Deep Image Prior

for noise reduction
in optical coherence tomography images

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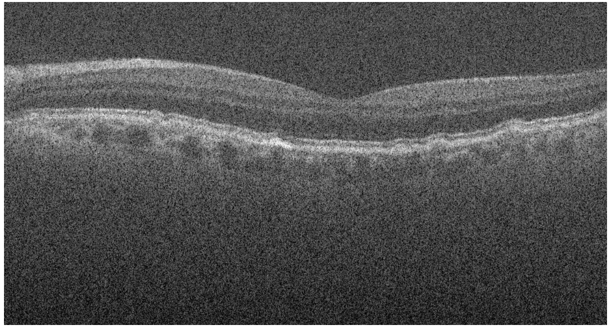
Introduction

- Optical coherence tomography (OCT): 3D optical imaging technique using interferometry to acquire reflectance profiles
- Variety of clinical uses - but most prominently ophthalmology for screening and diagnosis
- OCT imaging is corrupted by shot noise and speckle

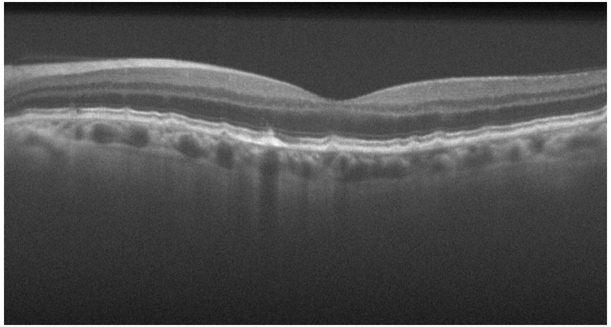
Leica Microsystems

Data Set

- 22 sets of OCT scans (raw and averaged) [1]
- 5 scans selected for optimization
- Cropped to uniform size and normalized
- Averaged scans are used as a “ground truth”



