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

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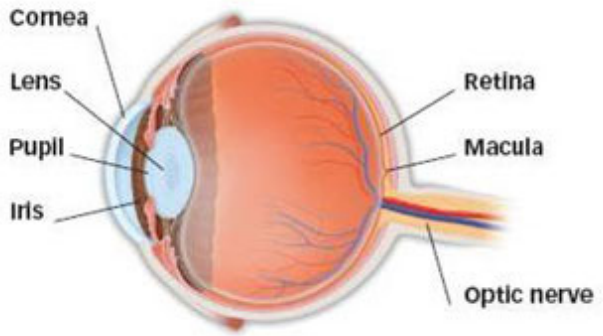
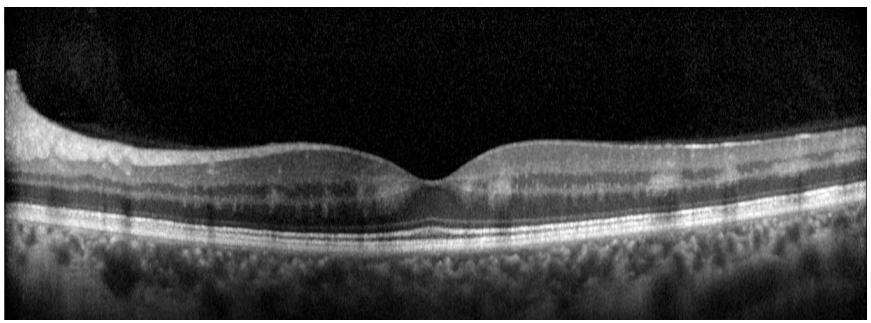
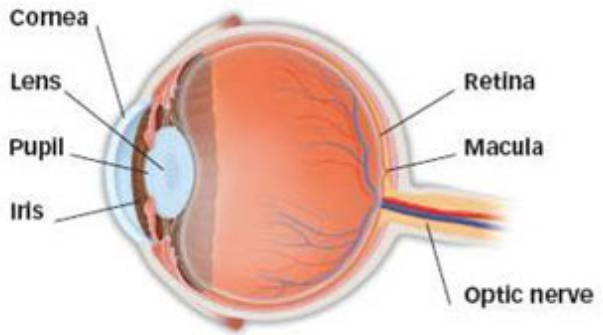


Study of the retina: information about some diseases.

Improvement of imaging techniques in the 20th century with **holography**.



Real-time retina imaging: issues



Goal: **Real-time digital** holography of the retina.

Problems:

→ Handle physiological **movements**.

→ spoil visualization and data encoding.

→ Distorsion of the light path through the cornea.

→ **aberrations**.

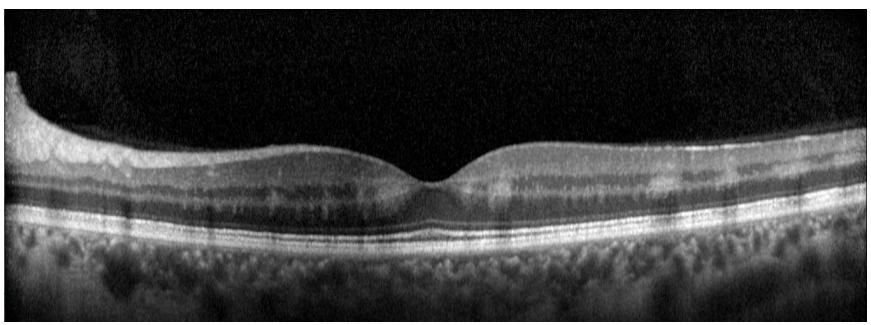
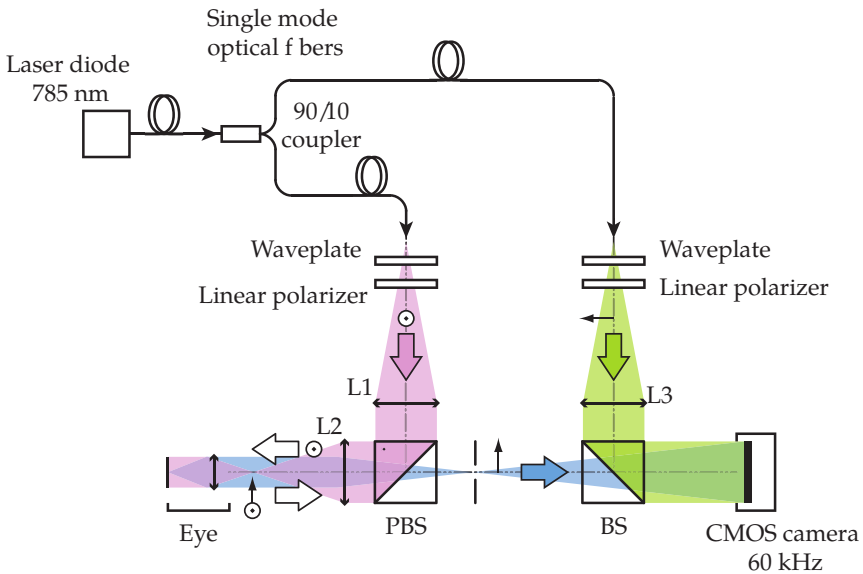
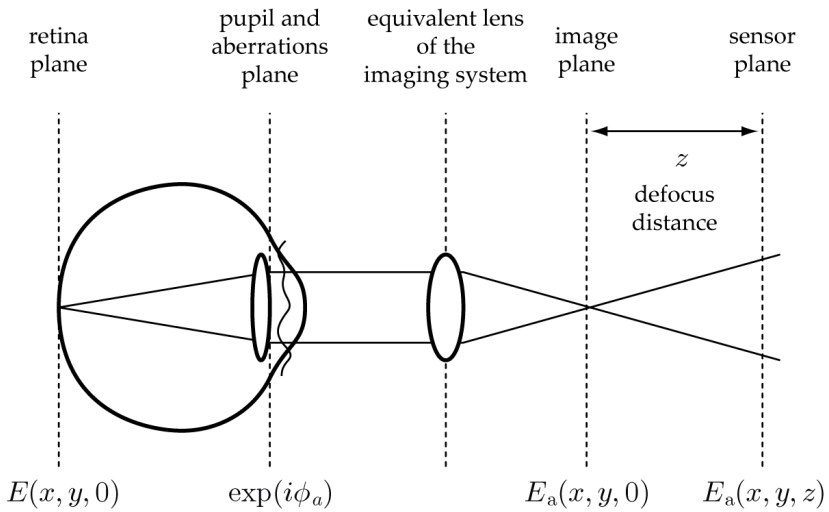


