CWI

Centrum Wiskunde & Informatica

Self-supervised deep denoising for synchrotron tomography

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Joint work

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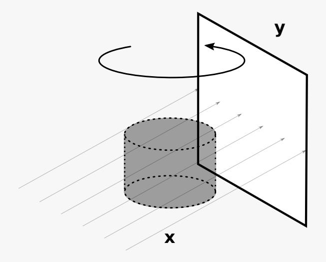
Overview

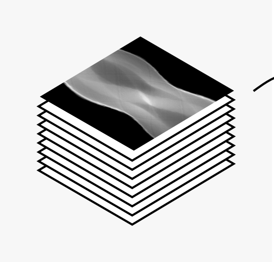
- Noise in tomography
- Deep learning for denoising
- Problem statement
- Denoising without supervision
- Results
  - Micro-tomography
  - Dynamic micro-tomography
  - X-ray diffraction CT
- Conclusion and Outlook

Tomography

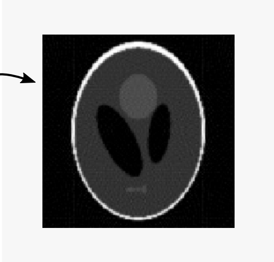
Acquisition



Stack of sinograms



Reconstruction
(horizontal cross-section)



Gives rise to a linear system

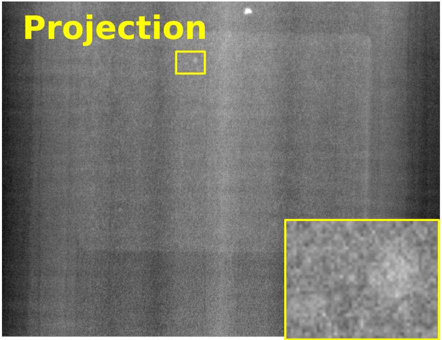
$$\mathbf{A}\,\mathbf{x} = \mathbf{y}$$

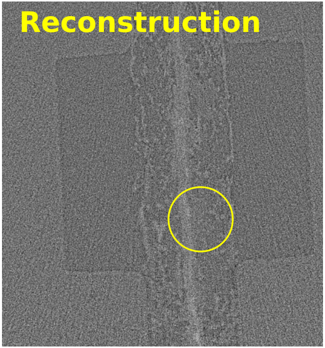
Can be solved with backprojection-type algorithms (such as FBP)

$$\mathbf{x}_{\mathbf{rec}} = \mathbf{R}\,\mathbf{y}$$

Noise in tomography

TomoBank 81: fuel cell
@ SLS TOMCAT

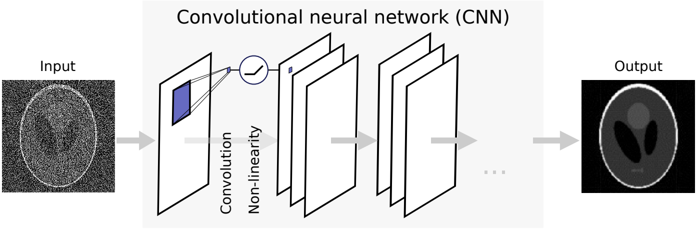




- In each pixel: noise intensity depends on signal intensity
- Noise is zero-mean (approximately correct after log-correction)
- May be due to unavoidable experimental constraints:
  1. Dose limit on object (batteries heat up, etc)
  2. Time-limited dynamic acquisition

Deep learning for denoising

Convolutional neural networks have emerged as a powerful tool for denoising



A CNN is a function with thousands to millions of parameters

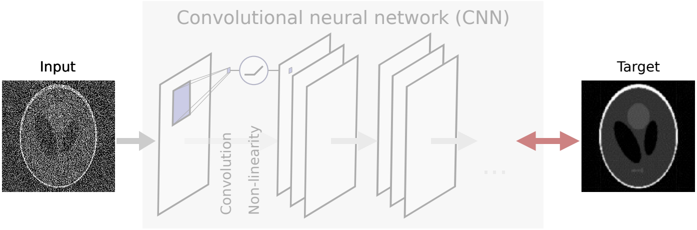
Tuned to minimize:

$$\underset{\theta}{\operatorname{argmin}} \left\| \mathrm{CNN}_\theta \left(X + N_X \right) - \left(X \right) \right\|_2^2$$

Image + Noise

"Clean image"

Training requires high-quality data



A CNN is a function with thousands to millions of parameters

Optimizing these parameters requires a high-quality dataset of paired noisy and low-noise training examples.

