

Learning denoising without clean images

- - **Noise2Noise: Learning Image Restoration without Clean Data**

Jaakko Lehtinen, Jacob Munkberg, Jon Hasselgren, Samuli Laine, Tero Karras, Miika Aittala and Timo Aila (2018)

- - **Noise2Void: Learning Denoising from Single Noisy Images**

Alexander Krull, Tim-Oliver Buchholz and Florian Jug (2019)

- - **DenoSeg: Joint Denoising and Segmentation**

Tim-Oliver Buchholz, Mangal Prakash, Alexander Krull and Florian Jug (2020)

Traditional method

- training networks for denoising requires pairs of noisy and clean images
- obtaining clean training targets is often difficult or tedious: a noise-free photograph requires a long exposure, This can be a difficult procedure since the biological sample must not move between exposures

Noise2Noise - Learning Image Restoration without Clean Data

- This method maps between a noisy input pixel and its noisy target and apply basic statistical reasoning to signal reconstruction by machine learning
- It requires that two images capturing the same content (s) with independent noises (n, n') can be acquired
- It attempts to learn a mapping between pairs of independently degraded versions of the same training image, i.e. $(s + n, s + n')$, that incorporate the same signal s , but independently drawn noise n and n'
- Works for different types of noises
- Works for reconstruction of undersampled MRI scans

(a) Gaussian ($\sigma = 25$)



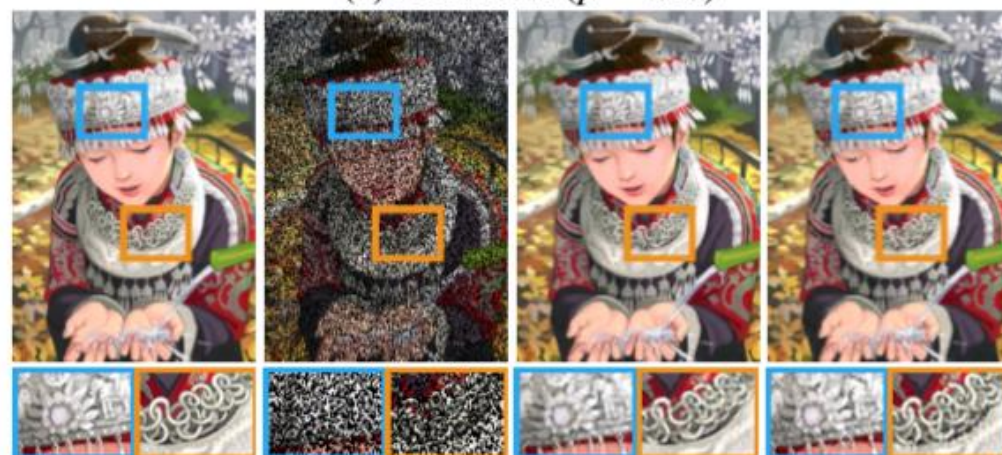
BM3D

(b) Poisson ($\lambda = 30$)



ANSCOMBE

(c) Bernoulli ($p = 0.5$)