Image formation



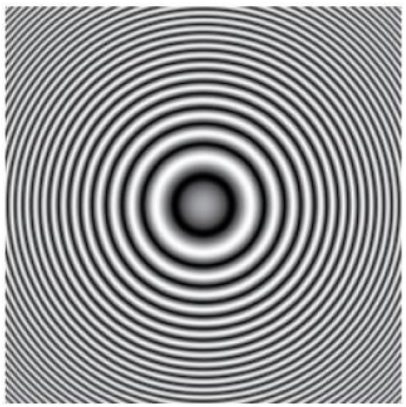


non-aberrated optical field in the retinal plane

$E(x, y, z = 0)$

$*$

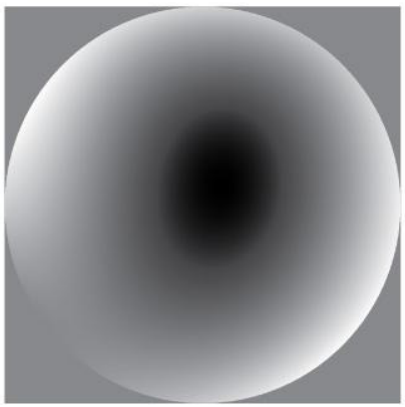
free-space propagation kernel



$\exp(i\phi_p)$

$*$

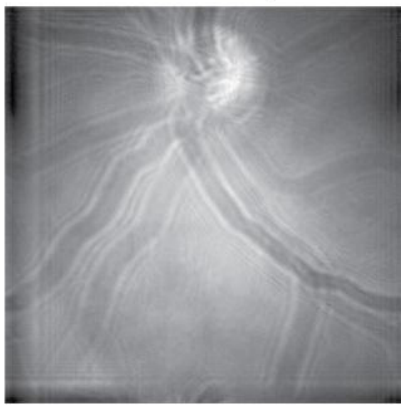
Fourier transform of the aberrator



$\mathcal{F}\{\exp(i\phi_a)\}$

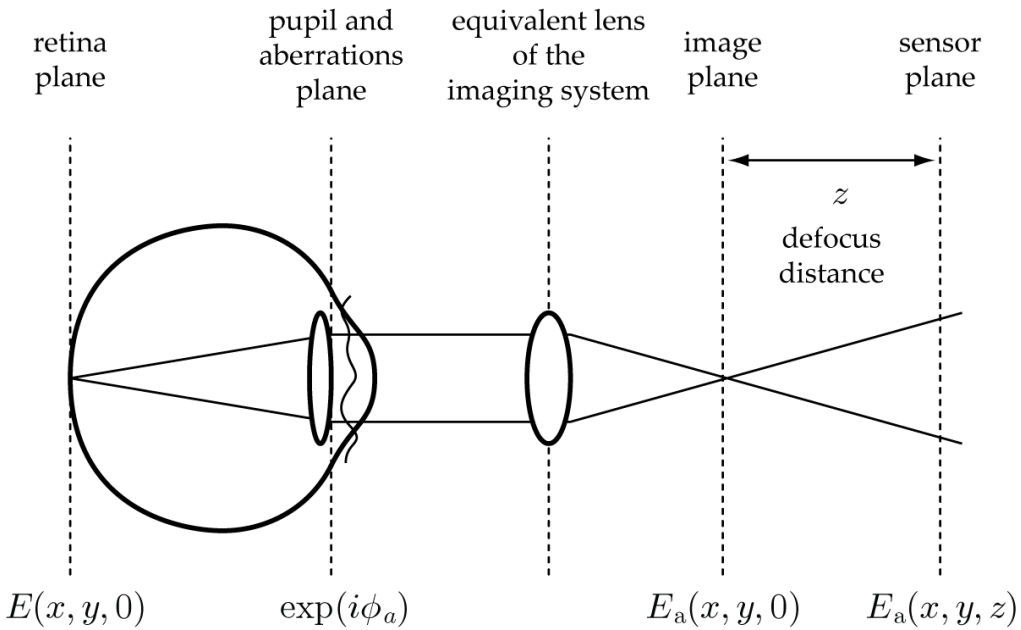
$=$

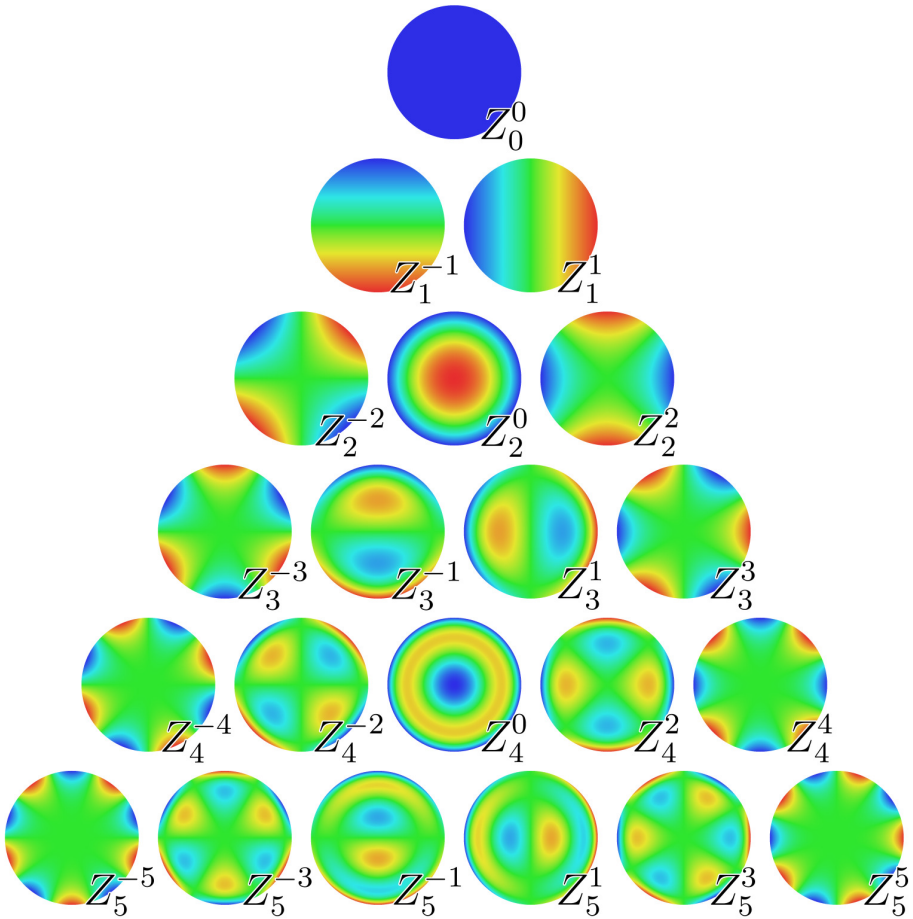
aberrated optical field in the detection plane



