CWI

Centrum Wiskunde & Informatica

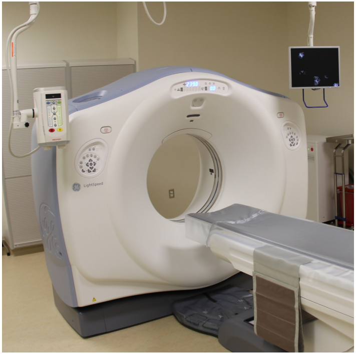
Deep Learning in Computational Imaging

Felix Lucka

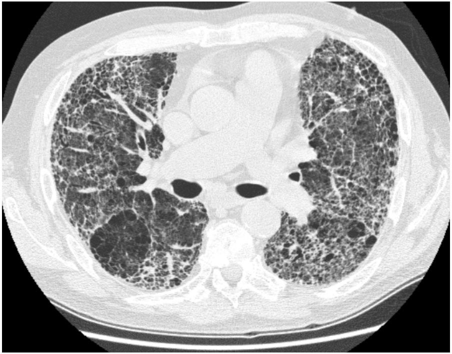
MaIGA Seminar - University of Genova

8 Nov 2021

And what do you do for a living?



(a) Modern CT scanner



(b) CT scan of a patient's lung

Source: Wikimedia Commons

Computational Imaging @ CWI

- headed by **Tristan van Leeuwen**, 18 members
- mathematics, computer science, (medical) physics & engineering
- advanced computational techniques for 3D imaging
- (inter-)national collaborations from science, industry & medicine
- one of the two main developers of the **ASTRA Toolbox**
- **FleX-ray Lab**: custom-made, fully-automated **X-ray CT** scanner linked to large-scale computing hardware

Imaging Across Disciplines

Observational astronomy

Life and material science

microscopy

Medical imaging

CT, MRI, US, PET, SPECT...

Geophysical imaging

(electrical) resistivity, seismic

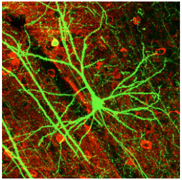
(ground-penetrating) radar...

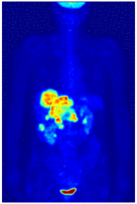
Remote sensing

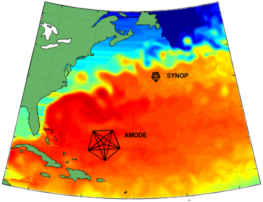
military/intelligence,

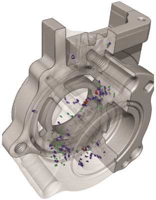
earth/climate science

Industrial process imaging









Source: Wikimedia Commons

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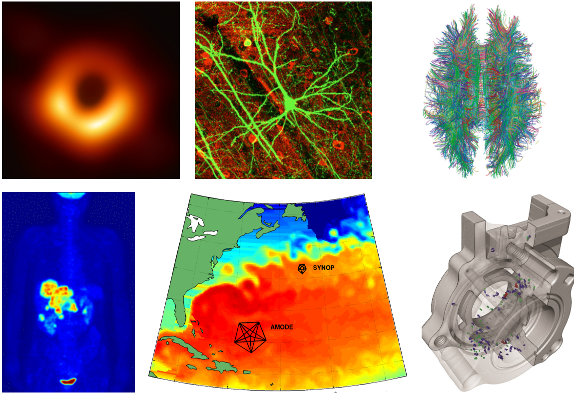


Source: Wikimedia Commons

Mathematical Imaging: *Reconstruct spatially distributed of quantities of interest from indirect observations through algorithms derived from rigorous mathematics.*

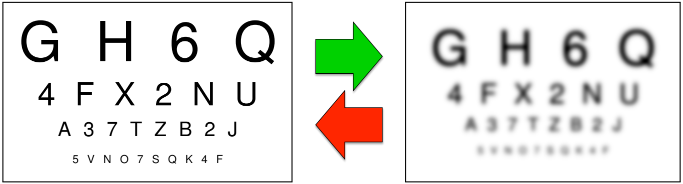
Imaging: An Inverse Problem

Inverse problem: Recover **unknowns** u (image) from **data** f via

$$\boxed{f = A(u) + \varepsilon}$$

- **Forward operator** A solution of **PDE** modelling underlying physics.