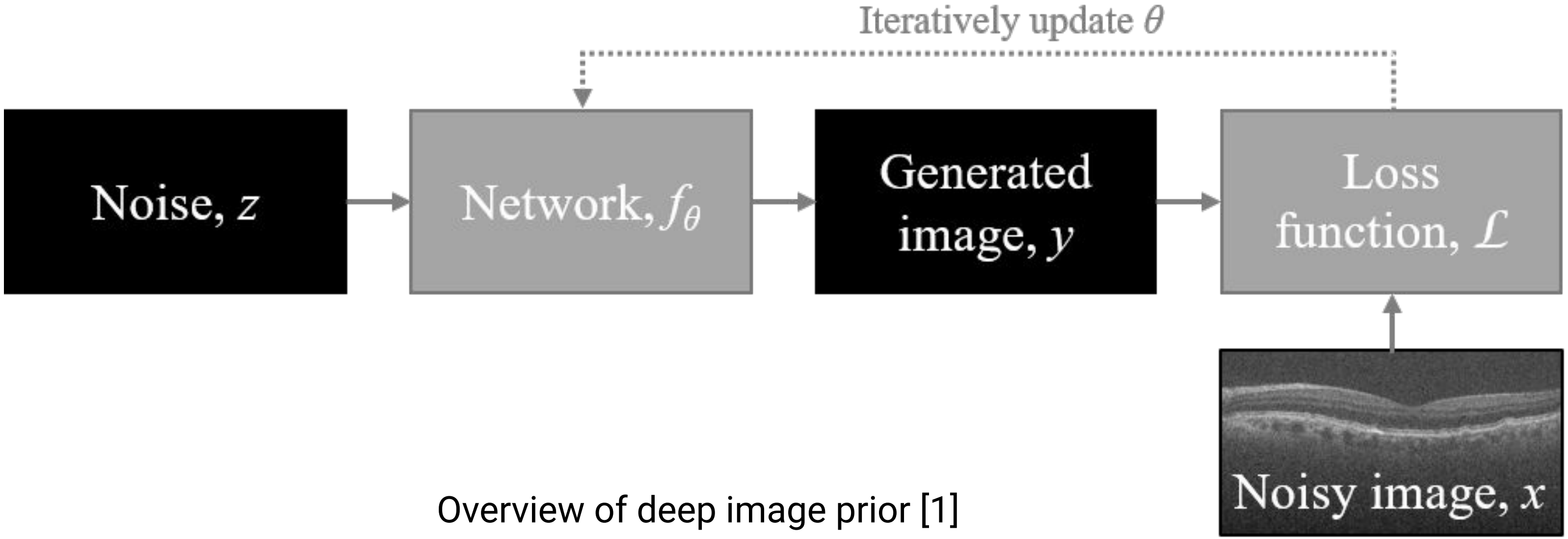
Raw



Averaged

[1] http://people.duke.edu/~sf59/Fang_BOE_2012.htm

Method



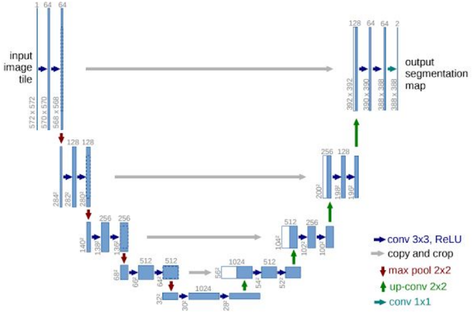
Overview of deep image prior [1]

[1] D. Ulyanov, A. Vedaldi, and V. Lempitsky, “Deep image prior,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 9446–9454.

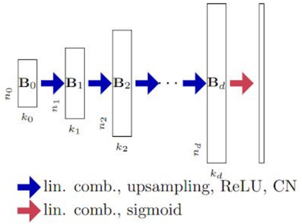
Method

Networks:

- U-Net [1]



- Deep Decoder [2]



Loss functions:

- $\mathcal{L}_{L_2} = |y - x|^2$
- $\mathcal{L}_{L_1} = |y - x|$
- $\mathcal{L}_{L_2\_L_1} = \mathcal{L}_{L_2} + w_0\, \mathcal{L}_{L_1}$
- $\mathcal{L}_{L_2\_tv} = w_1\, \mathcal{L}_{L_2} + w_2\, tv(y)$
- $\mathcal{L}_{L_2\_edge} = w_1\, \mathcal{L}_{L_2} + w_2\, edge_h(y) + w_3\, edge_v(y)$

[1] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2015, pp. 234–241.
[2] R. Heckel, and P. Hand, "Deep decoder: Concise image representations from untrained non-convolutional networks," *arXiv preprint arXiv:1810.03982,* 2018.

Results

$$CNR = \frac{|\mu_f - \mu_b|}{0.5\sqrt{\sigma_f^2 + \sigma_b^2}}$$

$$SSIM(g, y) = \frac{(2\mu_g\mu_y + C_1)(2\sigma_{gy} + C_2)}{(\mu_g^+ \mu_y^2 + C_1)(\sigma_g^+ \sigma_y^2 + C_2)}$$

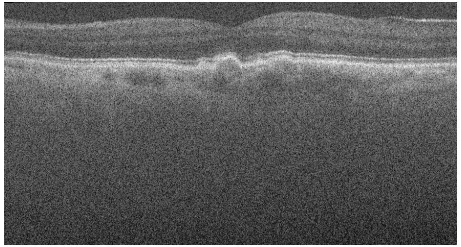
TABLE I
AVERAGE QUANTITATIVE METRICS

Network	**Loss**	**CNR**	**SSIM**
None	None	1.780	0.079
U-Net	$\mathcal{L}_{L_2}$	7.347	0.519
U-Net	$\mathcal{L}_{L_1}$	5.985	0.435
U-Net	$\mathcal{L}_{L_2\_L_1}$	6.426	0.507
U-Net	$\mathcal{L}_{L_2\_tv}$	8.295	**0.526**
U-Net	$\mathcal{L}_{L_2\_edge}$	**10.254**	0.510
Deep Decoder	$\mathcal{L}_{L_2\_tv}$	4.783	0.393
Deep Decoder	$\mathcal{L}_{L_2\_edge}$	7.807	0.492

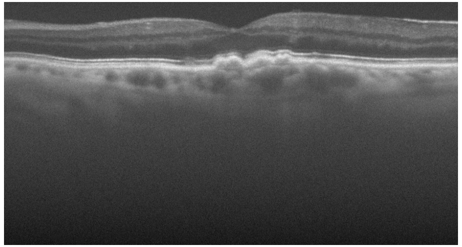
Network = None and **Loss** = None indicate the metrics of the original noisy image. The best metrics are shown in **bold**.