$E(x, y, z)$

Aberrations in the eye





Phase corresponding to aberrations with Zernike polynomials :

$\phi_a = \sum_{n,m} a_{n,m} Z_{n,m}$

Bibliography

What we are working on:

Ronneberger, Fischer, and Brox, "U-net: Convolutional networks for biomedical image segmentation," *International Conference on Medical image computing and computer-assisted intervention*, pp. 234–241, Springer, 2015.

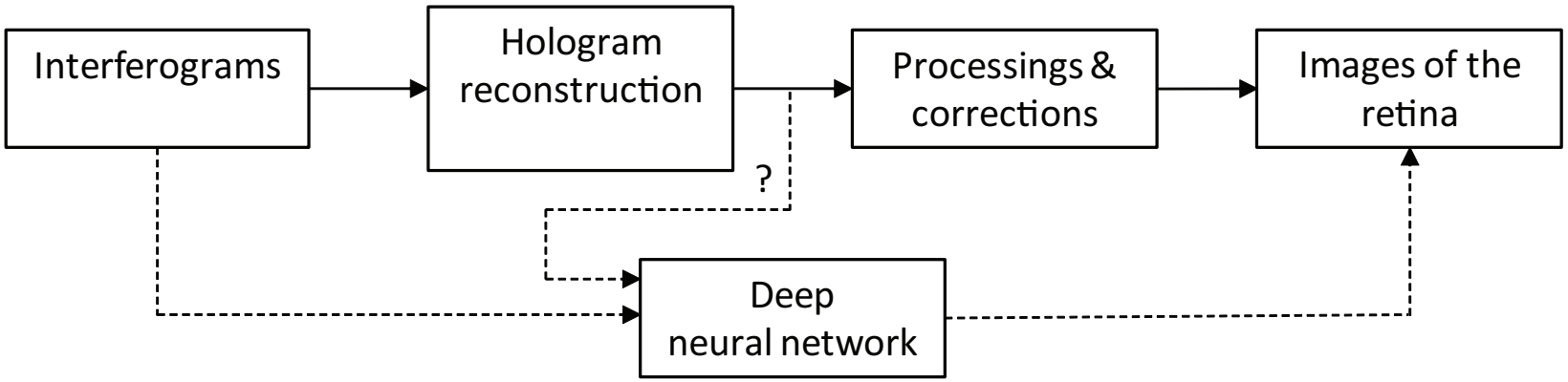
Related topics:

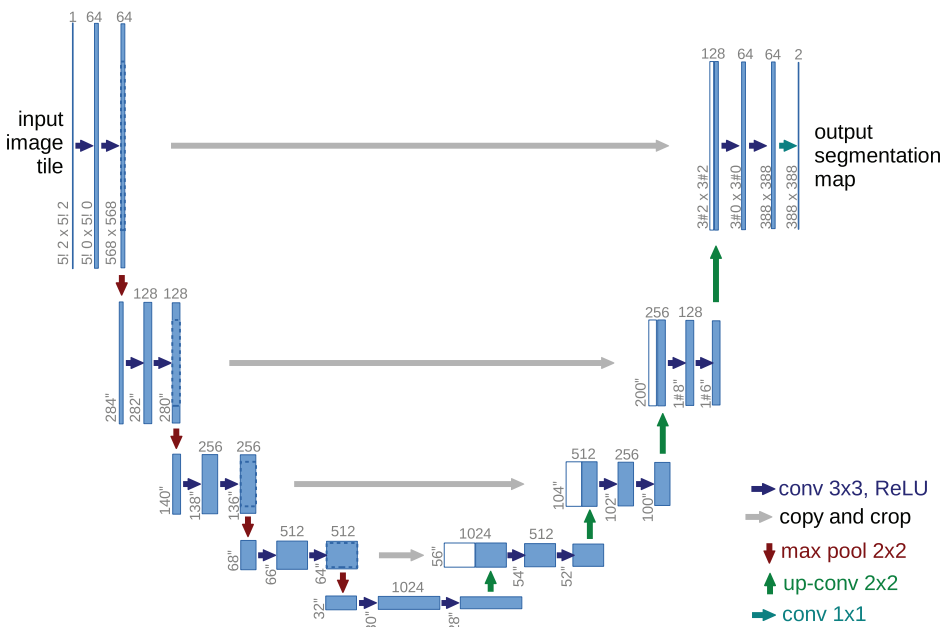
Li, Shuai, et al. "Imaging through glass diffusers using densely connected convolutional networks." *Optica* 5.7 (2018): 803-813.

Li, Yunzhe, Yujia Xue, and Lei Tian. "Deep speckle correlation: a deep learning approach towards scalable imaging through scattering media." *arXiv preprint arXiv:1806.04139* (2018).

Huang, Gao, et al. "Densely connected convolutional networks." *Conference on Computer Vision and Pattern Recognition*. Vol. 1. No. 2. 2017.

Aberrations correction with deep learning





U-net [1]

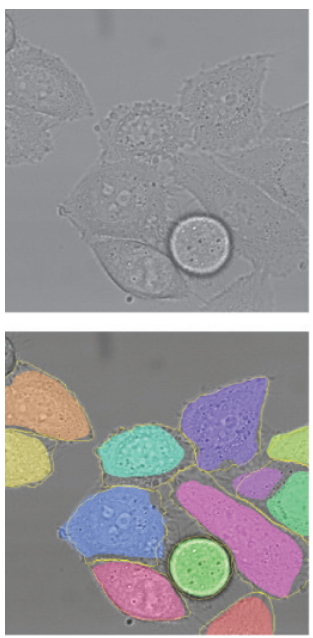
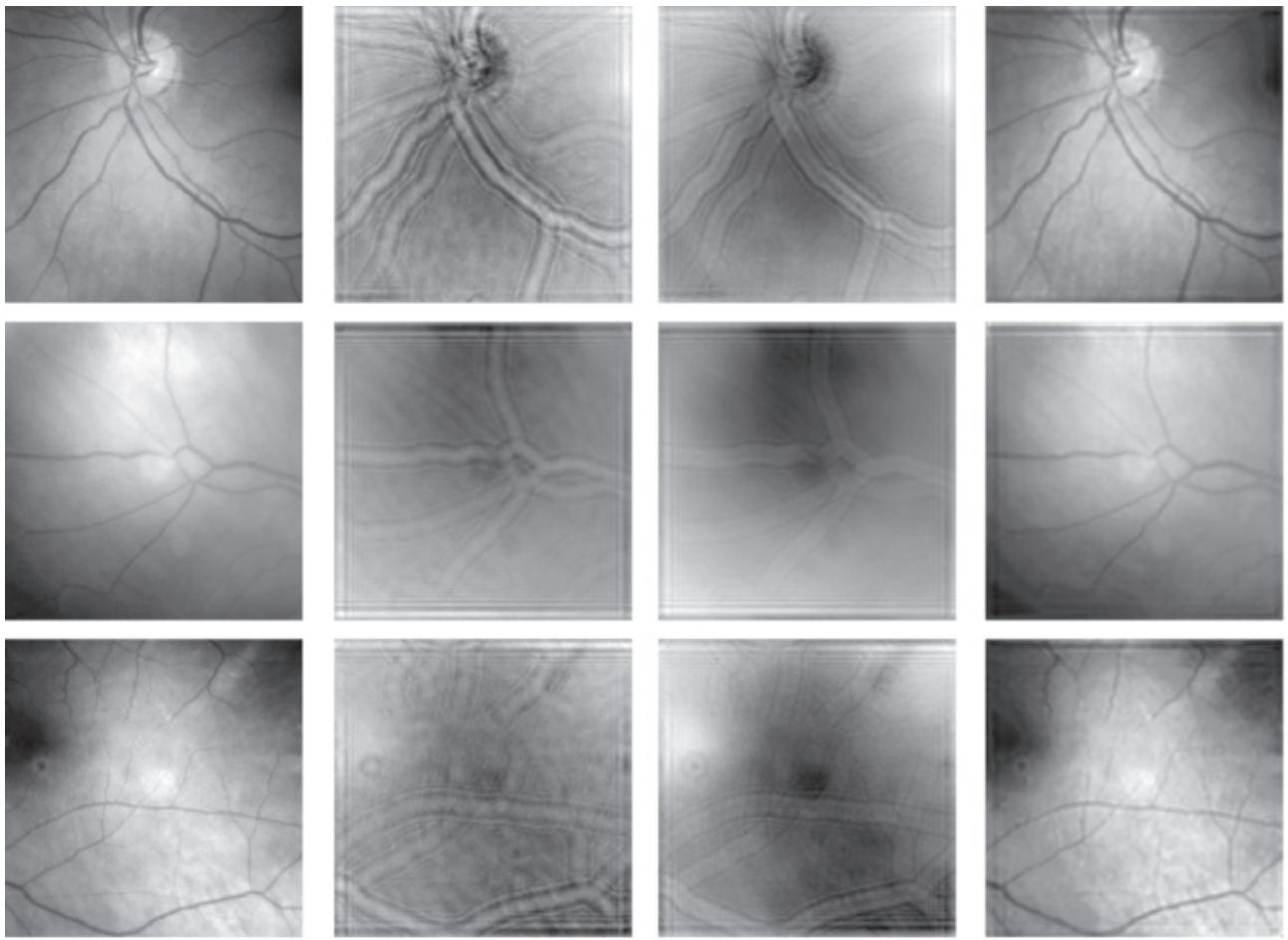


