


浙江大学爱丁堡大学联合学院

ZJU-UoE Institute

Lecture 19 - Recents advances in image analysis using deep learning

Part 1 - Image improvement

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Learning objectives

- Discuss recent advances in image analysis using deep learning.

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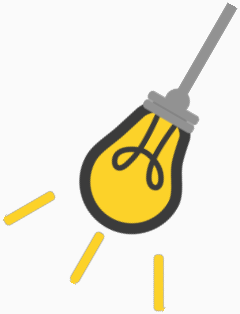
Today we are going to analyse recent articles related to image improvement using deep learning.

- Noise removal
  - Lehtinen et al. 2018 - Noise2Noise: Learning Image Restoration without Clean Data
  - Krull et al. 2019 - Noise2Void: Learning Denoising from Single Noisy Images
- Superresolution
  - Wang et al. 2019 - Deep learning enables cross-modality super-resolution in fluorescence microscopy
- Refocusing
  - Wu et al. 2019 - Three-dimensional virtual refocusing of fluorescence microscopy images using deep learning



Noise removal

The problem

- Noise is a major problem in image analysis and very common in biomedical imaging.
- Image denoising tries to separate the image signal from noise. Existing methods rely on the assumptions that pixel values in the noise component are uncorrelated.
- CNN can be used to remove noise from images by training them on pairs of noisy and clean images.
- Often we don't have access to clean images.
- Can we just train on noisy images?

Noise2Noise: Learning Image Restoration without Clean Data

Jaakko Lehtinen[1 2] Jacob Munkberg[1] Jon Hasselgren[1] Samuli Laine[1] Tero Karras[1] Miika Aittala[3] Timo Aila[1]

Noise2Noise - architecture

NAME	N_{out}	FUNCTION
INPUT	n	
ENC_CONV0	48	Convolution 3×3
ENC_CONV1	48	Convolution 3×3
POOL1	48	Maxpool 2×2
ENC_CONV2	48	Convolution 3×3
POOL2	48	Maxpool 2×2
ENC_CONV3	48	Convolution 3×3
POOL3	48	Maxpool 2×2
ENC_CONV4	48	Convolution 3×3
POOL4	48	Maxpool 2×2
ENC_CONV5	48	Convolution 3×3
POOL5	48	Maxpool 2×2
ENC_CONV6	48	Convolution 3×3
UPSAMPLE5	48	Upsample 2×2
CONCAT5	96	Concatenate output of POOL4
DEC_CONV5A	96	Convolution 3×3
DEC_CONV5B	96	Convolution 3×3
UPSAMPLE4	96	Upsample 2×2
CONCAT4	144	Concatenate output of POOL3
DEC_CONV4A	96	Convolution 3×3
DEC_CONV4B	96	Convolution 3×3
UPSAMPLE3	96	Upsample 2×2
CONCAT3	144	Concatenate output of POOL2
DEC_CONV3A	96	Convolution 3×3
DEC_CONV3B	96	Convolution 3×3
UPSAMPLE2	96	Upsample 2×2
CONCAT2	144	Concatenate output of POOL1
DEC_CONV2A	96	Convolution 3×3
DEC_CONV2B	96	Convolution 3×3
UPSAMPLE1	96	Upsample 2×2
CONCAT1	$96+n$	Concatenate INPUT
DEC_CONV1A	64	Convolution 3×3
DEC_CONV1B	32	Convolution 3×3
DEV_CONV1C	m	Convolution 3×3, linear act.