Results – 1

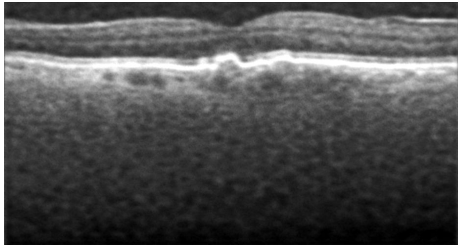
Noisy image:



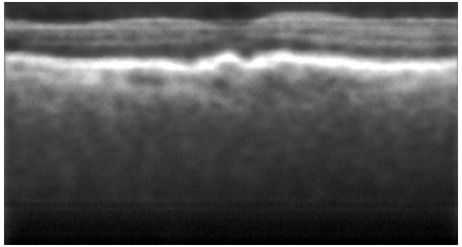
Averaged image:



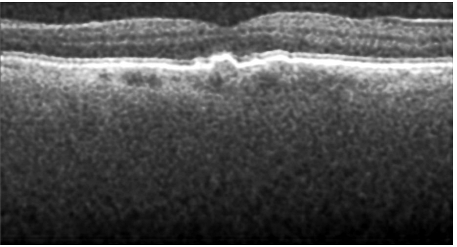
U-Net (L2):



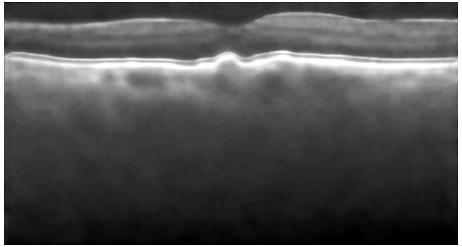
U-Net (L1):



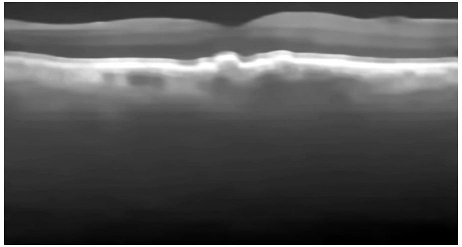
U-Net (L2_L1):



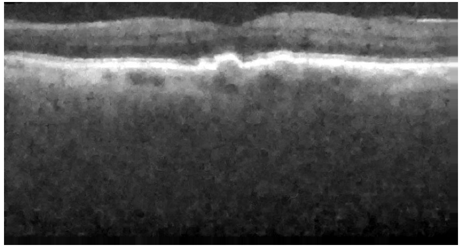
U-Net (L2_tv):



U-Net (L2_edge):

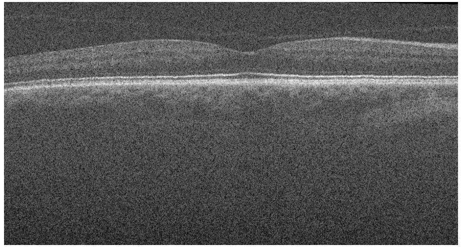


Deep Decoder (L2_edge):

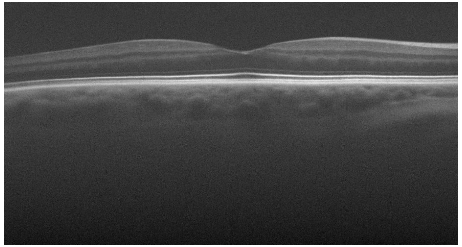


Results - 2

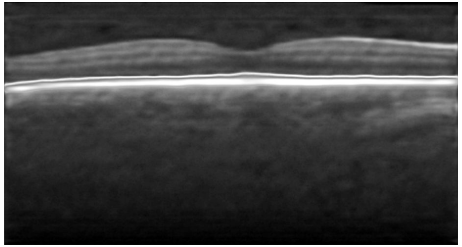
Noisy image:



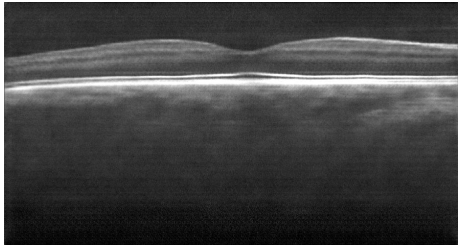
Averaged image:



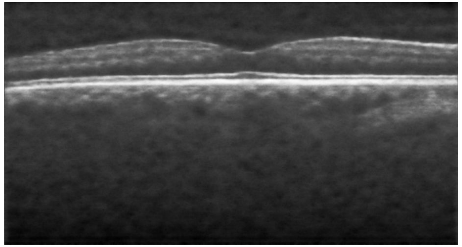
U-Net (L2):



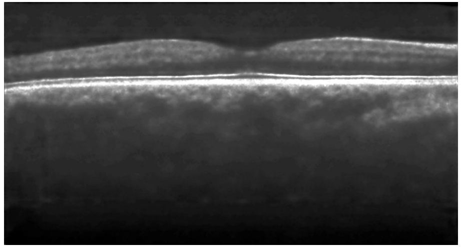
U-Net (L1):



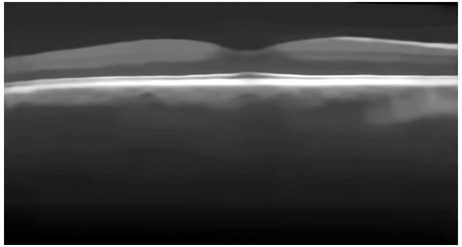
U-Net (L2_L1):



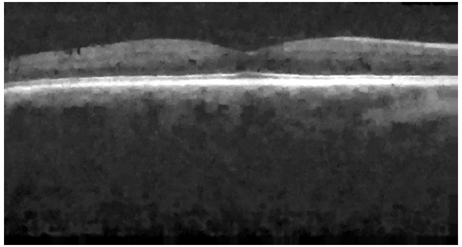
U-Net (L2_tv):



U-Net (L2_edge):

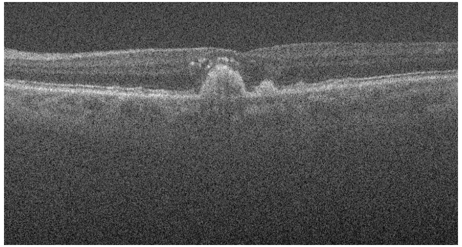


Deep Decoder (L2_edge):

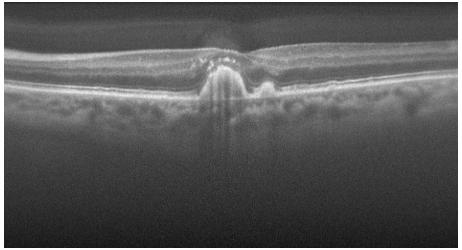


Results - 3

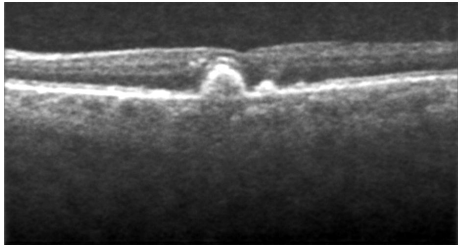
Noisy image:



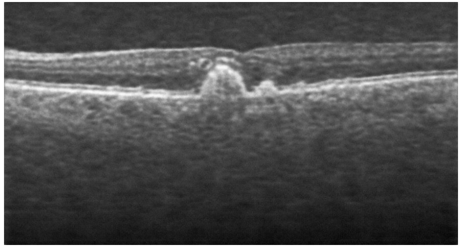
Averaged image:



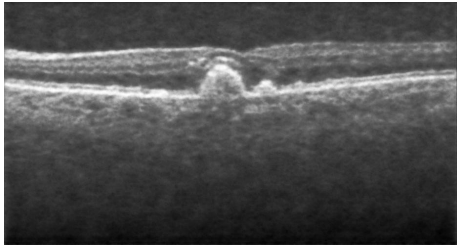
U-Net (L2):



