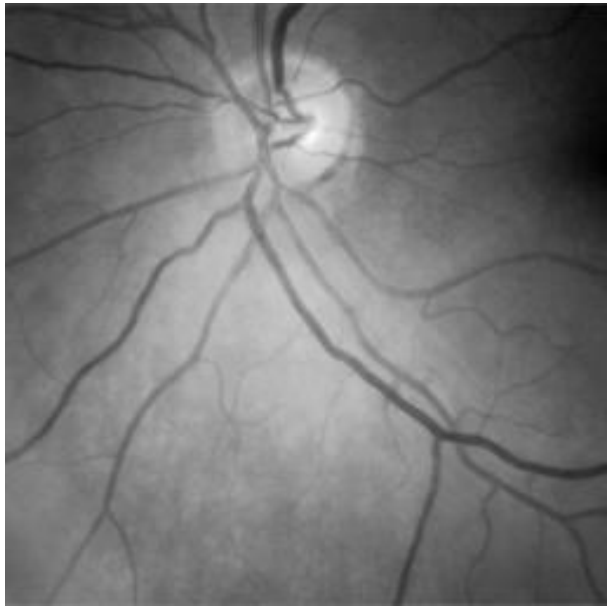
UNet



Training on 28 000
Input/output
image couples



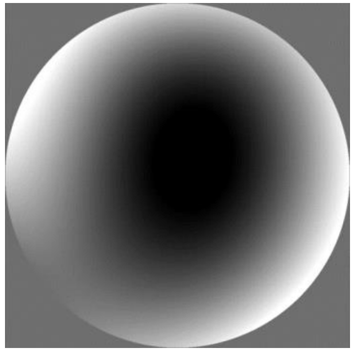
Reconstructed image



Ground truth

Training: one defocus
Reconstruction: the same amount of defocus
Results: good correction