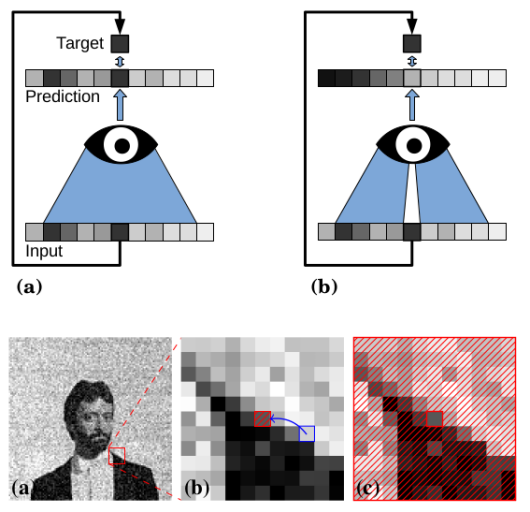
Noise2Noise - results

Input ($p = 0.70$)	L_0	Clean targets	Ground truth
8.89 dB	28.43 dB	28.86 dB	PSNR

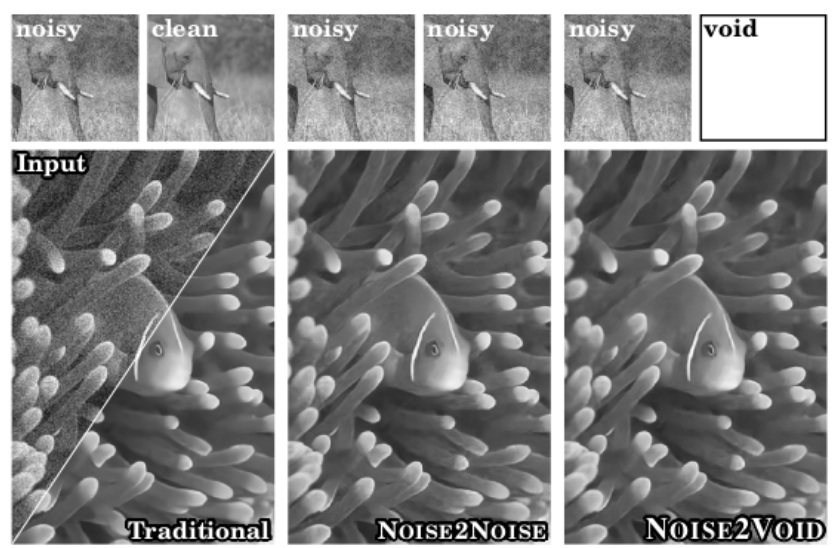
Noise2Void - Learning Denoising from Single Noisy Images