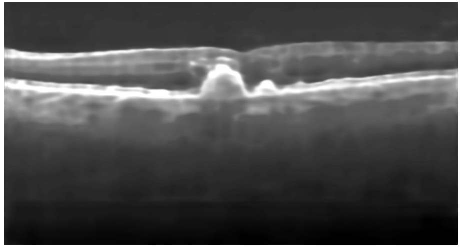
U-Net (L1):



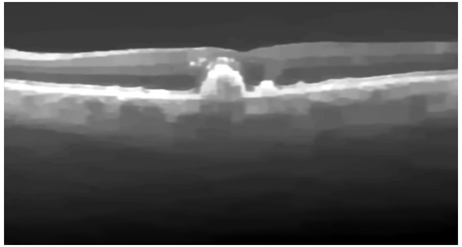
U-Net (L2_L1):



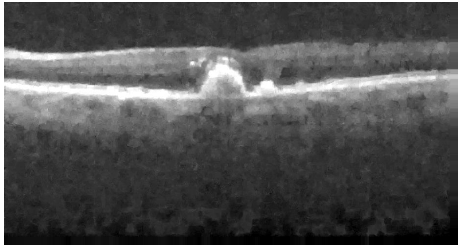
U-Net (L2_tv):



U-Net (L2_edge):

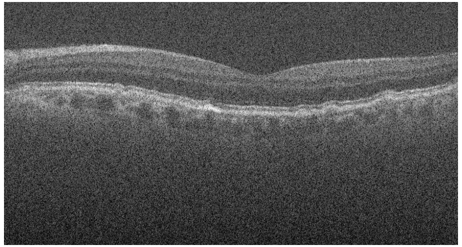


Deep Decoder (L2_edge):

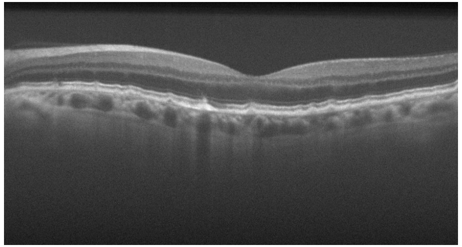


Results - 4

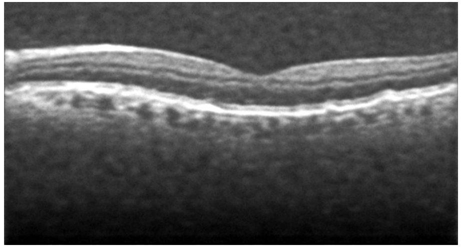
Noisy image:



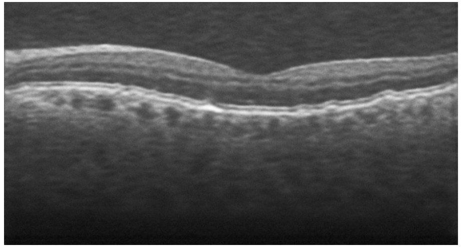
Averaged image:



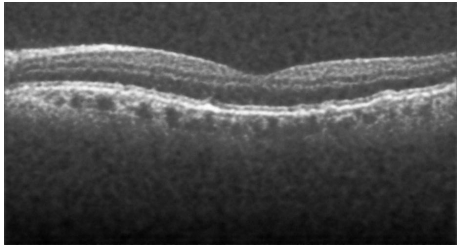
U-Net (L2):



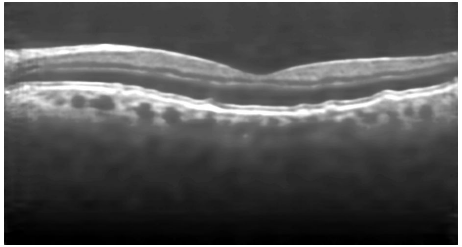
U-Net (L1):



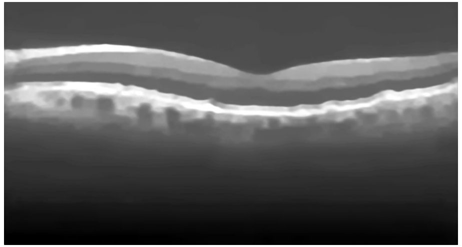
U-Net (L2_L1):