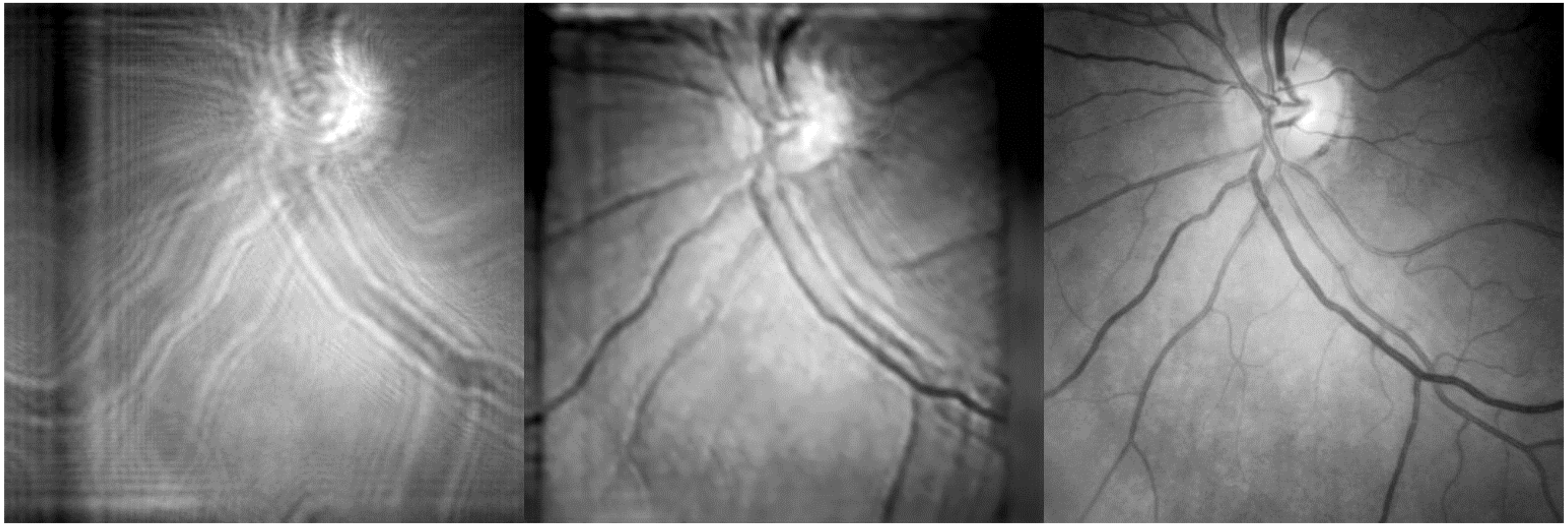
Hologram rendering with a U-Net



Φ_a

N=30

Time sequence of aberrations taken from real eyes with 30 different types of aberrations



Aberrated image *Aberration compensation through deep learning* *Ground truth*

Training: one average aberration
Reconstruction: variety of aberrations close to the avg.
Results: U-Net not suitable as is to learn a diversity of aberrators