Image segmentation with U-net.

[1] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," *International Conference on Medical image computing and computer-assisted intervention*, pp. 234–241, Springer, 2015.

Aberrations correction with Deep learning

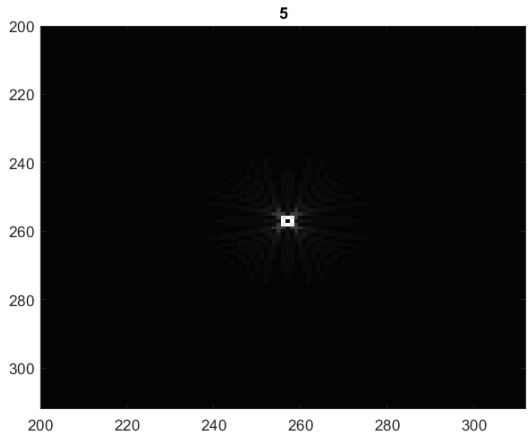
One aberration (defocus), one amplitude.



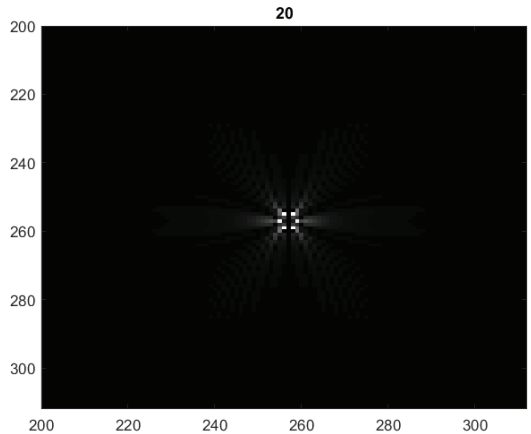
Original Real part Imaginary part Output

Aberrations correction with Deep learning

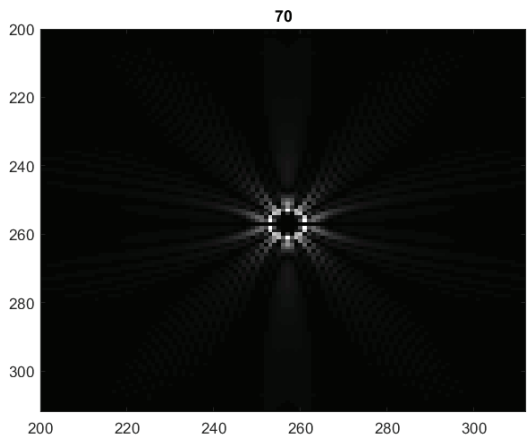
Influence of Fourier support, $|F\{\phi_a\}|$:



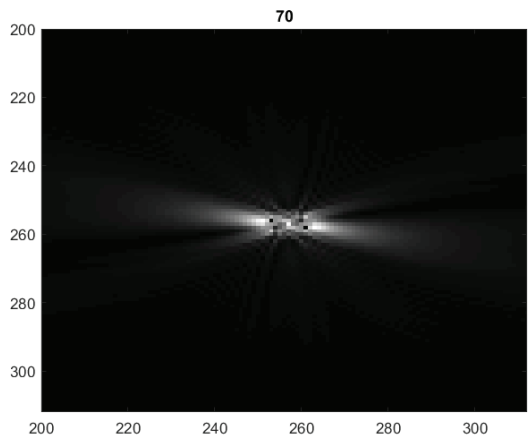
Mode 5 Zernike



Mode 20 Zernike



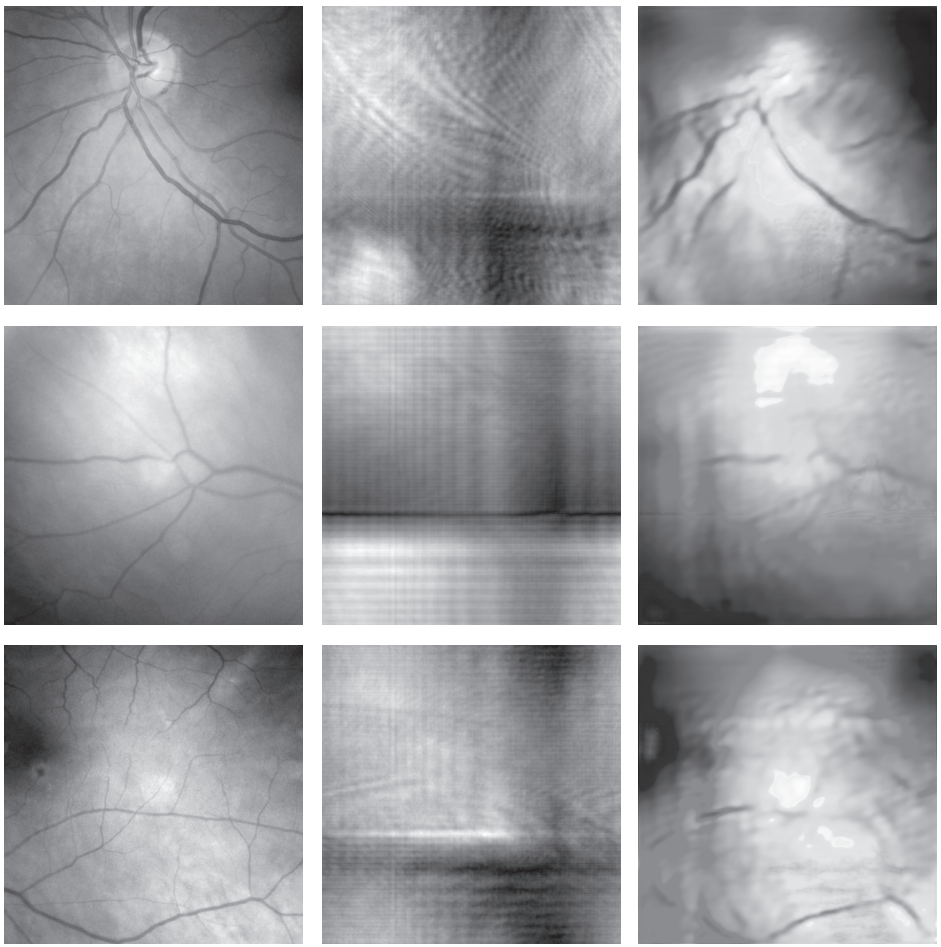
Mode 70 Zernike



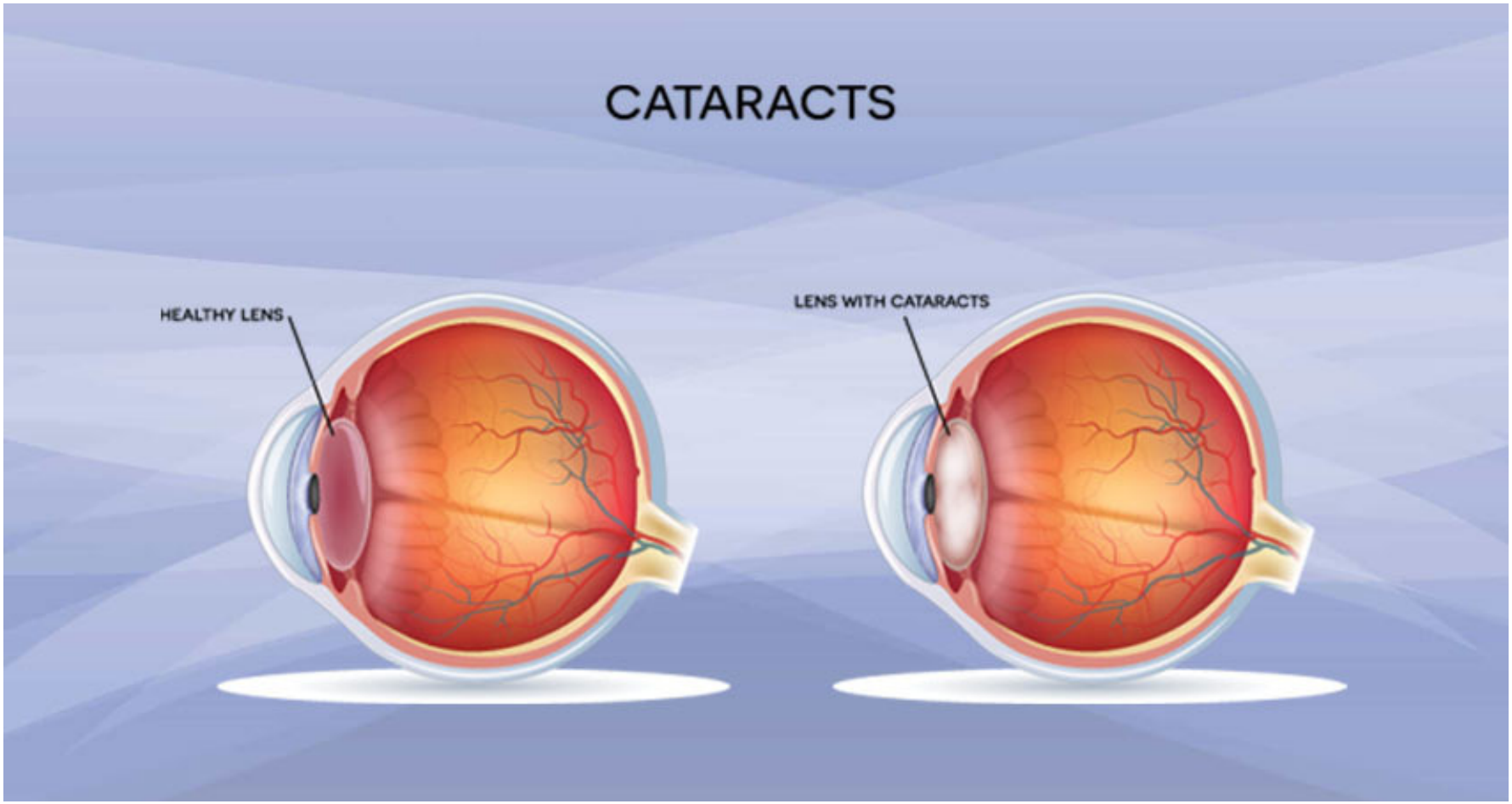
Modes 1 to 70 Zernike

Aberrations correction with Deep learning

Aberrations of amplitude 1, for 1 to 70 Zernike modes.



