

# On-the-fly machine learning for tomography

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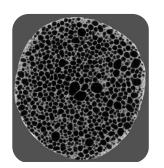
Wed 13 Nov 2019, Artificial Intelligence Applied to Photon and Neutron Science

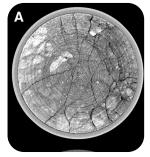
#### Can we do deep learning with less data?

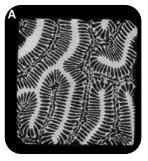
- ImageNet (classification): millions of examples
- Low-dose CT Grand Challenge (denoising): 20 chest CTs
- Today (resolution improvement): 2 scans of same object
- Future: 1 scan?

Today: Can we use machine learning with two scans of single object?

#### A need for high-resolution imaging







Saadatfar et al, Imaging of metallic foams using x-ray micro-CT, 2009

Ketcham et al, Acquisition, optimization and interpretation of x-ray CT imagery, 2001

#### Fine details and regular structure

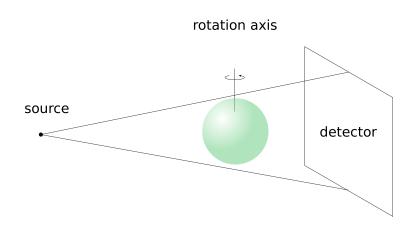
#### Goal

Improve resolution on single object CT reconstruction

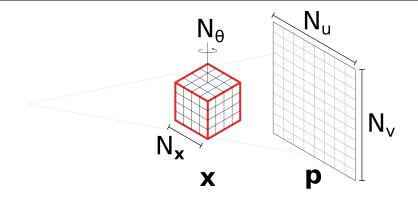
- ☐ with same scanner
- ☐ with limited increase in computation time
- ☐ with limited increase in scan time
- ☐ for unique objects

Can we use machine learning to improve resolution in tomography?

#### **Cone beam CT**



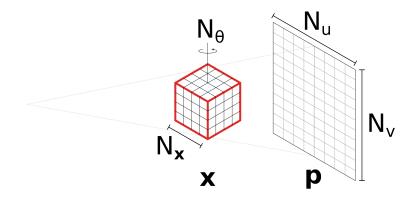
#### **Discretization**



#### Discretize:

- volume on voxel grid  $\mathbf{x} \in \mathbb{R}^{N_{\mathbf{x}} \times N_{\mathbf{x}} \times N_{\mathbf{x}}}$
- projection on  $\mathbf{p} \in \mathbb{R}^{N_{ heta} imes N_{u} imes N_{v}}$

#### Linear system

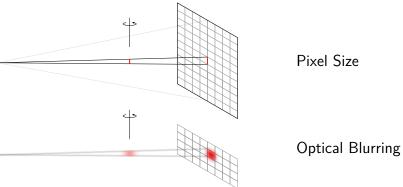


Gives rise to linear system projecting volume onto detector

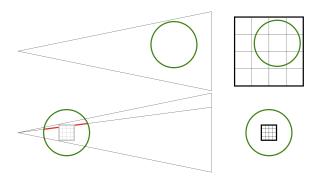
$$\mathbf{A}\mathbf{x} = \mathbf{p}$$

#### **Voxel resolution**

How is voxel resolution determined?



#### Improving resolution: Region of interest



- Problem 1: truncation artifacts due to red contribution to projection
- Problem 2: reconstructs only part of object

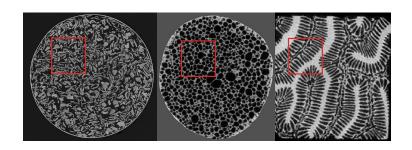
#### How to improve resolution

- Purely tomographic techniques often infeasible due to
  - detector size
  - scanning time

#### How to improve resolution

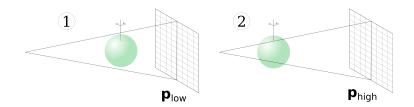
- Purely tomographic techniques often infeasible due to
  - detector size
  - scanning time
- Use deep learning
  - Good results on natural images
  - How to get training data?

#### Deep learning: A training set of one object



Use region of interest as training dataset

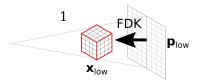
#### **Acquisition**



#### Scan the object twice:

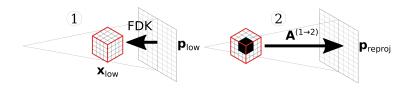
- lacktriangle Once at low magnification yielding lacktriangle lacktriangle Once at low magnification yielding lacktriangle
- Once at high magnification yielding  $\mathbf{p}_{high}$

#### Reconstruction



- 1. Reconstruct a coarse full volume  $\mathbf{x}_{low} = \mathbf{FDK}(\mathbf{p}_{low})$
- 2.
- 3.