Imaging: An Inverse Problem



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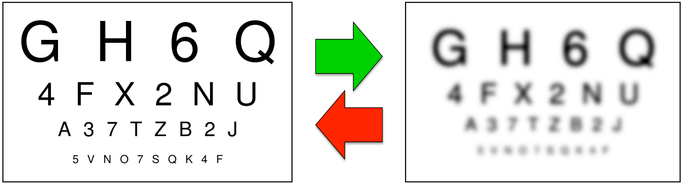

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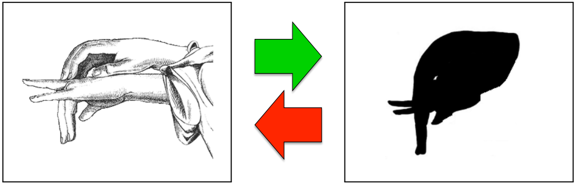

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Overview Inverse Problems / Imaging Workflow

mathematical modeling:
physics, PDEs, approximations

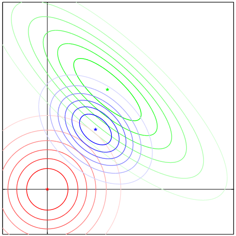
reconstruction/inference approach:
regularization, statistical inference, machine learning

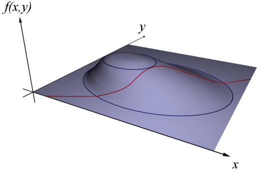
theoretical analysis:
uniqueness, recovery conditions, stability

reconstruction algorithm:
PDEs, numerical linear algebra, optimization, MCMC

large-scale computing:
parallel computing, GPU computing

$$(s \cdot \nabla + \mu_a(x) + \mu_s(x))\, \phi(x, s)$$
$$= q(x, s) + \mu_s(x) \int \Theta(s, s')\phi(x, s') ds'$$





Current Challenges in Computational Imaging

core development for new modalities:
hybrid imaging

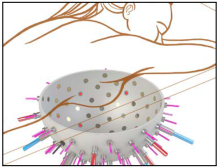
more from more:
multi-spectral, multi-modal, higher resolution

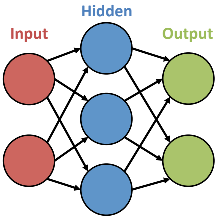
same from less:
low-dose, limited-view, compressed, dynamic

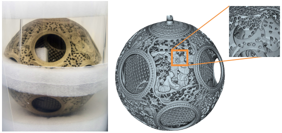
break the routine:
real-time, adaptive, explorative

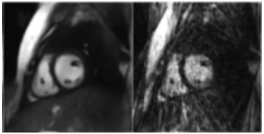
quantitative imaging & uncertainty quantification

machine learning:
embedding, networks for 3D/4D, training data

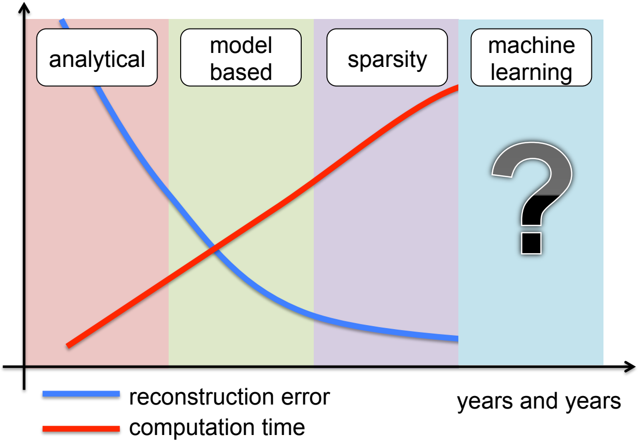








4 Waves of Image Reconstruction



Ravishankar, Ye, Fessler, 2020. Image Reconstruction: From Sparsity to Data-adaptive Methods and Machine Learning, *Proc IEEE Inst Electr Electron Eng. 2020;108(1):86-109.*

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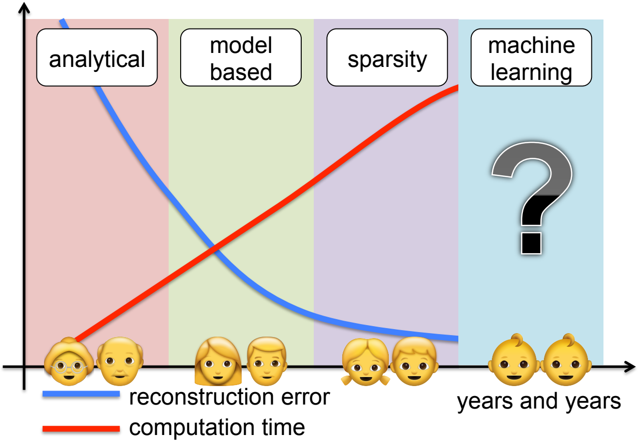