Jessica Jarosz, Pedro Mecê, Jean-Marc Conan, Cyril Petit, Michel Paques, and Serge Meimon, "High temporal resolution aberrometry in a 50-eye population and implications for adaptive optics error budget," Biomed. Opt. Express 8, 2088-2105 (2017)

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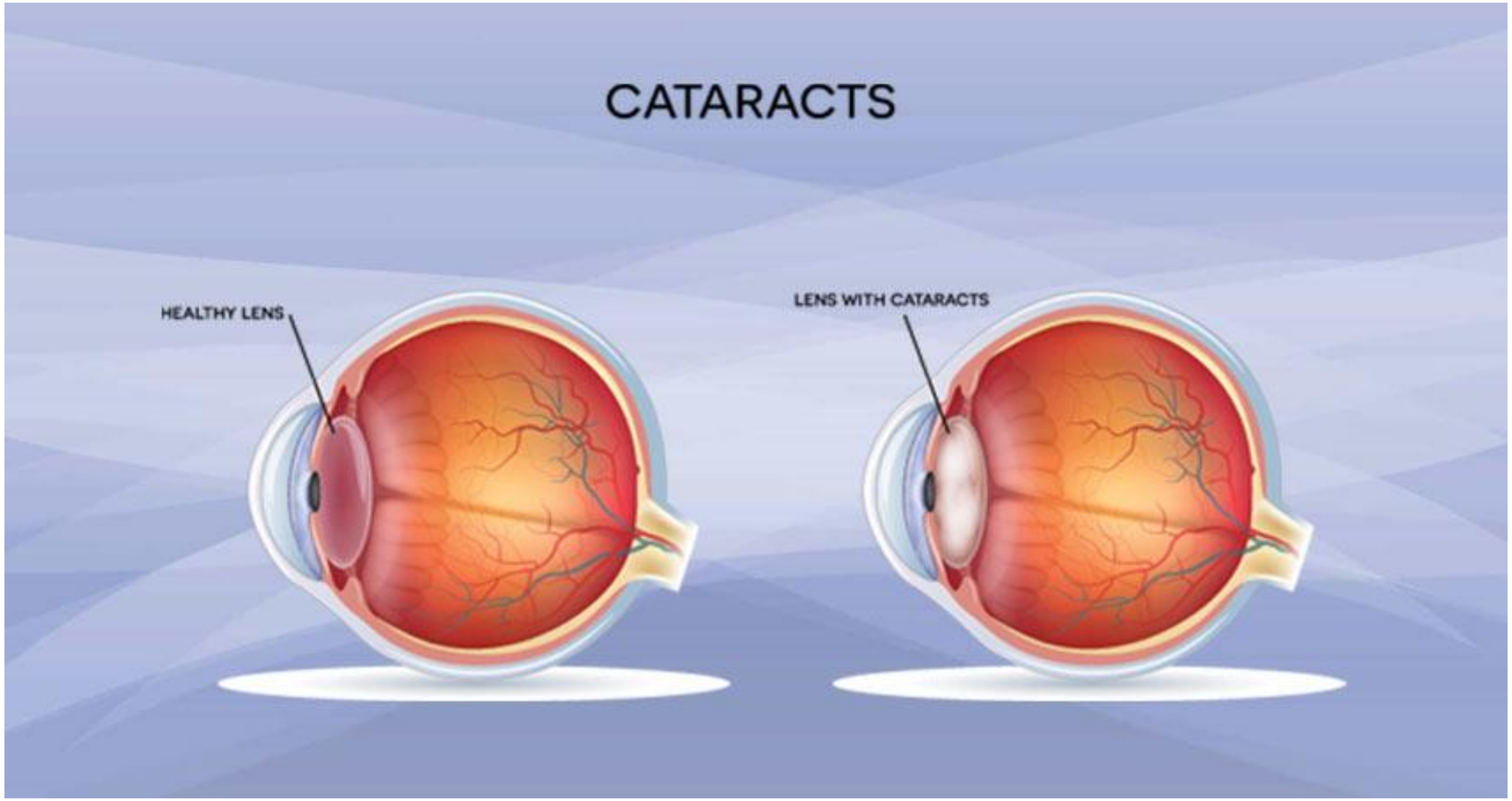
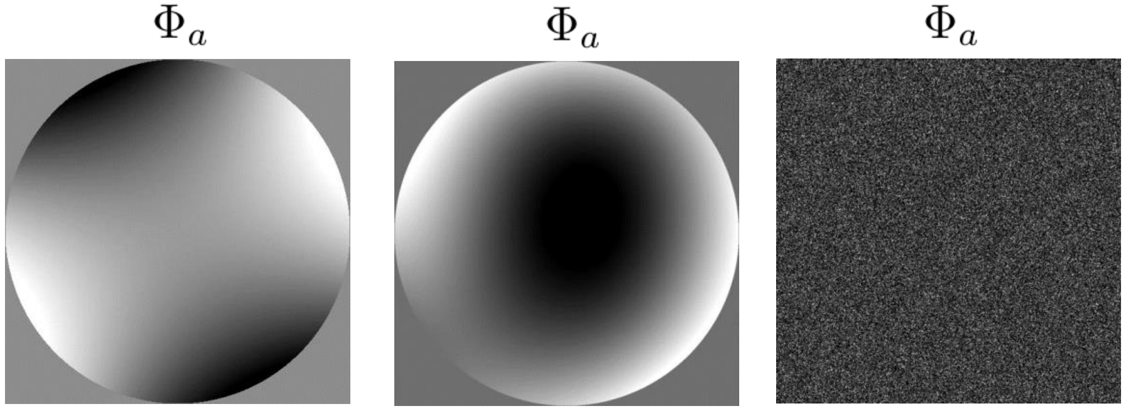
Prospects