Alexander Krull[1,2], Tim-Oliver Buchholz[2], Florian Jug

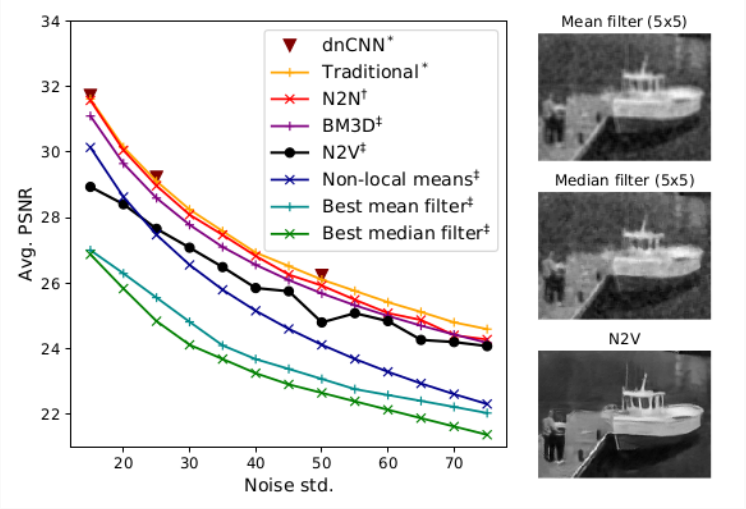
Noise2Void - the process



Noise2Void - results



Comparison of denoising methods



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Refocusing

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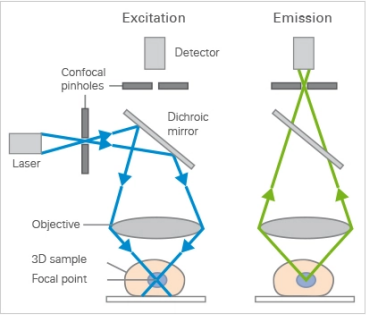
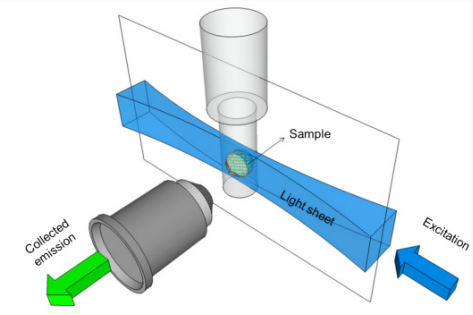
- Acquired e.g. using confocal, two photon or light sheet microscopy.





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- Acquired e.g. using confocal, two photon or light sheet microscopy.
- Problems include speed, phototoxicity, photobleaching.
- Widefield microscopy is much faster but has lower resolution and loses the volumetric information.

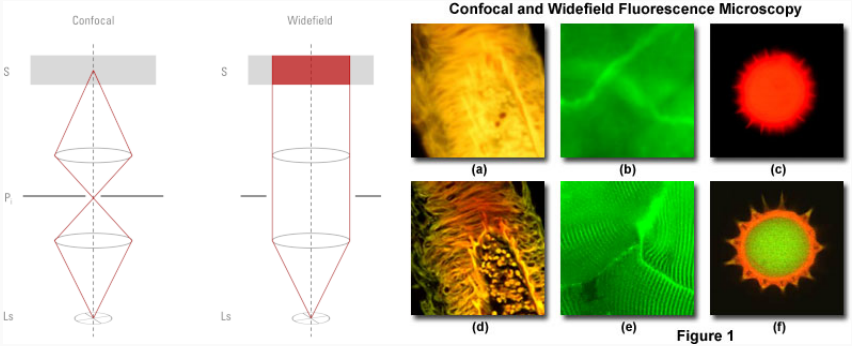

Figure 1

Can we refocus using deep learning? Can we use widefield microscopy images to reconstruct the lost volumetric information?

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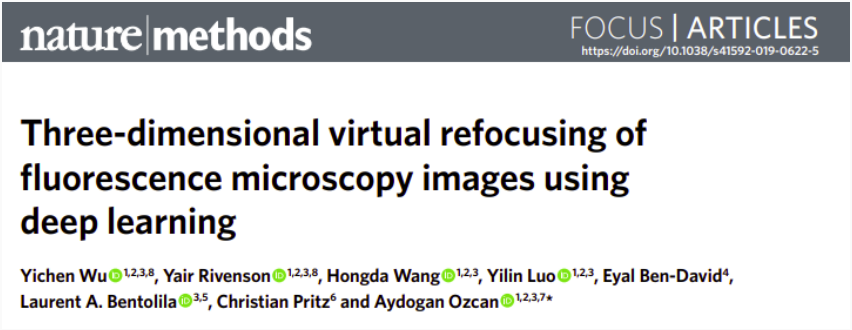
Three-dimensional virtual refocusing of fluorescence microscopy images using deep learning

Yichen Wu[1,2,3,8], Yair Rivenson[1,2,3,8], Hongda Wang[1,2,3], Yilin Luo[1,2,3], Eyal Ben-David[4], Laurent A. Bentolila[3,5], Christian Pritz[6] and Aydogan Ozcan[1,2,3,7*]

Can we refocus using deep learning? Can we use widefield microscopy images to reconstruct the lost volumetric information?



“Here we introduce a digital image refocusing framework in fluorescence microscopy by training a deep neural network using microscopic image data, enabling 3D imaging of fluorescent samples using a single 2D wide-field image, without the need for any mechanical scanning, additional hardware or parameter estimation.”

How does it work?