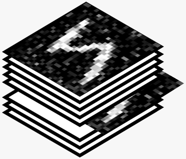
Problem statement

Challenges in applying deep learning to synchrotron tomography:

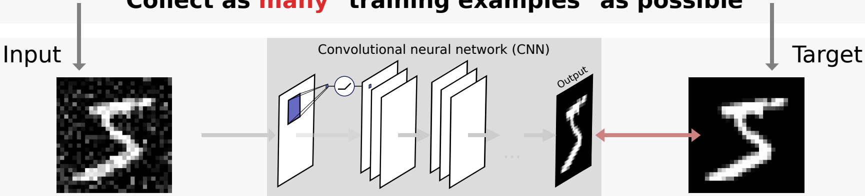
1. Generalizability: need to train for new kinds of objects
2. Supervision: need high-quality target data
3. Alignment: need perfect registration of input and target images

Can we use deep learning for denoising without any high-quality training data?

Typical deep learning process



Collect as many "training examples" as possible



Optimize model with thousands to millions of parameters

Apply to new data

Self-supervised image denoising

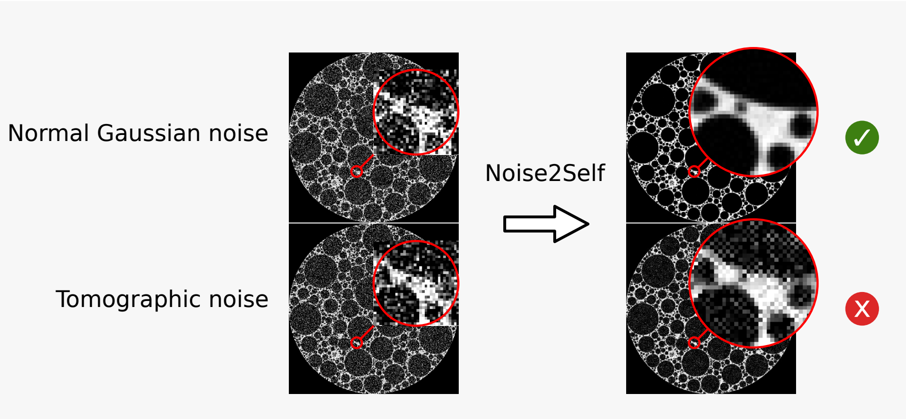
Approaches for self-supervised deep image denoising exist.

Assumptions:

1. Noise in adjacent pixels is uncorrelated
2. Noise is mean-zero

However: they do not take into account tomographic noise model.

Flaws in existing self-supervised approaches

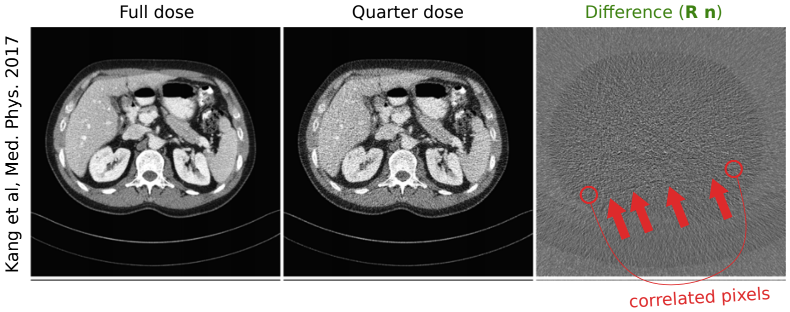


Hendriksen et al, IEEE TCI 2020

- ✗ Noise in adjacent pixels is correlated
- ✓ Noise is mean-zero

Noise2Self training fits the noise

Noise in reconstruction



Noise on detector gives rise to:

$$\mathbf{A\,x} = \mathbf{y_{noisy}} = \mathbf{y} + \mathbf{n}$$

FBP-type algorithms are linear, so we get:

$$\mathbf{x_{rec}} = \mathbf{R\,(y + n)} = \mathbf{R\,y} + \mathbf{R\,n}$$

Detector noise n:

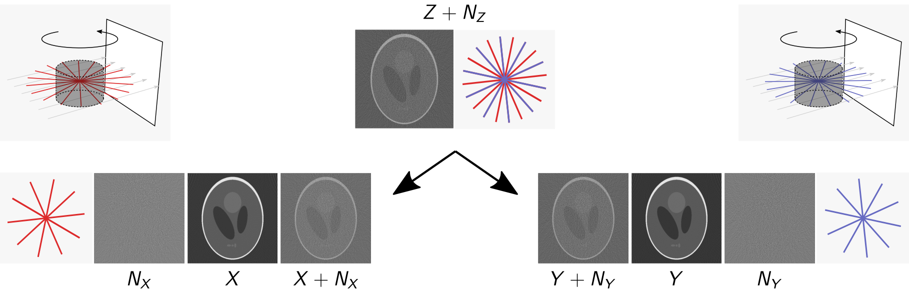
Is not necessarily additive
But notationally convenient

Reconstructed noise R n:

Smeared across lines

⇒ Pixels not independent

Noise2Inverse



$$\underset{\theta}{\operatorname{argmin}} \; \| \, \mathrm{CNN}_\theta \, (X + N_X) - (Y + N_Y) \|_2^2$$

- ✓ N_X and N_Y are statistically independent (separate measurements)
- ✓ Noise is mean-zero

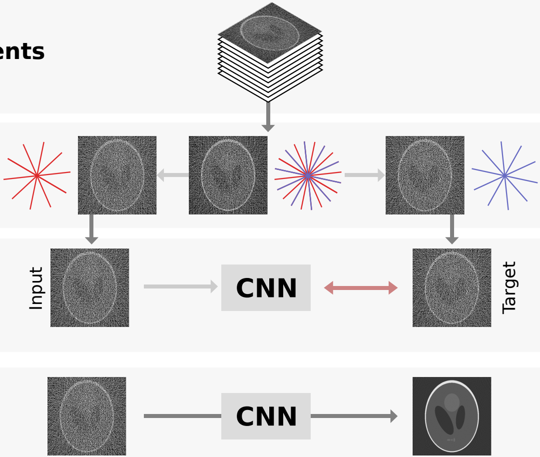
Noise2Inverse process

Collect **noisy** **measurements**

Split **measurements**

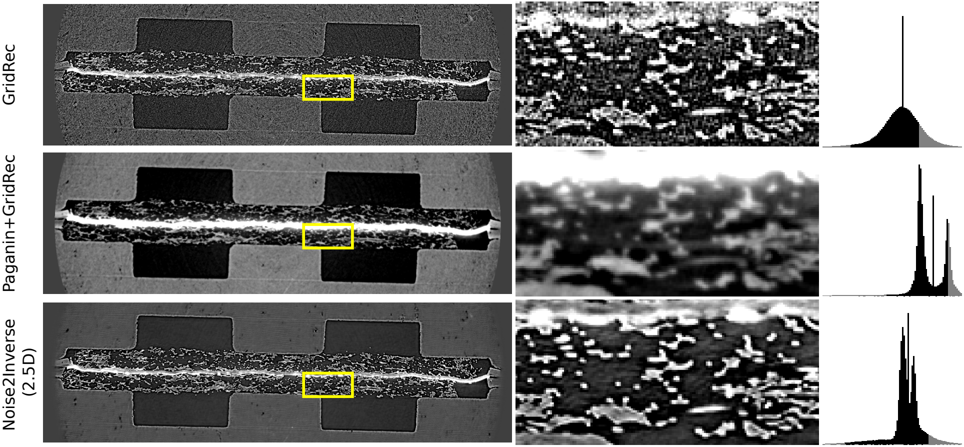
Optimize model with
noisy **target images**