What if the aberrator has a large number of degrees of freedom?

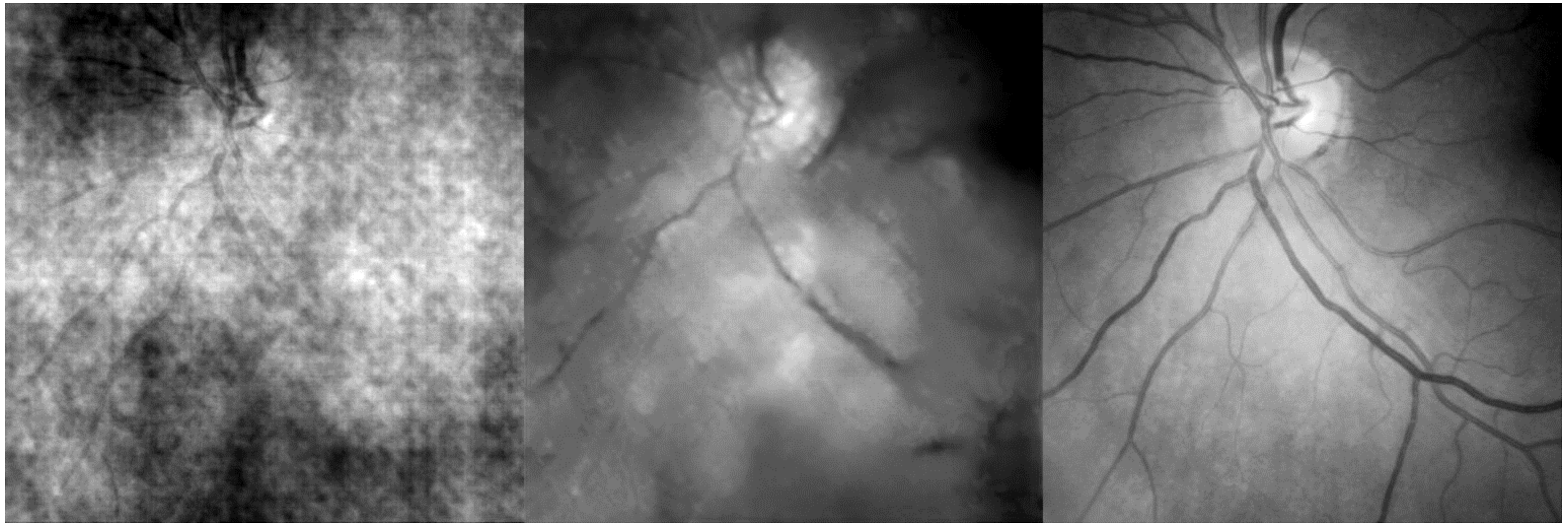


Cataracts compensation using deep neural networks

Increase of # of degrees of freedom



N=1 *N=30* *N=100000*



Aberrated image *Aberration compensation through deep learning* *Ground truth*

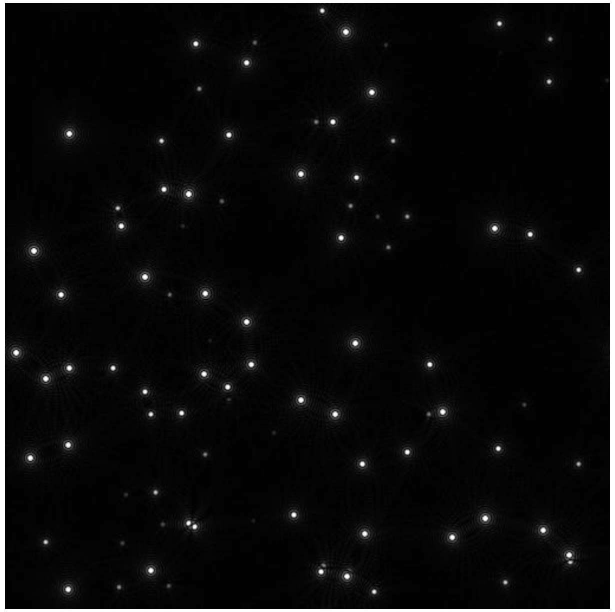
Training : one random phase screen filtered by gaussian filter (σ=0,4)
Reconstruction : variety of phase screens « close » to the one used for training
Issue : UNET not suitable « as is » to learn a diversity of « aberrators »

To go further

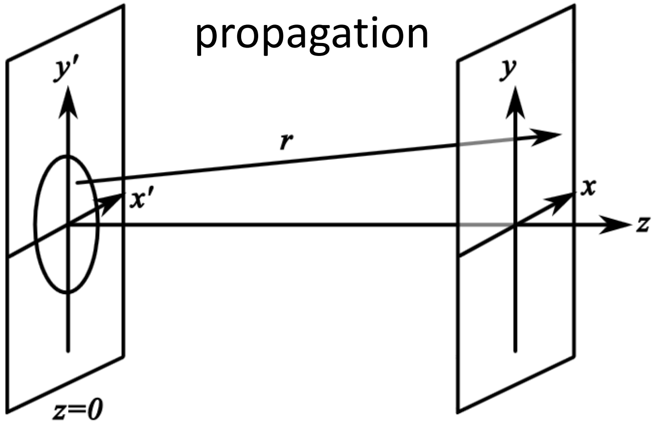
Work on the training database:

- With a large amount of images with **several types of complex objects**, increasing the **degrees of freedom** to correct more and more aberrations.
- What if the object is the **simplest one** ?