- Given a widefield image, Deep-Z associates to it a user-defined *digital propagation matrix* (DPM) containing the desired axial distance of the target surface from the plane of the input image.

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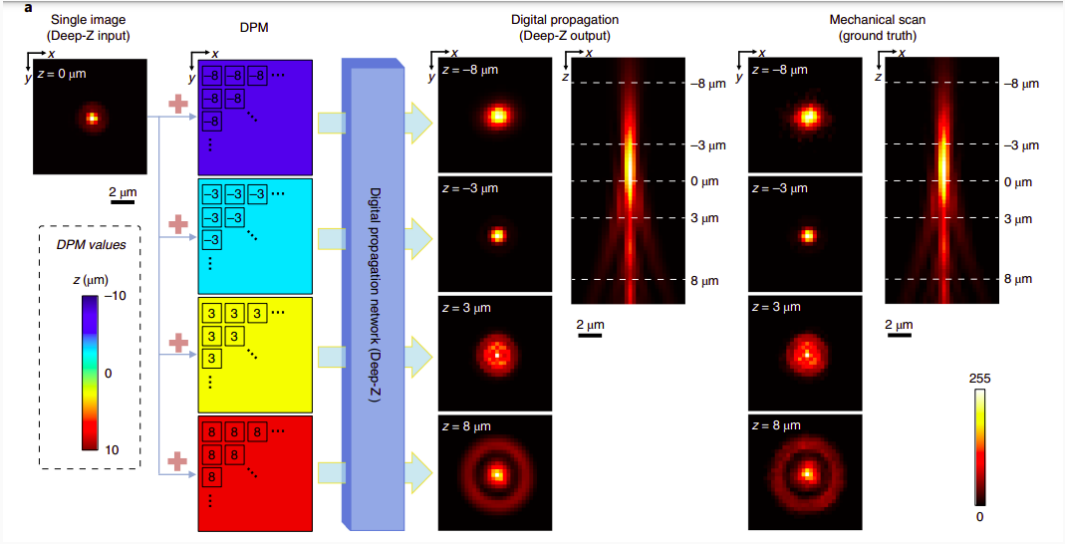
- Given a widefield image, Deep-Z associates to it a user-defined *digital propagation matrix* (DPM) containing the desired axial distance of the target surface from the plane of the input image.
- Deep-Z uses a generative-adversarial network (GAN) to generate synthetic images that approximates the desired depth.
- It is trained on “matched pairs of (1) various fluorescence images axially focused at different depths and appended with different DPMs, and (2) the corresponding fluorescence images (that is, the ground-truth labels) captured at the correct (target) focus plane defined by the corresponding DPM.”

Deep-Z - the process



Generative-adversarial-networks (GANs)

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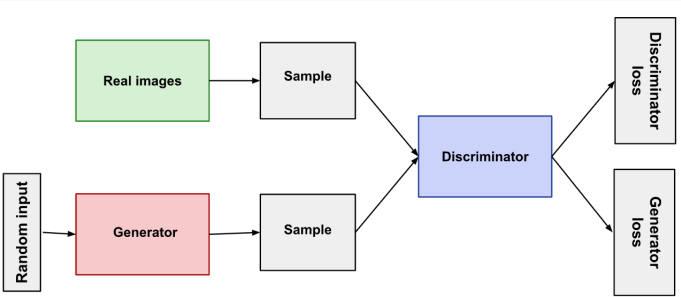
- The **discriminator**, a neural network that determines whether an image is real or generated.