Apply to **training** **data**
(and new data)

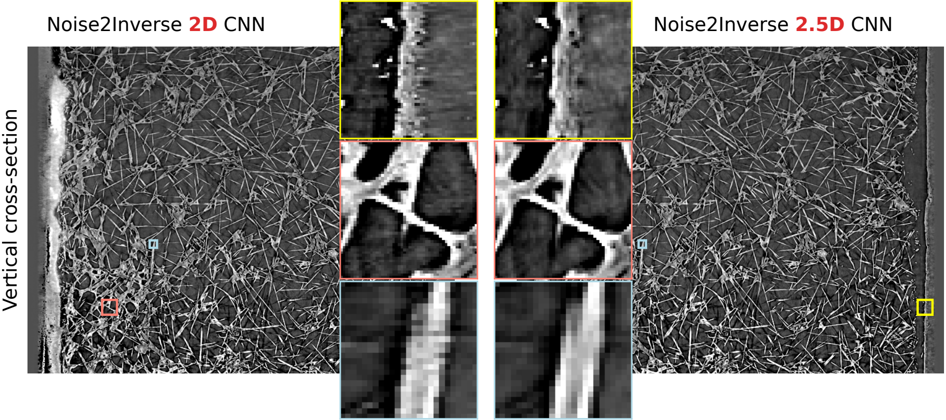


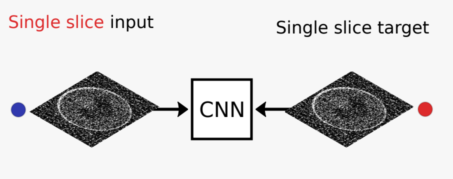
Results: Fuel cell reconstruction

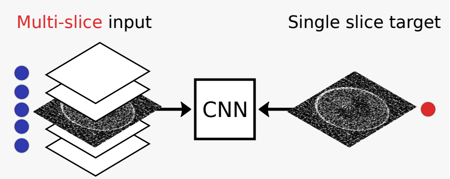
Tomobank 82: 1000 angles (30 KeV polychromatic) 1ms exposure



Results: Fuel cell reconstruction







Results: Dynamic fuel cell reconstruction

TomoBank 81: Dynamic fuel cell @ SLS TOMCAT

Acquisition

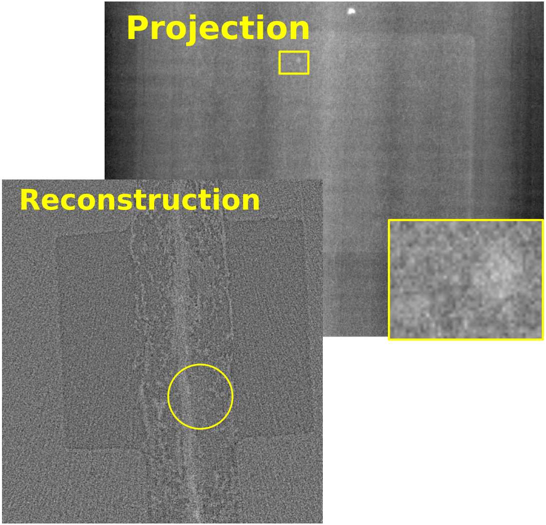
- 60 time steps
- 299.92 proj / time step
- 0.1 sec / time step

Problems:

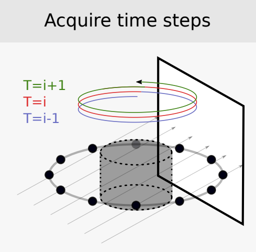
1. Noise
2. Angular undersampling

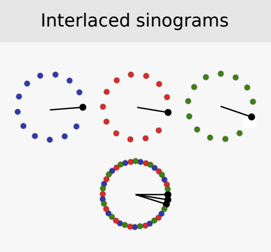
Saving grace:

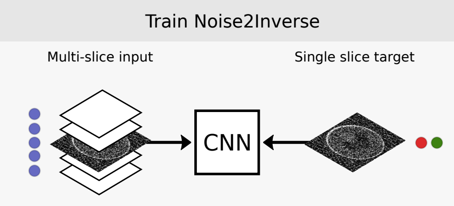
Interlaced sampling
299.92 proj / time step



Results: Dynamic fuel cell reconstruction

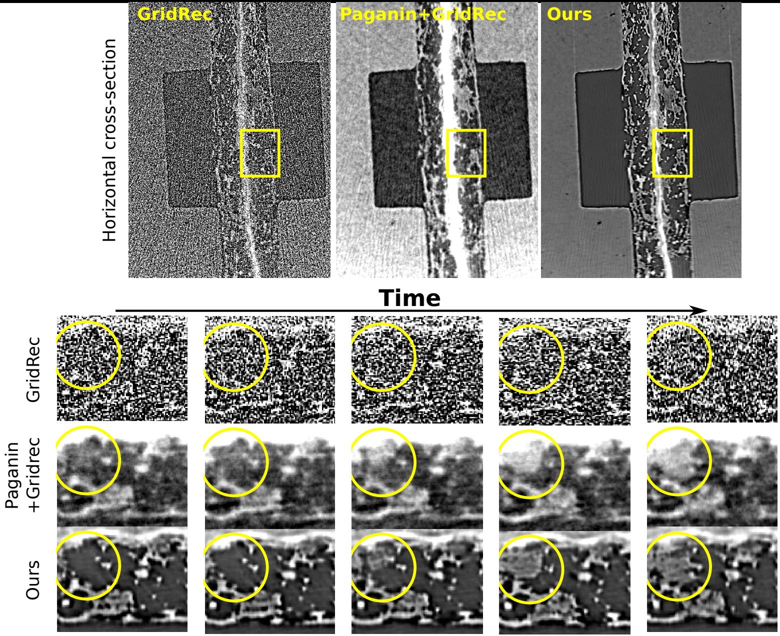






Multiple time steps (Counters undersampling)

Results: Dynamic fuel cell reconstruction



Results: X-ray diffraction CT

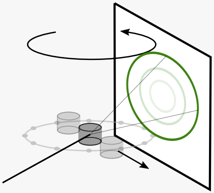
X-ray diffraction CT @ ESRF ID15a

Ceramic

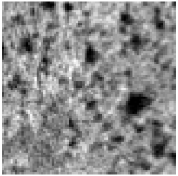
3 horizontal slices

11 channels corresponding to scattering angles (subset)