DEEP IMAGE PRIOR

Ground truth

Input

Our

Comparison



Input ($p \approx 0.25$)
17.12 dB



L_2
26.89 dB



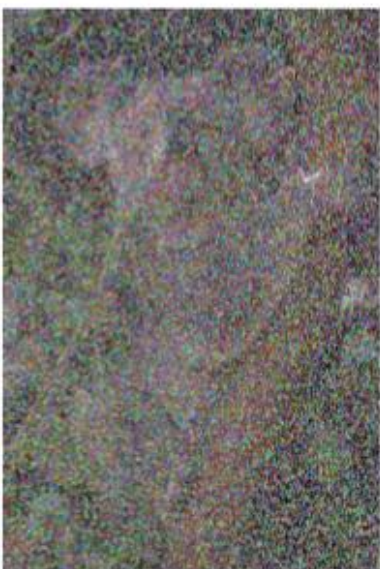
L_1
35.75 dB



Clean targets
35.82 dB



Ground truth
PSNR



Input ($p = 0.70$)
8.89 dB



L_2 / L_1
13.02 dB / 16.36 dB



L_0
28.43 dB

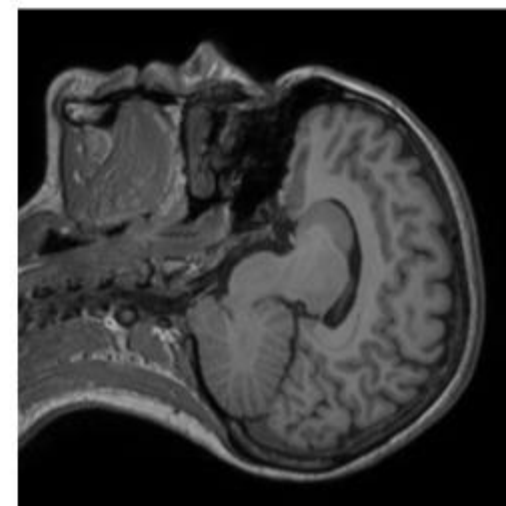
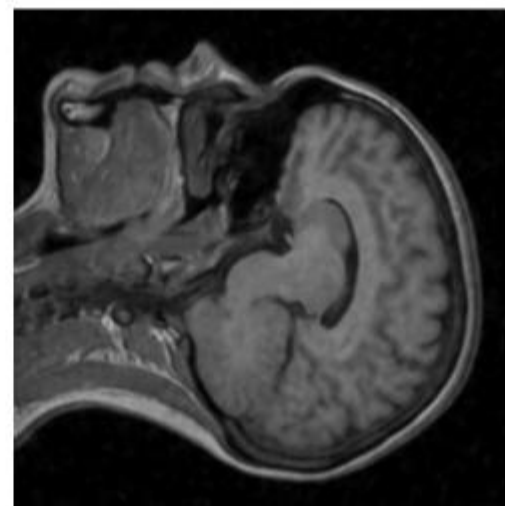
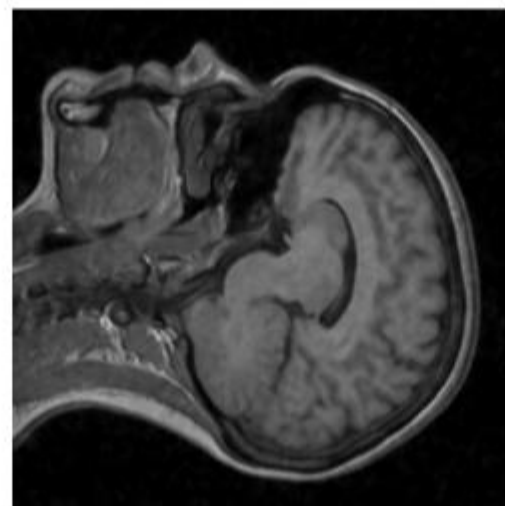