Digital Gabor hologram rendering with deep learning

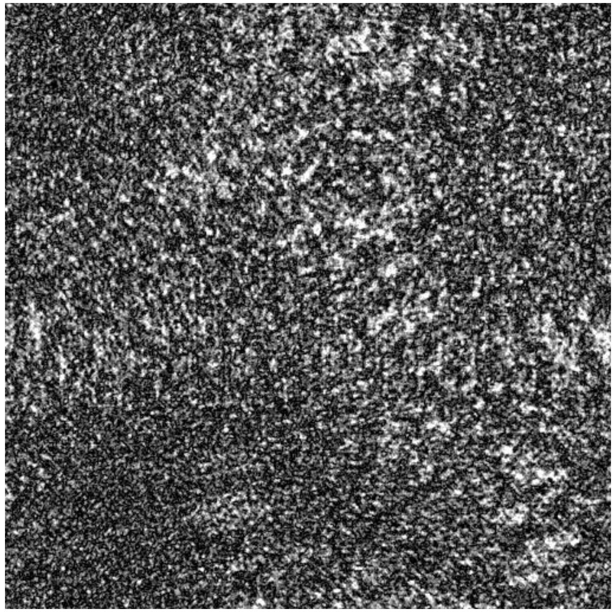


Angular spectrum propagation

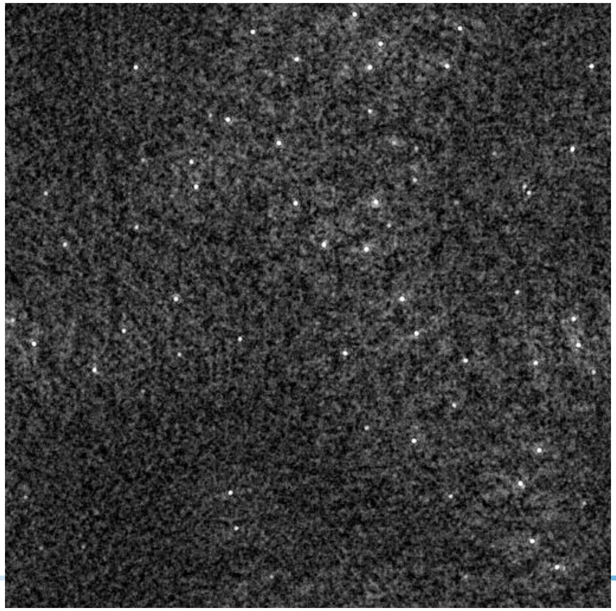


Collection of random points

Synthetic interferogram



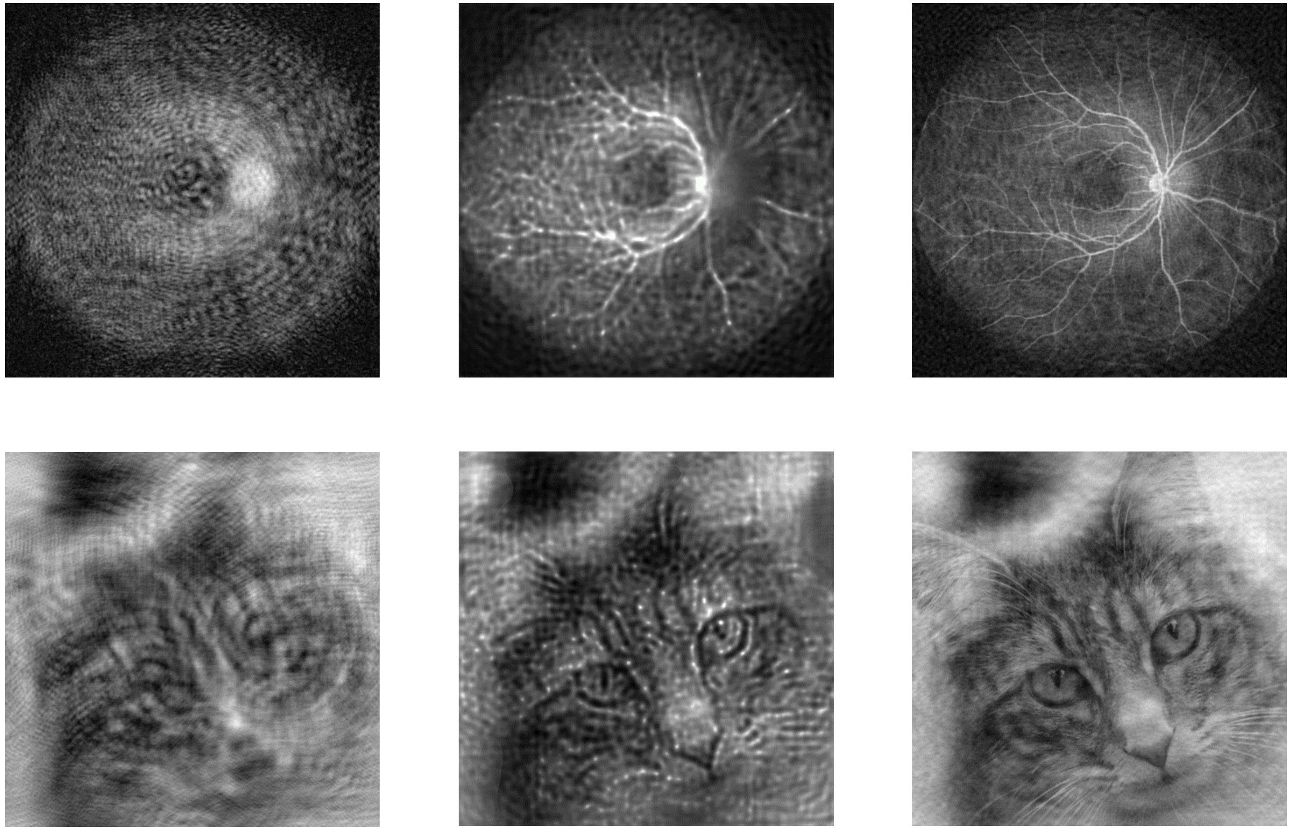