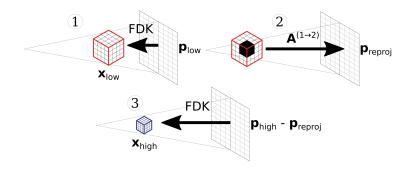
#### Reconstruction



- 1. Reconstruct a coarse full volume  $\mathbf{x}_{low} = \mathbf{FDK}(\mathbf{p}_{low})$
- 2. Mask and reproject at high magnification  $P_{reproj} = \mathbf{A}^{(1 \to 2)} \mathbf{M} \mathbf{x}_{low}$

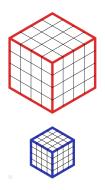
3.

#### Reconstruction



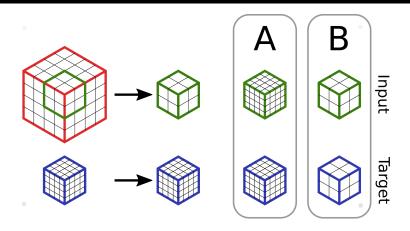
- 1. Reconstruct a coarse full volume  $\mathbf{x}_{low} = \mathbf{FDK}(\mathbf{p}_{low})$
- 2. Mask and reproject at high magnification  $P_{reproj} = \mathbf{A}^{(1 \to 2)} \mathbf{M} \mathbf{x}_{low}$
- 3. Reconstruct a ROI  $\mathbf{x}_{high} = \mathbf{FDK}(\mathbf{p}_{high} \mathbf{p}_{reproj})$

#### Prepare training set



Low-resolution full-volume reconstruction and high-resolution region of interest reconstruction do not match in physical volume and voxel size

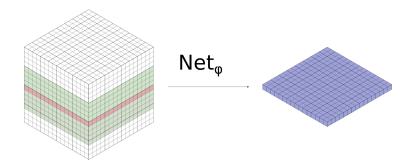
#### Prepare training set: same grid



To match resolution, there are two choices:

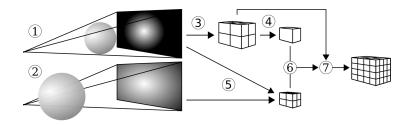
- Method A: Upsample input
- Method B: Downsample target

#### Training: slice by slice



- Network is trained slice by slice
- Also input some slices above and below in a slab to supply network with quasi-3D information

#### Recap



- Acquisition (1) and (2)
- Reconstruction (3) and (5)
- Preparing a training set (4)
- Training (6)
- Improving resolution (7)

#### **Experiments**

- Tomography: Use ASTRA toolbox
- Deep learning: Use Mixed-Scale Dense network architecture <sup>1, 2, 3</sup>
  - Can be applied to large images
  - Good results for tomographic images
  - Does not easily overfit!

<sup>&</sup>lt;sup>1</sup>Pelt et al, PNAS 2018

<sup>&</sup>lt;sup>2</sup>https://GitHub.com/ahendriksen/msd\_pytorch

<sup>3</sup>https://github.com/dmpelt/msdnet

#### **Results: Oatmeal**







Projection image

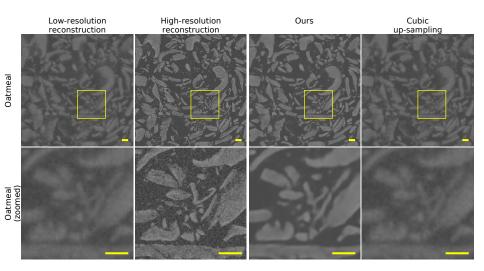
Central slice

#### **Results: Oatmeal**



- Scanned in FlexRay CT scanner, developed by XRE NV
- $\blacksquare$  Detector: 1944  $\times$  1536 square pixels of size 75  $\mu\mathrm{m}$
- Magnification factor  $\sim$  4
- Voxel size: 68  $\mu$ m and 17  $\mu$ m

#### **Results: Oatmeal**

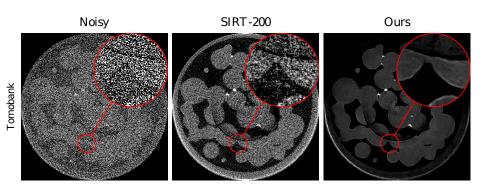


#### Summary

A novel acquisition + reconstruction + machine learning method that improves resolution

- ☑ with same scanner
- ☐ with limited increase in computation time
- ☑ with limited increase in scan time
- ☑ for unique objects

#### Future work: 1 scan denoising



Deep CNN 1 scan No additional data!