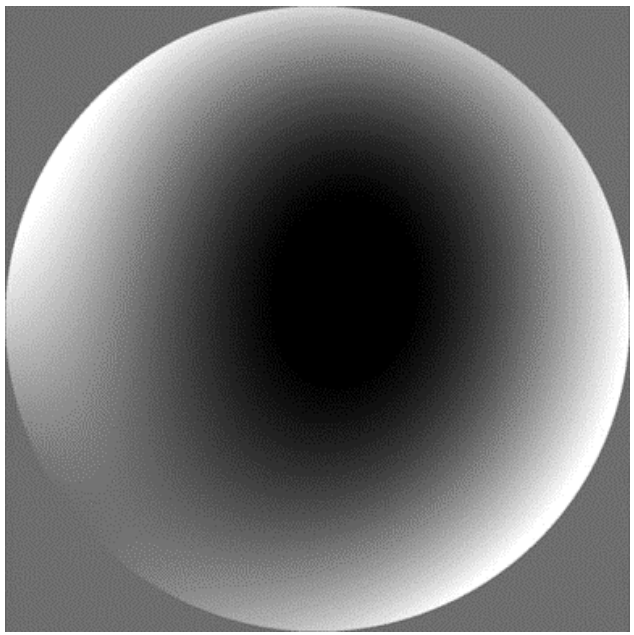
Original | Aberrated image (amplitude) | Output


CATARACTS
HEALTHY LENS
LENS WITH CATARACTS

Going further with cataracts...

Cataract: adding a random phase to the image $\rightarrow$ degrees of freedom N increased.