Synthetic magnitude hologram



For training database

Digital Gabor hologram rendering with deep learning

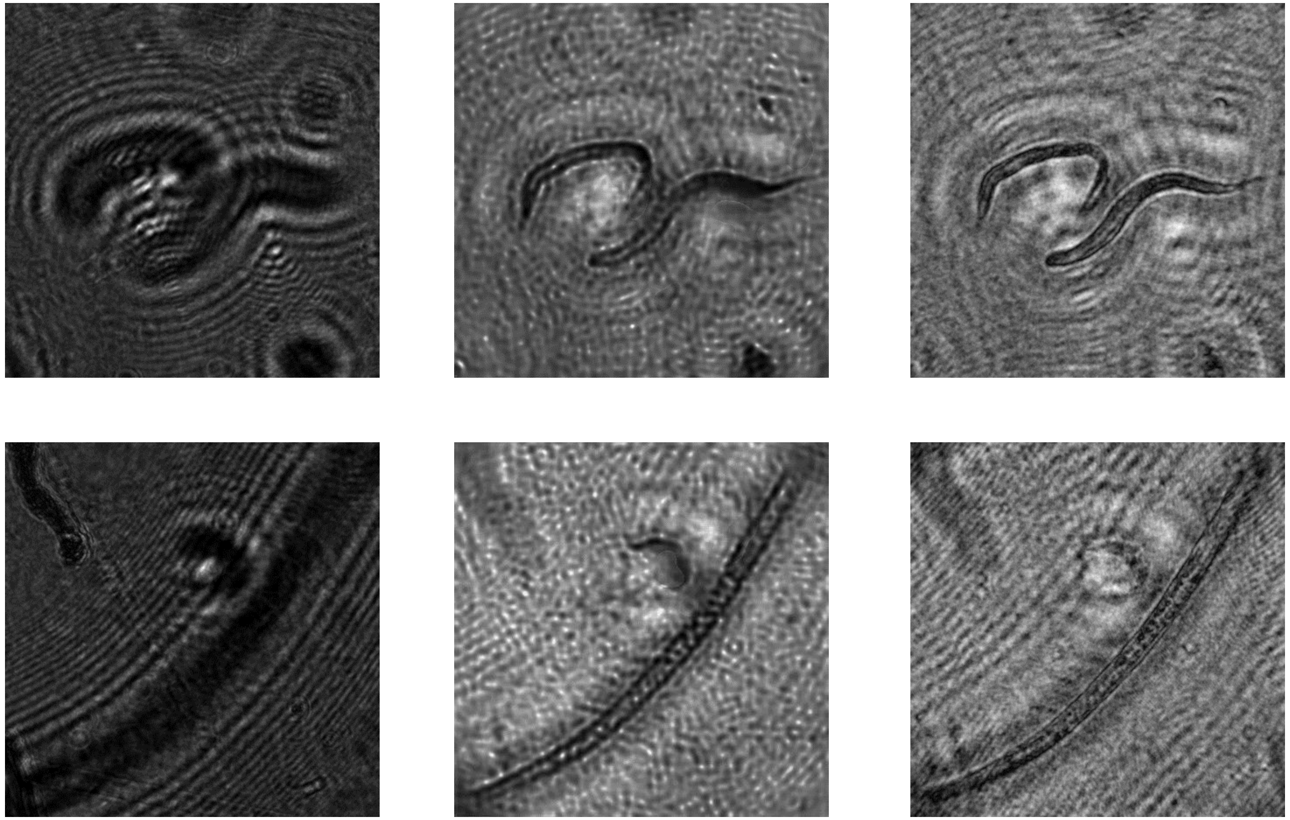
With simulated images



Synthetic interferogram | *Reconstructed hologram with neural networks* | *Synthetic magnitude hologram*