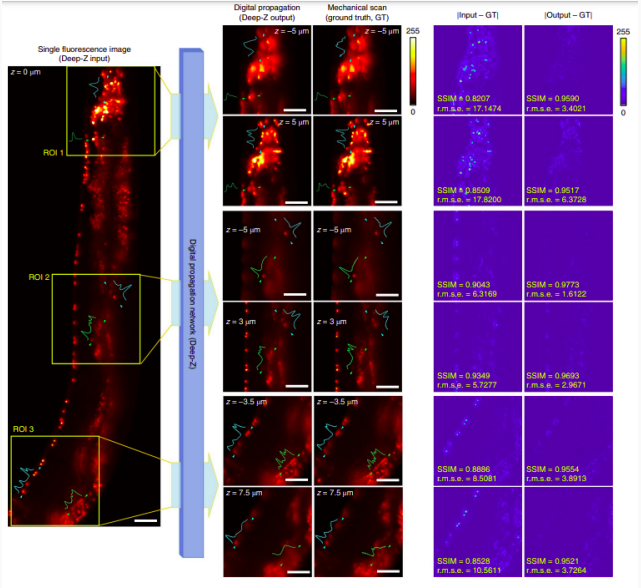
The generator and the discriminator *fight* each other (hence the network is *adversarial*), so the generator has to improve in order to be able to *fool* the discriminator into thinking its images are real.

GAN - simplified schematic

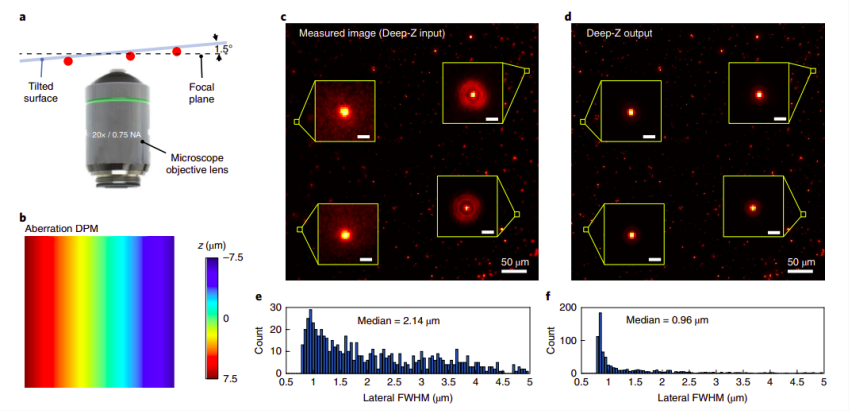


Source: Google Developers

Deep-Z - results



Non-uniform DPMs



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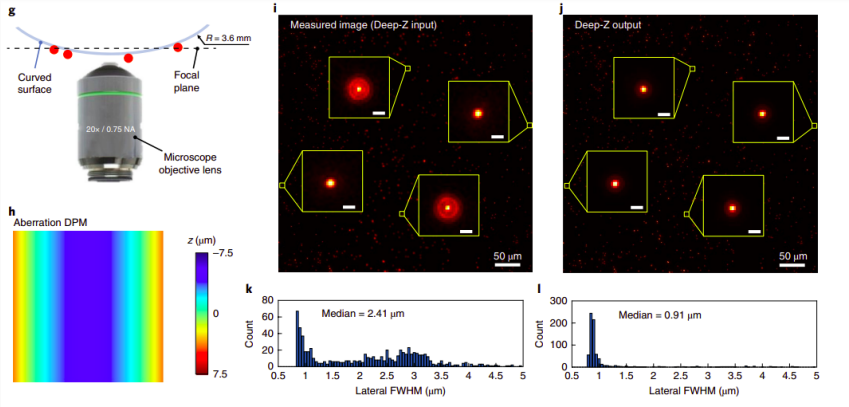
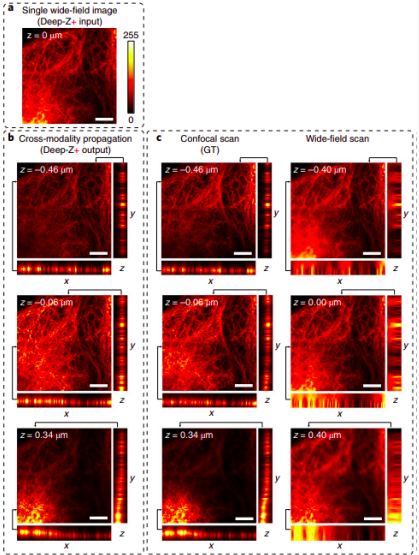


Deep-Z+ - cross-modality refocusing

Deep-Z+ allows cross-modality refocusing.



