Noise2Inverse: Deep tomographic denoising without high-quality target data

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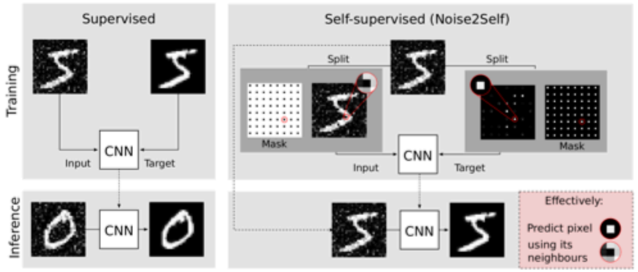
Problem statement

- In the tomography community, substantial interest has arisen in reducing dose — thus increasing measurement noise
- Deep convolutional neural networks (CNNs) have been shown to be effective for removing tomographic noise
- However, these networks generally require training data, and specifically high-quality target data

Can a denoising CNN be trained from a single noisy 3D tomographic acquisition, i.e., without acquiring high-quality target data?

Supervised and self-supervised image denoising



Supervised training minimizes training objective

$$\|\mathrm{CNN}_\varphi(y_{\text{noisy}}) - y_{\text{true}}\|_2^2$$

Self-supervised training minimizes training objective

$$\|(1 - y_{\text{mask}}) \odot (\mathrm{CNN}_\varphi(y_{\text{mask}} \odot y_{\text{noisy}}) - y_{\text{noisy}})\|_2^2$$

Self-supervised denoising is possible, if:

- Noise in adjacent pixels is statistically independent
- Noise is mean-zero

Noise need not be stationary, i.e., identically distributed everywhere

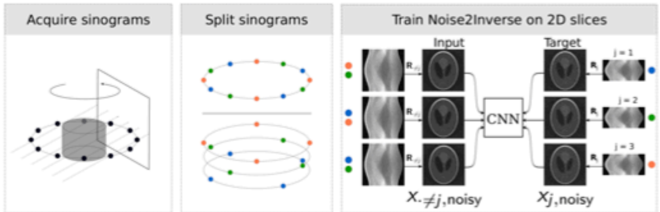
Noise in tomography

We assume:

- In each detector pixel, noise intensity depends on signal intensity
- Noise in adjacent detector pixels is statistically independent
- Noise on detector is zero-mean (approximately correct after log-correction)
- Noise in pixels of reconstructed image is inherently coupled

$\Rightarrow$ self-supervised image denoising on reconstructed images is unlikely to work!

Noise2Inverse for 3D tomography



If reconstruction operators $\mathbf{R}_j$ are linear*, then, in expectation, the training objective permits the following decomposition:

$$\sum_{j=1}^{N_{\text{splits}}} \|\mathrm{CNN}_\varphi(\mathbf{R}_{\neq j}\, y_{\text{noisy}}) - \mathbf{R}_j\, y_{\text{noisy}}\|_2^2$$

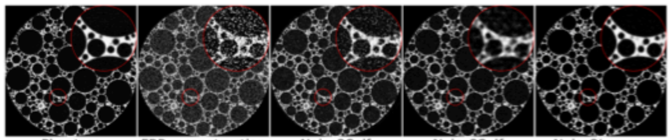
$$=$$

$$\sum_{j=1}^{N_{\text{splits}}} \underbrace{\|\mathrm{CNN}_\varphi(x_{\neq j,\text{noisy}}) - x_{j,\text{noise-free}}\|_2^2}_{\text{Parameters are optimized w.r.t. noise-free reconstruction}} + \underbrace{\|x_{j,\text{noise-free}} - \overbrace{x_{j,\text{noisy}}}^{\mathbf{R}_j\, y_{\text{noisy}}}\|_2^2}_{\text{Variance of the reconstructed noise}},$$

* We use the filtered back-projection algorithm (FBP)

(details in paper).

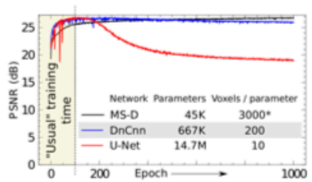
How to split the measurement



Phantom | FBP reconstruction | Noise2Self on reconstruction | Noise2Self on sinogram | Noise2Inverse

Approach	Reconstruct, split, denoise	Split, denoise, reconstruct	Split, reconstruct, denoise
Noise in input and target is independent	✗	✓	✓
Integrates physical forward model	✗	✗	✓
	PSNR: 15.4	PSNR: 20.6	PSNR: **26.3**

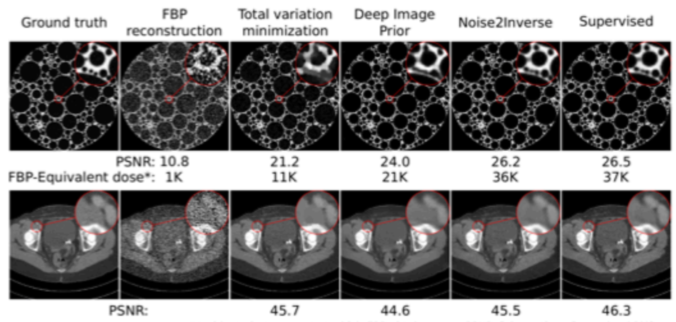
Overfitting



1. Noise2Inverse trains on full 3D volume: 512^3 voxels in this case
2. Networks with fewer parameters perform well
3. For these networks: information-theoretically impossible to represent the noise*
4. Early stopping is thus not necessary!

* For reference, JPEG compresses this poster by a factor of 38

Results



* Incident photon count at which FBP obtains same PSNR. [absorption of sample=10%]

Conclusion

- Self-supervised training error decomposes into supervised training error and variance of the noise
- This enables training denoising CNNs for tomography without acquiring any additional data
- Self-supervised denoising in tomography requires taking account of both the physical forward model and statistical independence
- Reconstruction accuracy exceeds conventional reconstruction algorithms and is close to supervised deep learning methods

What's more

- **Paper:** Hendriksen et al. Noise2Inverse: Self-supervised deep convolutional denoising for linear image reconstruction. arXiv:2001.11801 (2020)
- **Code:** `https://github.com/ahendriksen/noise2inverse`

Surge in related developments for MRI, deconvolution microscopy, and single-image denoising:

- Liu et al. RARE: Image reconstruction using deep priors learned without ground truth. IEEE J Sel Top Signal Process 2020
- Yaman et al. Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. Magn Reson Med 2020
- Kobayashi et al, Image Deconvolution via Noise-Tolerant Self-Supervised Inversion. arXiv:2006.06156 2020
- Quan et al, Self2Self With Dropout: Learning Self-Supervised Denoising From Single Image, CVPR 2020

Self-supervised image denoising (Noise2Self and Noise2Void):

- Batson & Royer. Noise2Self: blind denoising by self-supervision. PMLR 2019
- Krull et al. Noise2Void — learning denoising from single noisy images. CVPR 2019

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