Clean targets
28.86 dB

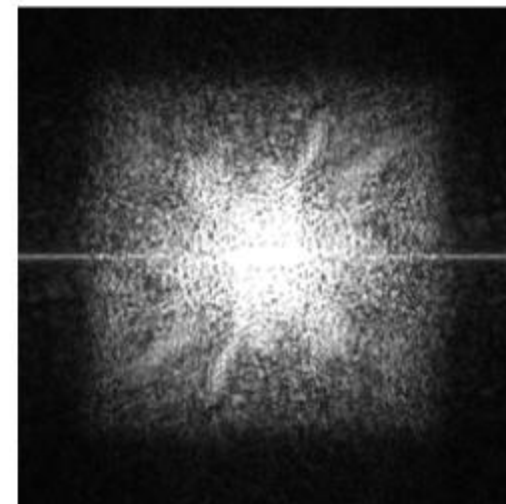
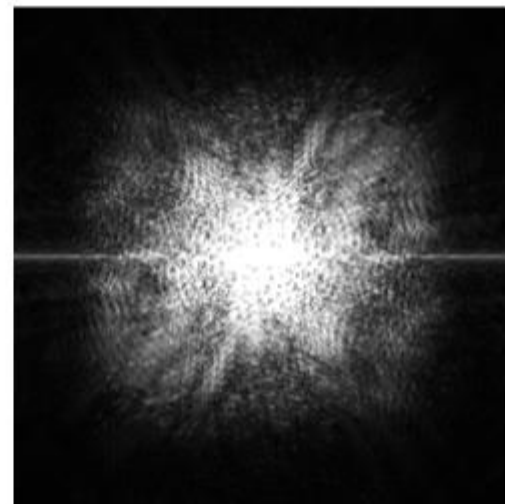
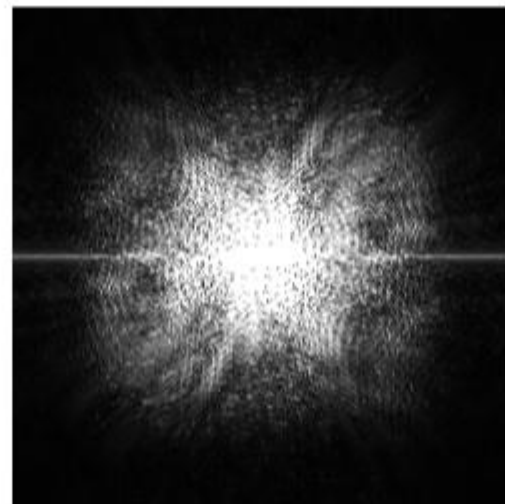
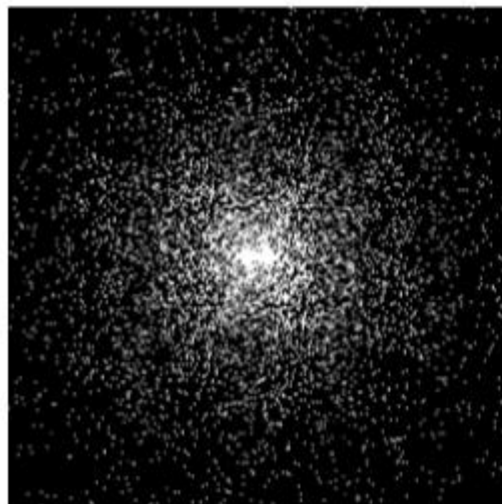