Acquire projections

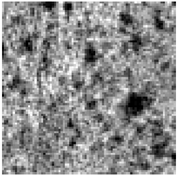


Add synthetic noise →



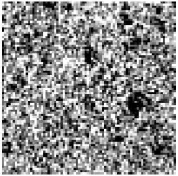
Original

20 min



Virtual acquisition time: ~70%

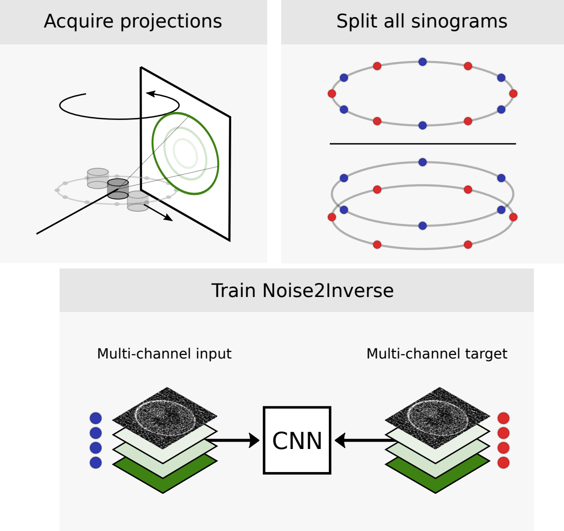
14 min



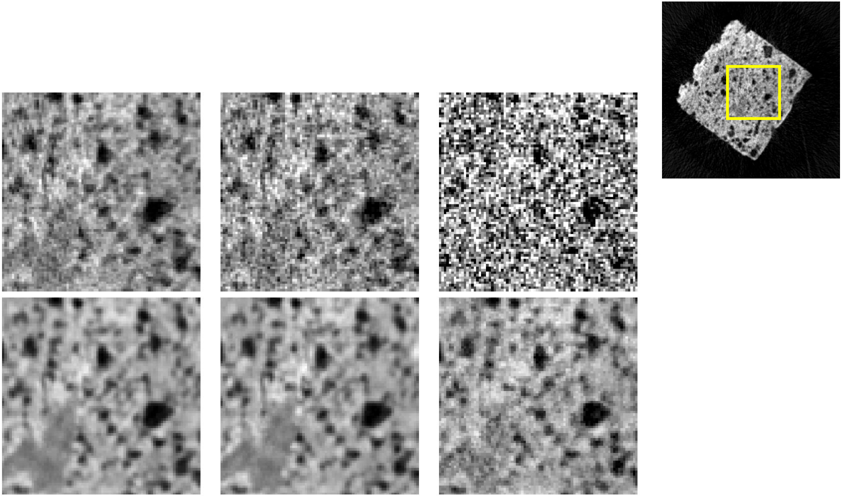
Virtual acquisition time: ~20%

4 min

Results: X-ray diffraction CT



Results: X-ray diffraction CT



FBP (Shepp-Logan)

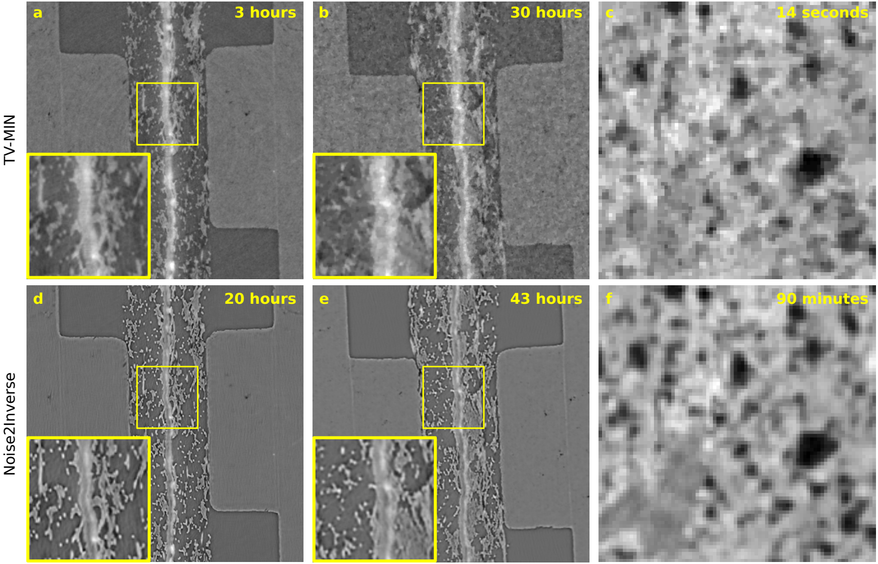
Ours

Original

Virtual acquisition time: ~70%

Virtual acquisition time: ~20%

Results: Total-Variation minimization



Static fuel cell

Dynamic fuel cell
(T = 69)

XRD-CT
(Virtual acquisition time: ~70%)

Practical observations

- Better results when using more projection data for input than for target
  - e.g.: Split sinogram in 4 parts, use 3 parts for input and 1 part for target
- Better results with more angles at the expense of exposure time
- With parameter-efficient neural network (MS-D): no overfitting to the noise observed
- With few projection angles: some blurring observed
- Artifacts not related to noise are not removed

Outlook

- Field is rapidly developing, developments in:
  - (Electron) microscopy
  - MRI
  - Tomography
- Undersampling: self-supervised techniques have been developed for MRI. Computationally expensive.
- Self-supervision and classical methods:
  - Center of rotation, acquisition geometry calibration
  - Optimizing Paganin-filtering