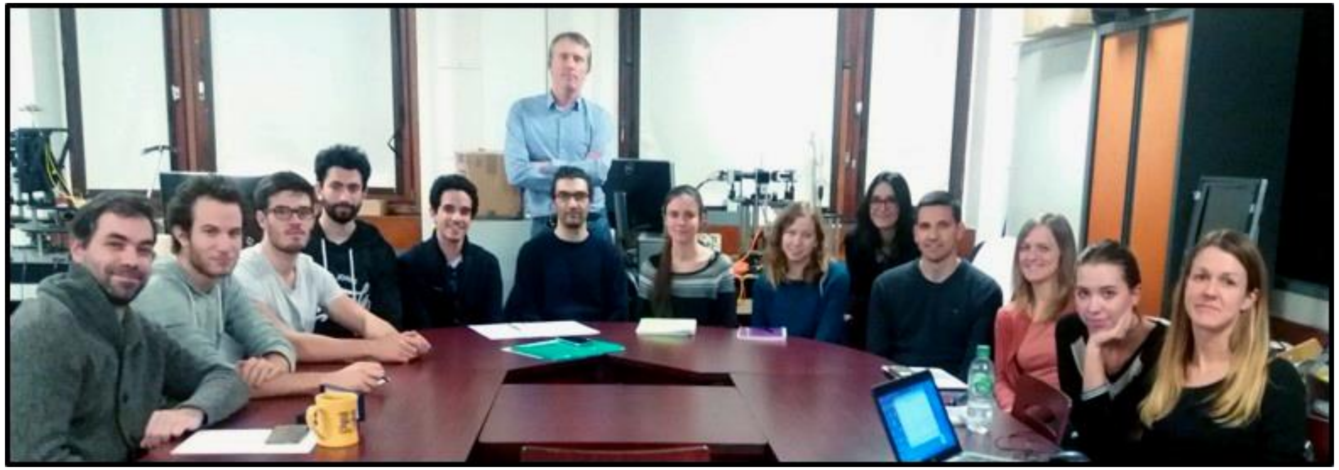
Digital Gabor hologram rendering with deep learning

With real data (worms)



Experimental interferogram | *Reconstructed hologram with neural networks* | *Magnitude hologram*

Thank you !