Ground truth
PSNR

Image



Spectrum



(a) Input
18.93 dB

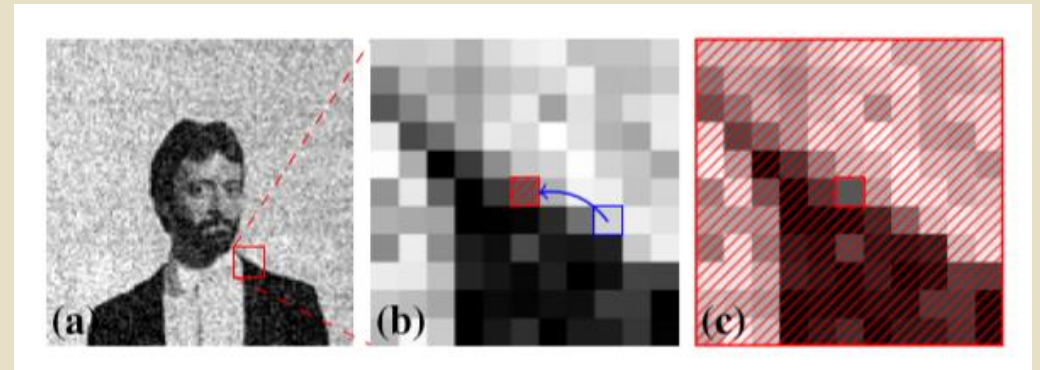
(b) Noisy trg.
29.77 dB

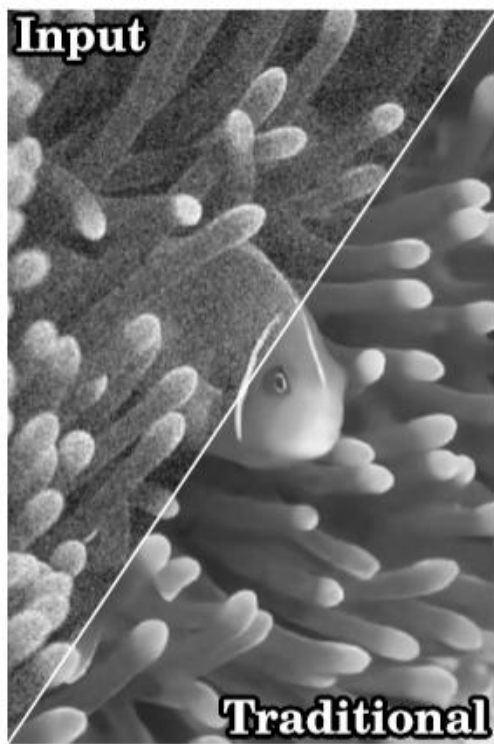
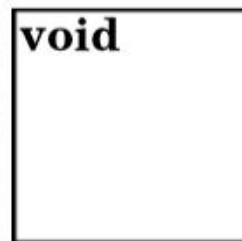
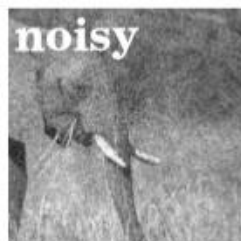
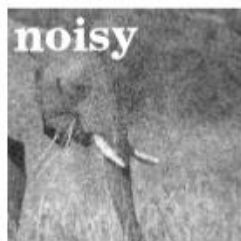
(c) Clean trg.
29.81 dB







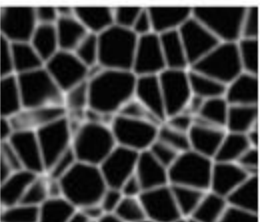
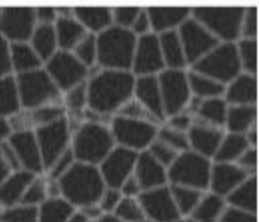
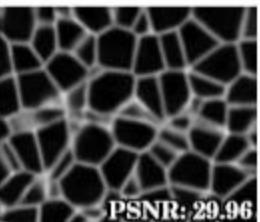
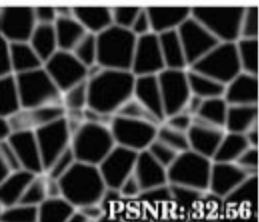
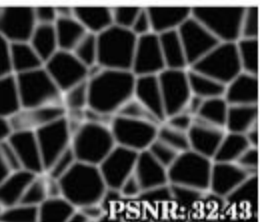
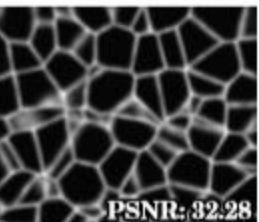

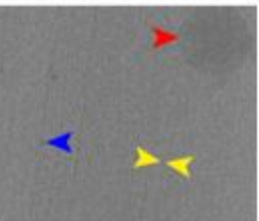
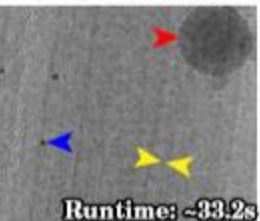

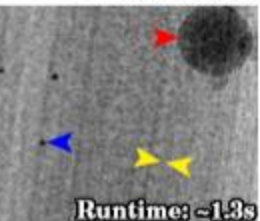
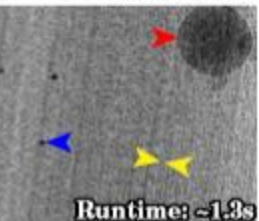

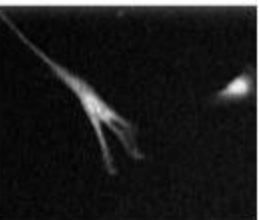





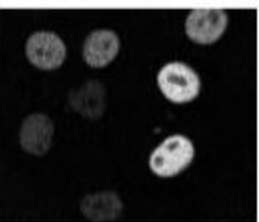
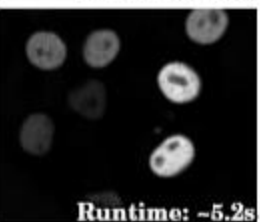