Conclusion

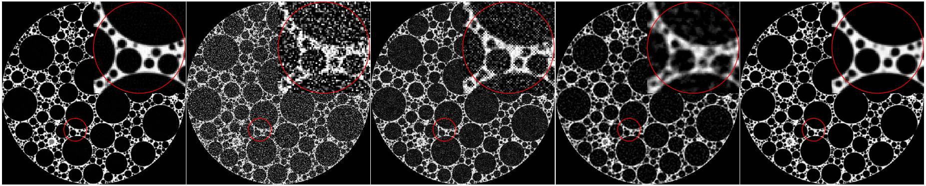
- Self-supervised denoising of tomographic reconstructions is possible using deep convolutional neural networks
- No additional training data is necessary
- For optimal results: take into account statistical independence and physical forward model
  - 3D
  - Dynamic 3D
  - X-ray diffraction computed tomography
- Denoising accuracy exceeds variational techniques and approaches supervised deep learning methods (trained with ground truth data)

Thank you

- Self-supervised denoising of tomographic reconstructions is possible using deep convolutional neural networks
- No additional training data is necessary
- Denoising accuracy exceeds variational techniques and approaches supervised deep learning methods (trained with ground truth data)

- Hendriksen, et al. (2020). Noise2inverse: self-supervised deep convolutional denoising for tomography. IEEE Transactions on Computational Imaging, `http://dx.doi.org/10.1109/tci.2020.3019647`
- Hendriksen, A.A., et al. Deep denoising for multi-dimensional synchrotron X-ray tomography without high-quality reference data. Sci Rep (2021). `https://doi.org/10.1038/s41598-021-91084-8`

Backup: Comparison to Noise2Self



Phantom | Noisy 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**

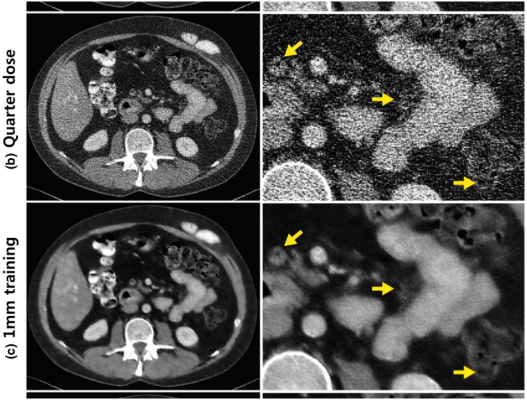
Practical challenges applying deep learning

Challenges in applying deep learning to synchrotron tomography:

1. Generalizability: need to train for new kinds of objects
2. Supervision: need high-quality target data
3. Alignment: need perfect registration of input and target images

Today we tackled supervision which has consequences for generalizability and alignment.

Deep learning results: medical imaging



Kang et al,
A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction.
Medical Physics, 2017

Deep learning results: synchrotron tomography

Al 7075 sample from tomobank

Pelt et al,
Improving Tomographic Reconstruction From Limited Data using Mixed-Scale Dense Convolutional Neural Networks
Journal of imaging 2018

Field is rapidly gaining popularity:

- Photographic imaging
    - Lehtinen, et al (2018). Noise2Noise: learning image restoration without clean data. PMLR.
    - Batson, Royer (2019). Noise2Self: blind denoising by self-supervision. PMLR.
    - Krull, et al (2019). Noise2Void - learning denoising from single noisy images. CVPR
    - Quan, et al (2020). Self2self with dropout: learning self-supervised denoising from single image. CVPR.
- MRI:
    - Liu et al (2020). RARE: image reconstruction using deep priors learned without ground truth. IEEE JSTSP
    - Yaman et al (2020). Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data.
- Microscopy
    - Kobayashi, et al (2020). Image Deconvolution Via Noise-Tolerant Self-Supervised Inversion. ArXiv.
    - Goncharova et al (2020). Improving Blind Spot Denoising for Microscopy. ECCV.

Field is rapidly gaining popularity

- Tomography:
  - Buchholz, et al (2019). Cryo-care: content-aware image restoration for cryo-transmission electron microscopy data. ISBI
  - Hendriksen et al (2020). Noise2inverse: self-supervised deep convolutional denoising for tomography. IEEE TCI