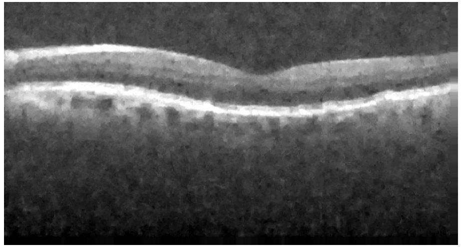
U-Net (L2_tv):



U-Net (L2_edge):

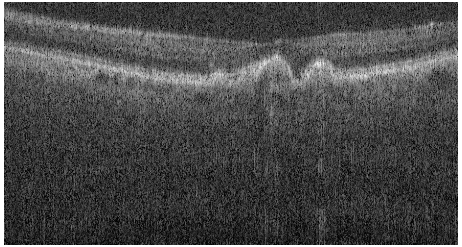


Deep Decoder (L2_edge):

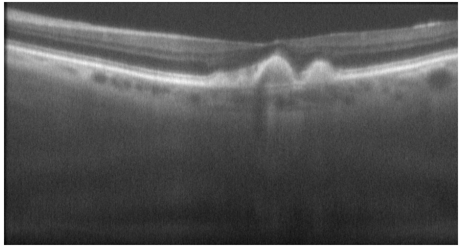


Results - 5

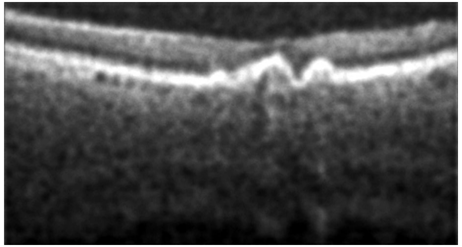
Noisy image:



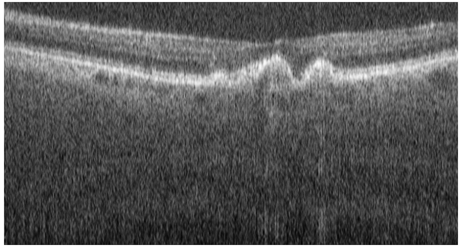
Averaged image:



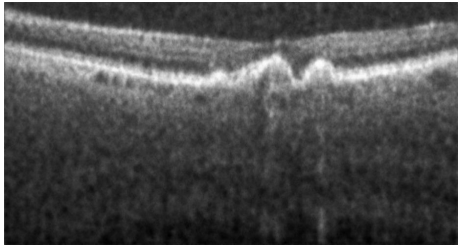
U-Net (L2):



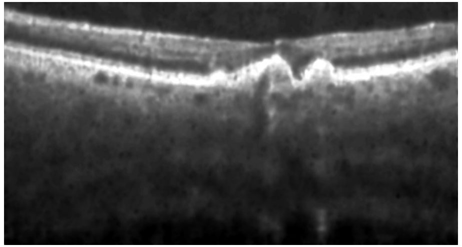
U-Net (L1):



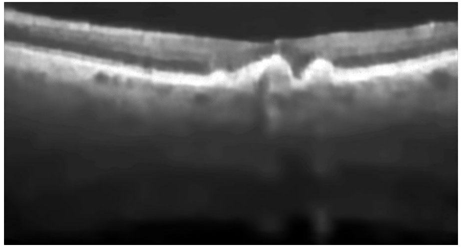
U-Net (L2_L1):



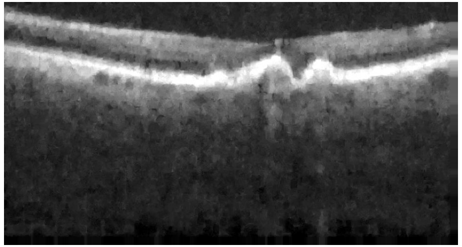
U-Net (L2_tv):



U-Net (L2_edge):



Deep Decoder (L2_edge):



Conclusion

- Combination of U-Net with $\mathcal{L}_{L_2\_tv}$ and $\mathcal{L}_{L_2\_edge}$ provided the best noise reduction
- Accuracy of downstream tasks (e.g. segmentation) as alternative evaluation method
- OCT-specific loss functions (e.g. noise model, retinal structures)