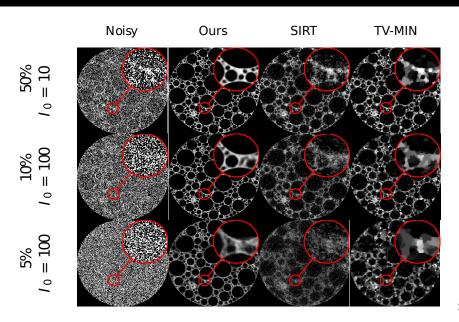
### Thank you for your listening

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Hendriksen, Pelt, Palenstijn, Coban, Batenburg, On-the-fly machine learning for improving image resolution in tomography, Applied Sciences, 9(12), (2019). http://dx.doi.org/10.3390/app9122445

#### **Backup slides**

#### Outlook II



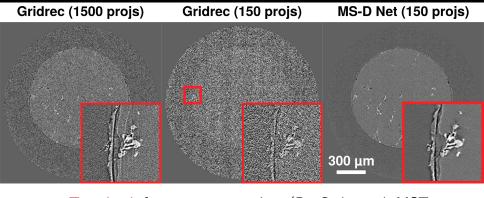
#### MSD network

- New neural network, MS-D-Net, specifically developed for scientific imaging problems
- Obtain accurate results with relatively few parameters
  - Less overfitting, better with limited data
- Able to process large images (e.g. 2k x 2k)
- Automatically adapt to various problems
- Can be applied to a wide variety of problems
  - Artifact removal, segmentation, etc...
- Open source implementation release soon!

Daniël Pelt et al, A mixed-scale dense convolutional neural network for image analysis, PNAS (2017)

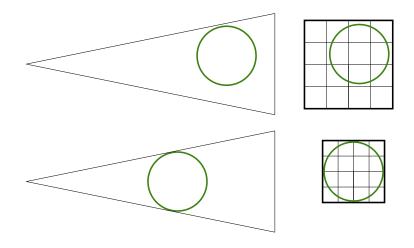
Daniël Pelt et al, Improving Tomographic Reconstruction From Limited Data Using Mixed-Scale Dense Convolutional Neural Networks, Journal of Imaging (2018)

#### MSD: real-world data



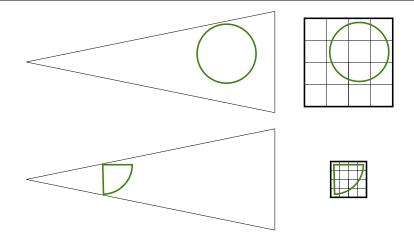
- Tomobank fatigue-corrosion data (De Carlo et al, MST 2018)
  - 2160x2560x2560 voxels
- Use first and last scans as training data
- Shown is an intermediate scan

#### How to improve resolution I: Center object



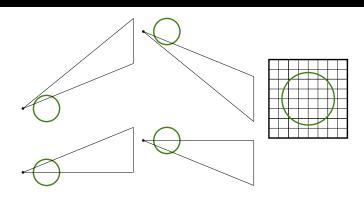
Making optimal use of the detector is always recommended.

#### How to improve resolution II: Smash & Scan



Geological samples are often broken into pieces before being scanned.

## How to improve resolution IV: Flexible detector setup



- Make a larger virtual detector by scanning 4 × 4 times
  - 16× more pixels, 4× more angles
- Problem 1: Not every detector setup is flexible
- Problem 2: 64 times more data

#### How to improve resolution: recap

#### Options for improving resolution:

- 1. Move object into field of view: nice, but not enough
- 2. Smash & scan: destructive, only part of object
- Region of interest: only part of object, truncation artifacts
- 4. **Tiling**: not always possible, long scan times, and more data / computation

What else can we do?  $\rightarrow$  Deep learning

#### Deep learning: A training set of CT data

Creating a training dataset for CT is expensive:

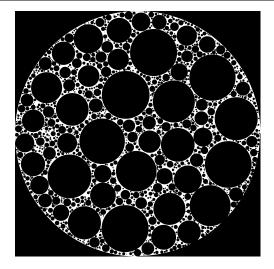
- high-resolution scans require long scanning time
- high-resolution reconstructions require long computation time

Creating a training dataset for CT must often be repeated:

- for different scanning geometries
- for different scanners
- for different beam settings (tube power and voltage)
- for different types of objects

Moreover, if the object under investigation is unique, then it is not possible to obtain such large set of training examples

#### **Results: Foam phantom**



Central slice of foam bubble

#### **Results: Foam phantom**

- 90,000 bubbles:
  - Non-overlapping
  - Randomly placed and randomly sized
- Projection dataset
  - With Gaussian blur on the detector ( $\sigma$  of 2 pixels)
- 1k x 1k detector, 1500 angles
- Magnification factor 4
- Projections generated using cone\_balls <sup>4</sup>

<sup>4</sup>https://github.com/ahendriksen/cone\_balls

#### **Results: Foam phantom**