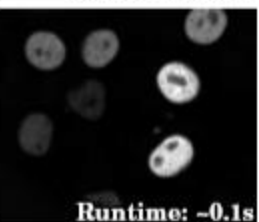
(d) Reference

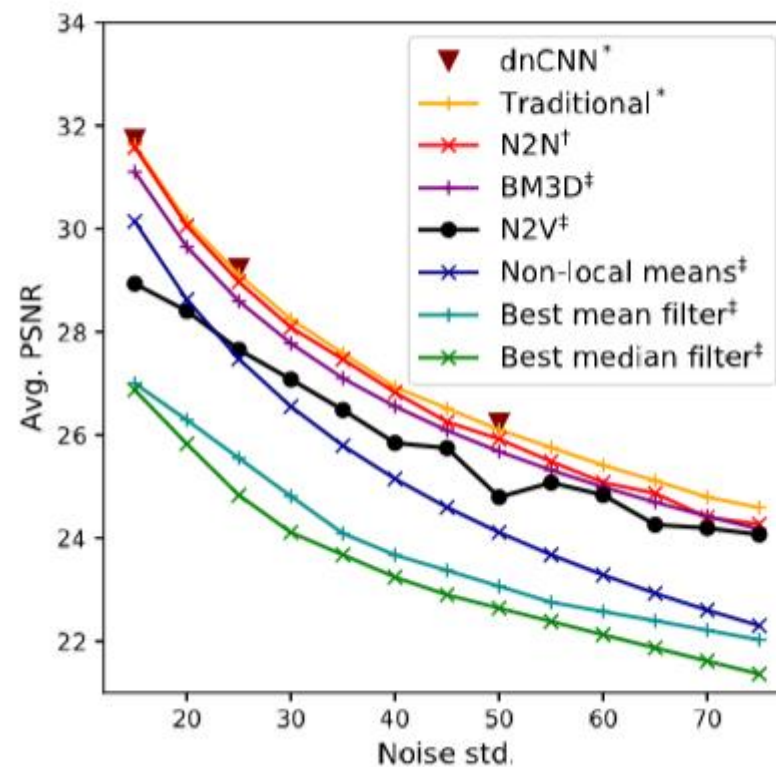
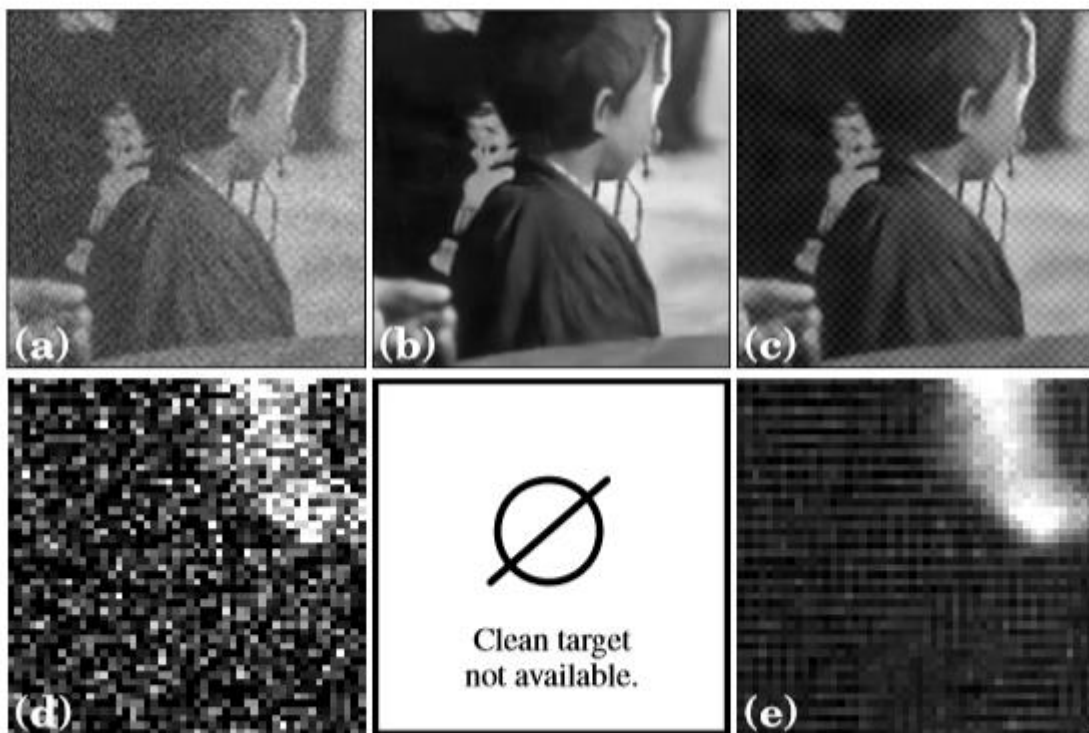
Noise2Void - Learning Denoising from Single Noisy Images

- This method can be applied to data for which neither noisy image pairs nor clean target images are available
- It predicts pixel values based on their noisy surroundings
- It shows that blind-spot networks can learn to remove pixel wise independent noise when they are trained on the same noisy images as input and target.