Superresolution

The problem

- Super-resolution methods such as STED or SIM allow the study of biological processes at a finer resolution than the resolution of the microscope.
- They require expensive setups, specific sample preparation and extensive post-processing.
- Post-processing requires *a priori* knowledge of the sample/mounting media/imaging system etc.

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https://doi.org/10.1038/s41592-018-0239-0

Deep learning enables cross-modality super-resolution in fluorescence microscopy

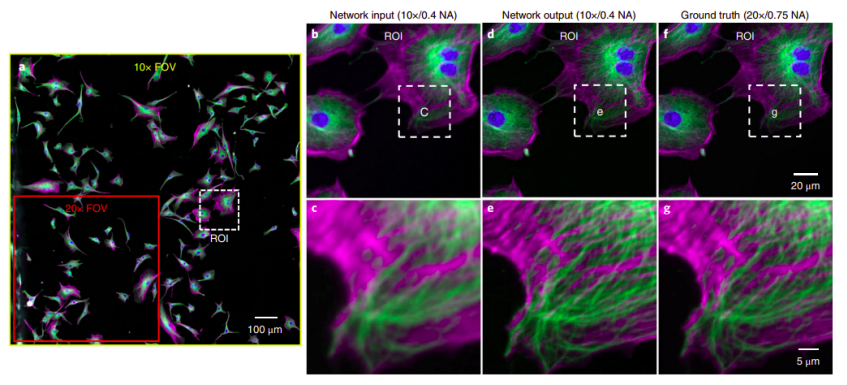
Hongda Wang[1,2,3,9], Yair Rivenson[1,2,3,9], Yiyin Jin[1], Zhensong Wei[1], Ronald Gao[4], Harun Günaydın[1], Laurent A. Bentolila[3,5], Comert Kural[6,7] and Aydogan Ozcan[1,2,3,8*]

"Here we present a deep-learning-based framework to achieve super-resolution and cross-modality image transformations in fluorescence microscopy without the need for making any assumptions about or modeling of the image-formation process."

The process

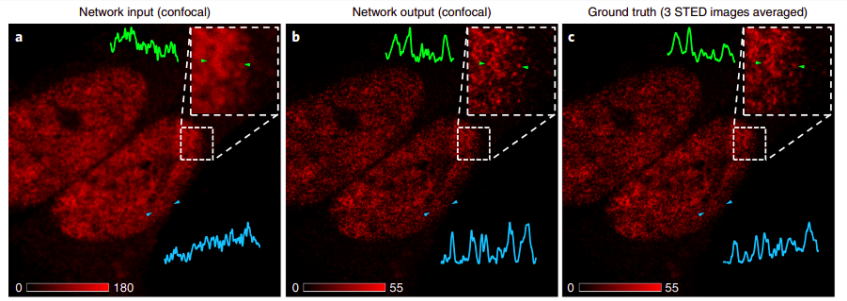
“We trained a deep neural network using a generative adversarial network (GAN)16 model to transform an acquired low-resolution image into a high-resolution one using matched pairs of experimentally acquired low- and higher-resolution images. [...] Once the deep network is trained, it remains fixed and can be used to rapidly output batches of high-resolution images in, for example, 0.4 s for an image size of 1,024×1,024 pixels using a single graphics processing unit (GPU).

The results



Deep-learning-based super-resolved images of bovine pulmonary artery endothelial cells.Color map: magenta for F-actin, green for microtubules, blue for nuclei.

The results



Cross-modality transformation from confocal to STED.