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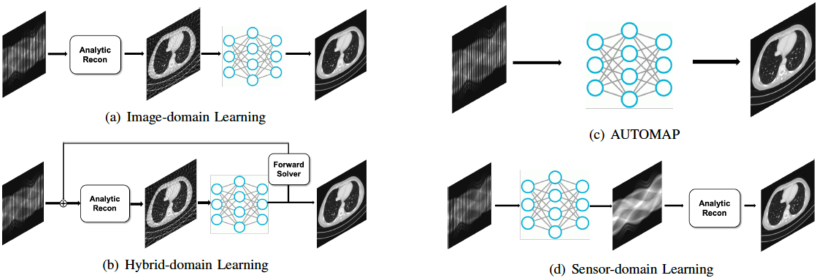
Deep Learning in Image Reconstruction



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Deep Learning Challenges in Image Reconstruction

Application

- training data
- evaluation
- robustness

Conceptual

- scaling - dimensional reduction
- algorithm design / incorporate imaging physics
- un/self supervised
- task-adaptation (end-to-end)

Software

- coupling CI - DL toolboxes
- real-time imaging

Training Data for Deep Learning

for algorithm development?

✓ lot's of large, open, bench-mark data collections for standard applications of deep learning (e.g., MNIST)

- few suitable imaging data sets (e.g., fastMRI)

! hardly any suitable projection data sets for X-ray CT

! ! clinical data sets are extra hard to get

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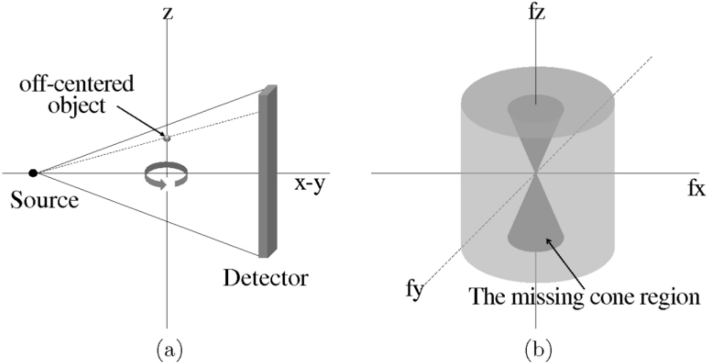
- ! hardly any suitable projection data sets for X-ray CT
- ! ! clinical data sets are extra hard to get

for real applications?

Cone Beam Computed Tomography (CBCT)

Circular cone beam scanning geometry

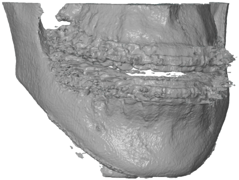
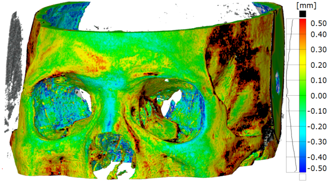
- common geometry for lab CTs
- certain advantages in medical imaging



taken from: Choi & Baek, "A new method to reduce cone beam artifacts by optimal combination of FDK and TV-IR images," Proc. SPIE 10574, Medical Imaging 2018.

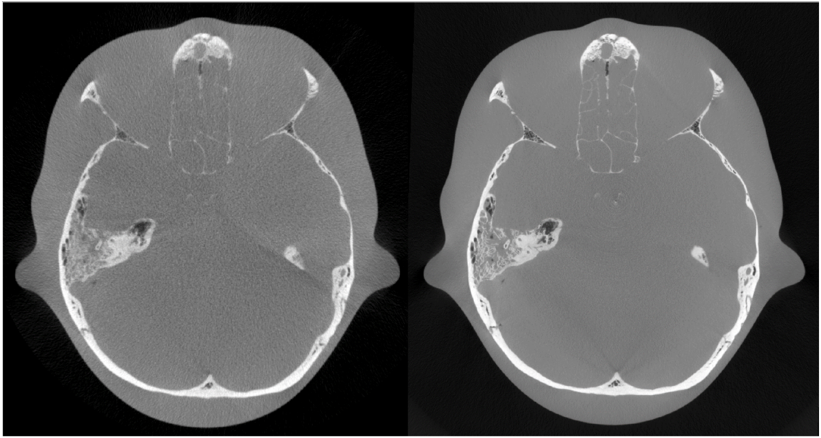
Public Private Partnership with Planmeca & AMC

- CBCT increasingly important in clinical applications
- tedious and time-consuming task: **segmentation** $\rightarrow$ **deep learning?**
- artifacts impair usability compared to conventional CT
- most challenging: **training data acquisition**