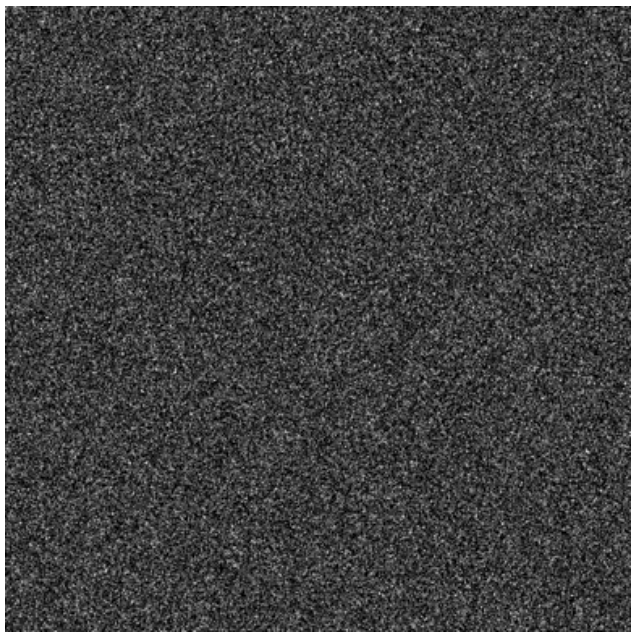
Φ_a



$N = 30$

to

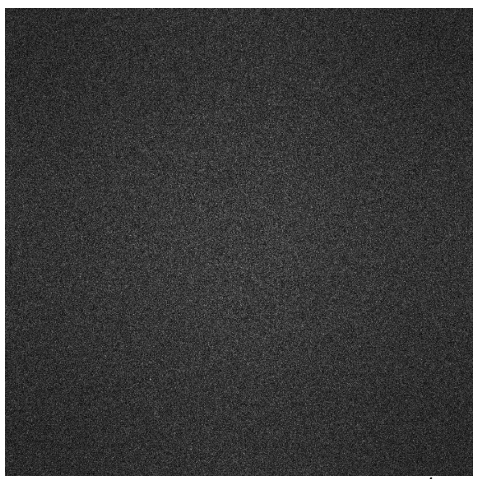
Φ_a



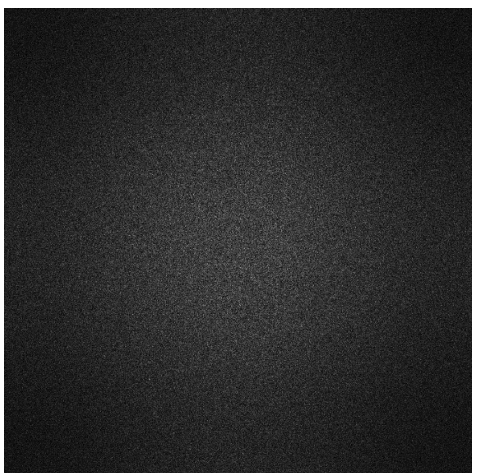
$N = 100000...$

Going further with cataracts...

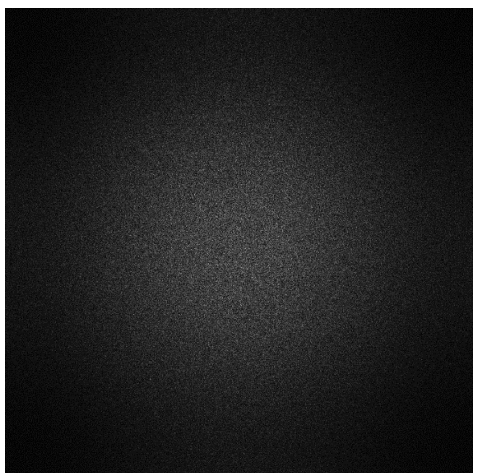
Cataract: adding a random phase to the image $\rightarrow$ bigger Fourier support.



Random phase, $std = \pi/3$



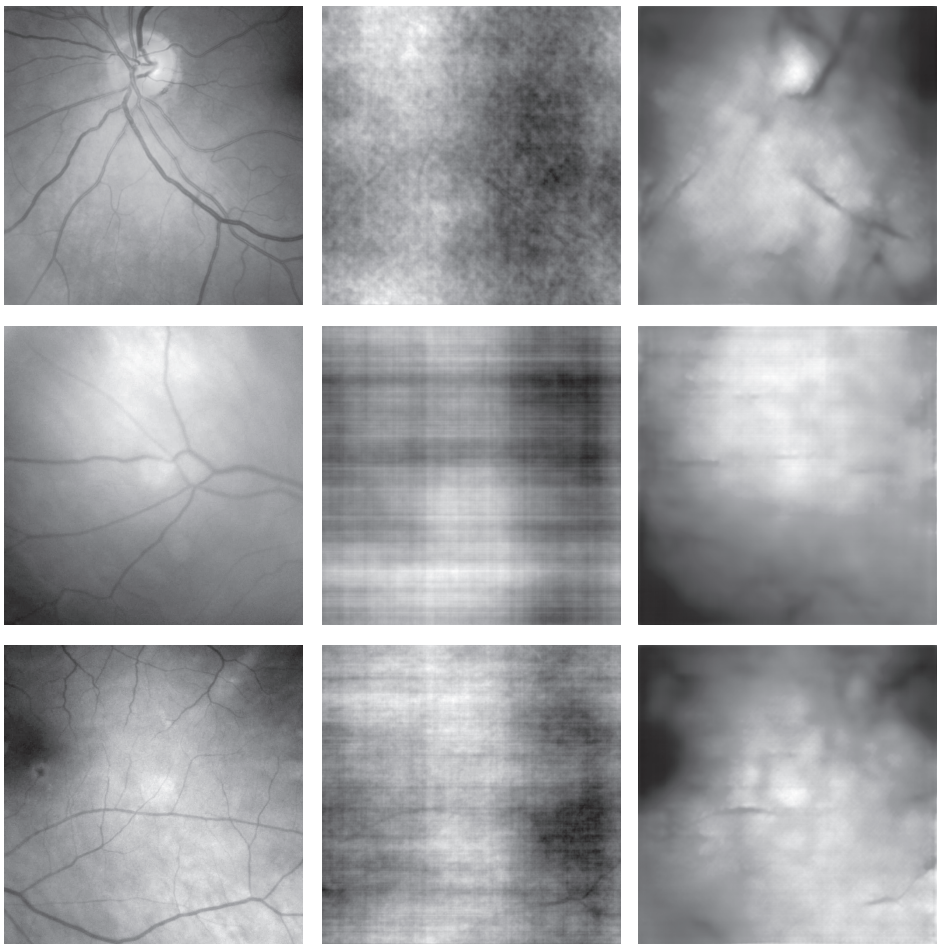
Gaussian filter, $std = 0.4$



Gaussian filter, $std = 0.5$

Going further with cataracts...

Tries with cataract.



Original | Aberrated image (amplitude) | Output

Perspectives

→ Go on testing limits.

→ Test new networks.

→ Compare to other aberrations correction methods.

→ Highlight on structures (vessels) with mathematical morphology.

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Thank you !