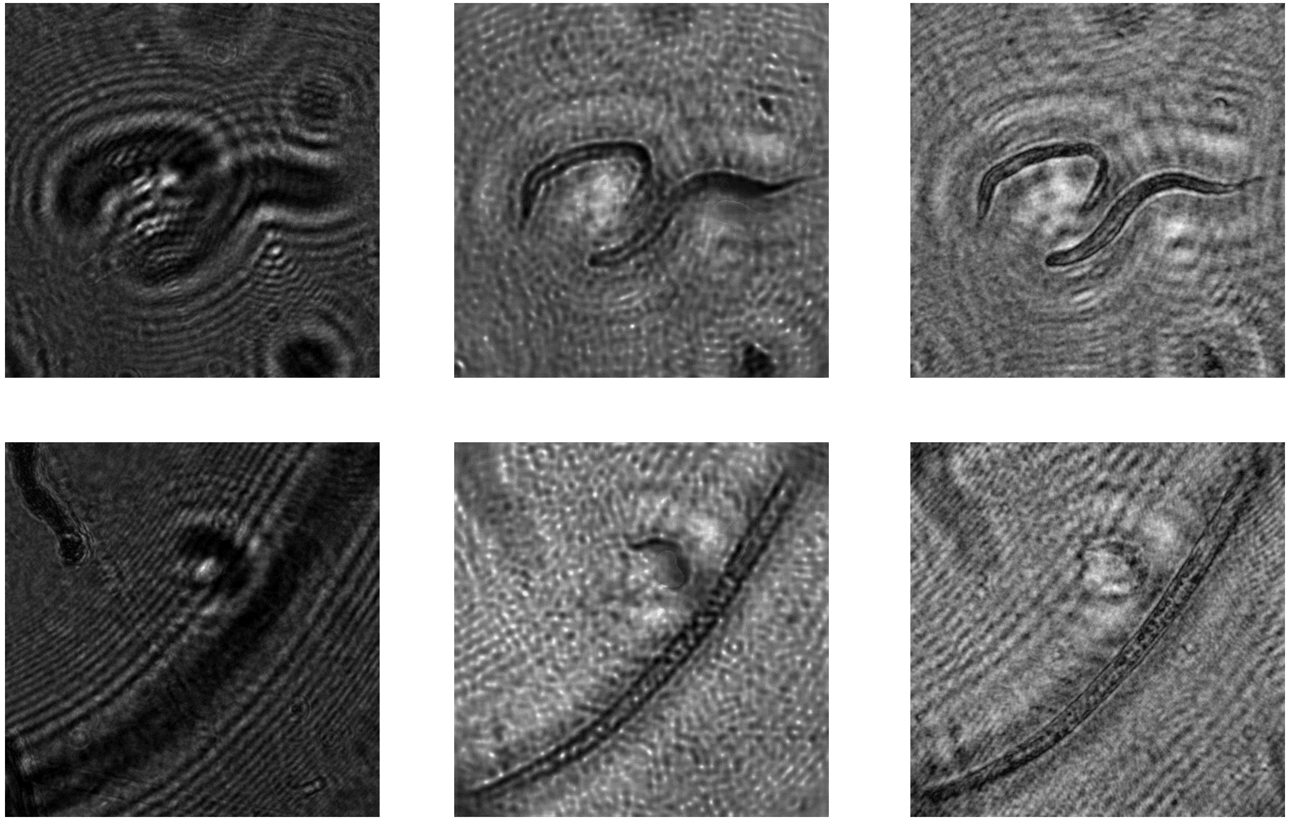


Contact: julie.rivet@espci.fr

Funding: European Research Council (ERC Helmholtz, grant agreement #610110)

Digital Gabor hologram rendering with deep learning

With real data (worms)



Experimental interferogram | *Reconstructed hologram with neural networks* | *Magnitude hologram*

*Data courtesy of **Stéphanie Rind** from Institut Langevin*

Aberrations