Deep Learning for Skull Segmentation from CBCT

- 5 anthropomorphic head phantoms
- scans with clinical CBCT and micro-CT
- semi-manual segmentation from micro-CT as gold standard

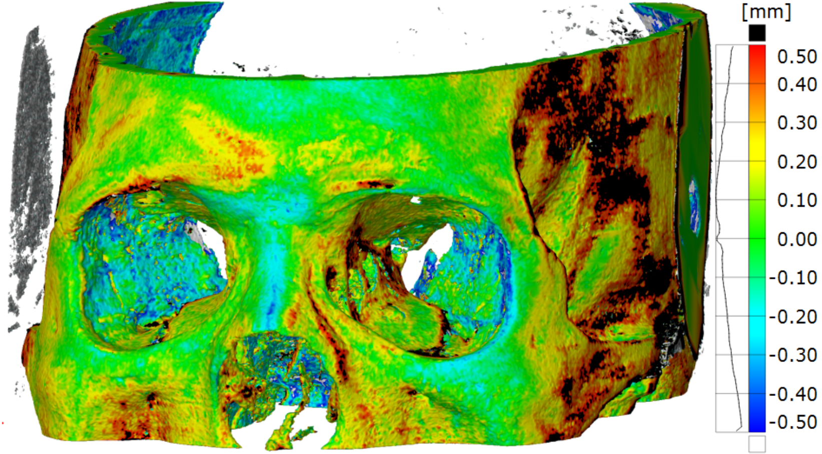


Deep Learning for Skull Segmentation from CBCT

- full 3D volume too large for DNNs
- comparison of different dimension-reduction strategies
- impact on particular anatomical structures

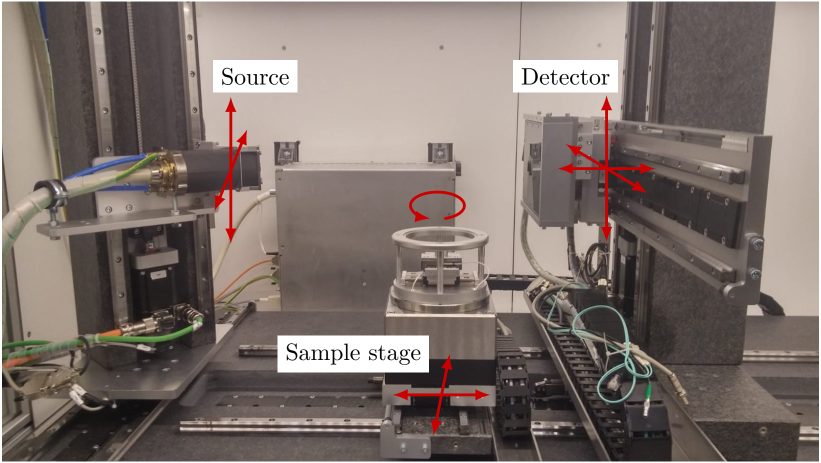
Minnema, Wolff, Koivisto, L, Batenburg, Forouzanfar, van Eijnatten, 2021. Comparison of convolutional neural network training strategies for cone-beam CT image segmentation, *Computer Methods and Programs in Biomedicine 207.*

Deep Learning for Skull Segmentation from CBCT



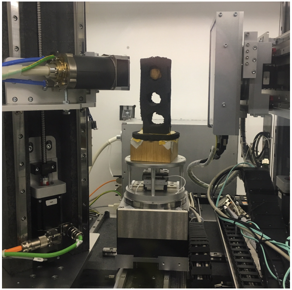
Difference between surface extracted from MS-D-Net segmented CBCT vs micro-CT-based ground truth segmentation

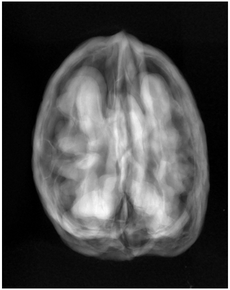
FleX-ray Lab @ CWI

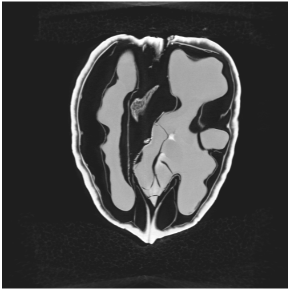


- custom-built (by TESCAN XRE), fully-automated, highly flexible
- linked to large-scale computing hardware
- **Aim: Proof-of-concept** experiments directly accessible to mathematicians and computer scientists.