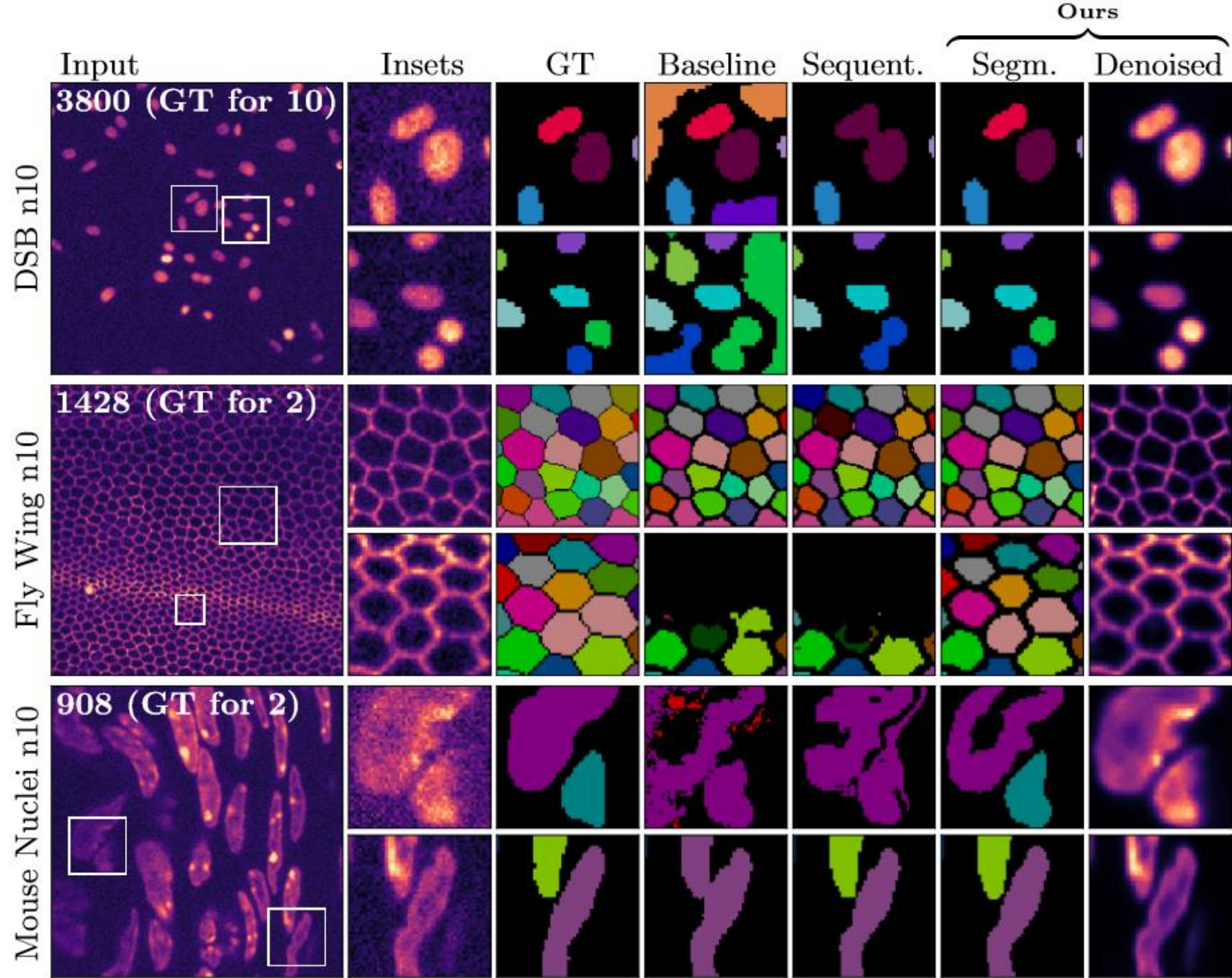


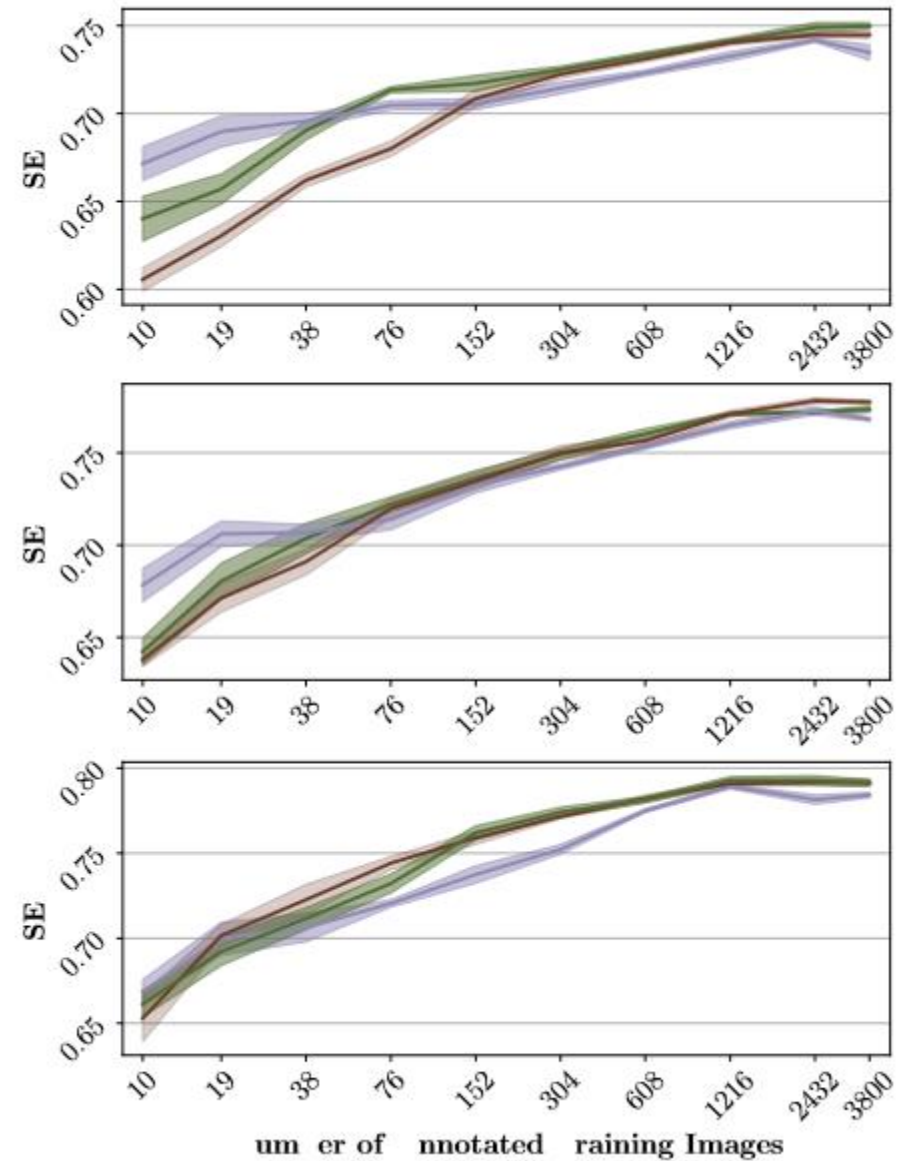
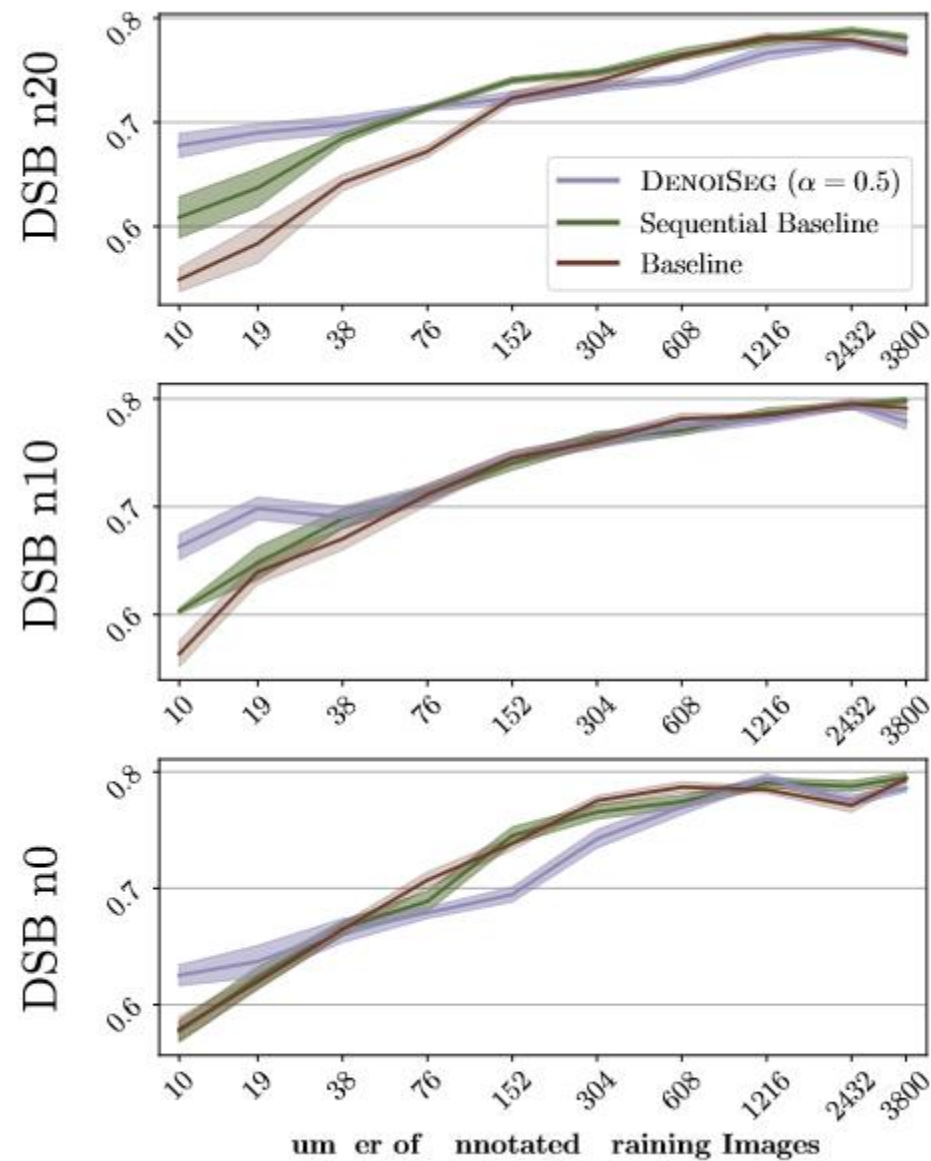
	Ground Truth	Input	BM3D	Traditional	NOISE2NOISE	NOISE2VOID
BSD68			 PSNR: 28.59	 PSNR: 29.06	 PSNR: 28.86	 PSNR: 27.71
Simulated Data			 PSNR: 29.96	 PSNR: 32.56	 PSNR: 32.43	 PSNR: 32.28
cryo-TEM	 Does not exist.		 Runtime: ~33.2s	 Clean target not available.	 Runtime: ~1.3s	 Runtime: ~1.3s
CTC-MSC	 Does not exist.		 Runtime: ~4.6s	 Clean target not available.	 Noisy target not available.	 Runtime: ~0.1s
CTC-N2DH	 Does not exist.		 Runtime: ~5.2s	 Clean target not available.	 Noisy target not available.	 Runtime: ~0.1s



DenoiseSeg - Joint Denoising and Segmentation

- This method is a single network that jointly predict the denoised image and the desired object segmentation
- It can be trained end-to-end on only a few annotated ground truth segmentations. They achieve this by extending Noise2Void
- A U-Net is trained with a joint self-supervised denoising loss (L_d) and a classical segmentation loss (L_s). Both losses are weighted with respect to each other by a hyperparameter α .
- The proposed network produces four output channels corresponding to denoised images, foreground, background and border segmentation







QUESTIONS?