CBCT Data Collection for Machine Learning

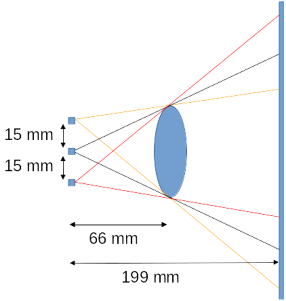




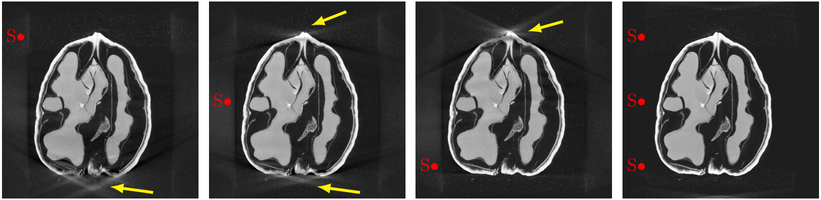


42 Walnuts:

- natural inter-population variability
- hard shell, a softer inside, air filled cavities
- variety of large-to-fine-scale features
- proxy for human head
- 42 3D samples = a lot of 2D data



CBCT Data Collection for Machine Learning

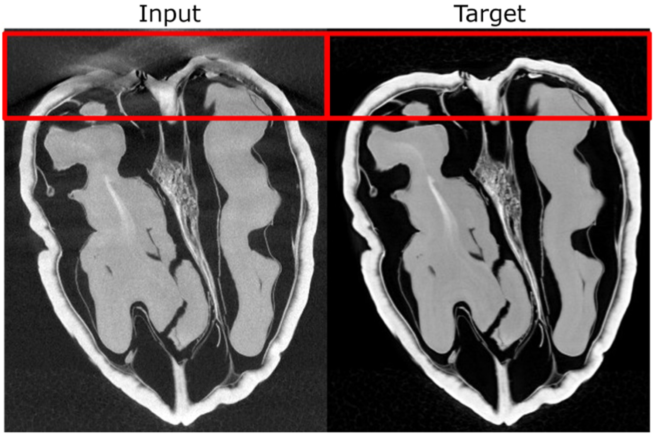


we provide

- this (and other) data sets on zenodo.org, community "CI-CWI"
- MATLAB and Python scripts for reading, pre-processing and image reconstruction on github.com/cicwi/WalnutReconstructionCodes

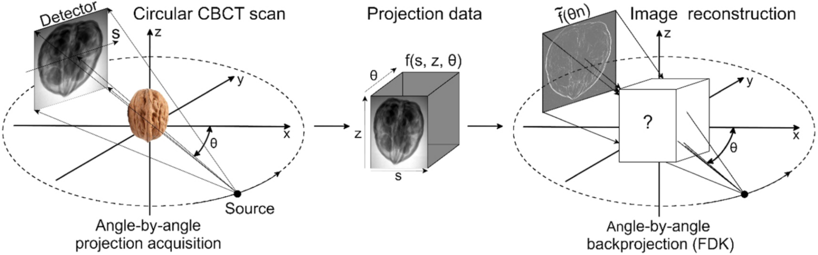
Der Sarkissian, L, van Eijnatten, Colacicco, Coban, Batenburg, 2019. A Cone-Beam X-Ray CT Data Collection Designed for Machine Learning, *Scientific Data 6(1).*

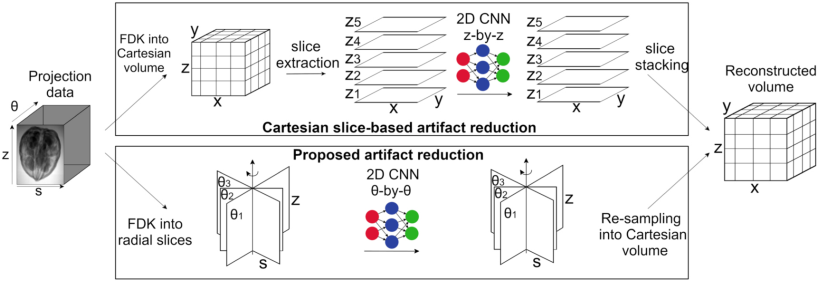
Deep Learning for High Cone-Angle Artifact Reduction



Minnema, van Eijnatten, Der Sarkissian, Doyle, Koivisto, Wolff, Forouzanfar, L, Batenburg, 2021. Efficient high cone-angle artifact reduction in circular cone-beam CT using deep learning with geometry-aware dimension reduction, *Phys. Med. Biol. 66.*

Geometry-Aware Dimension Reduction





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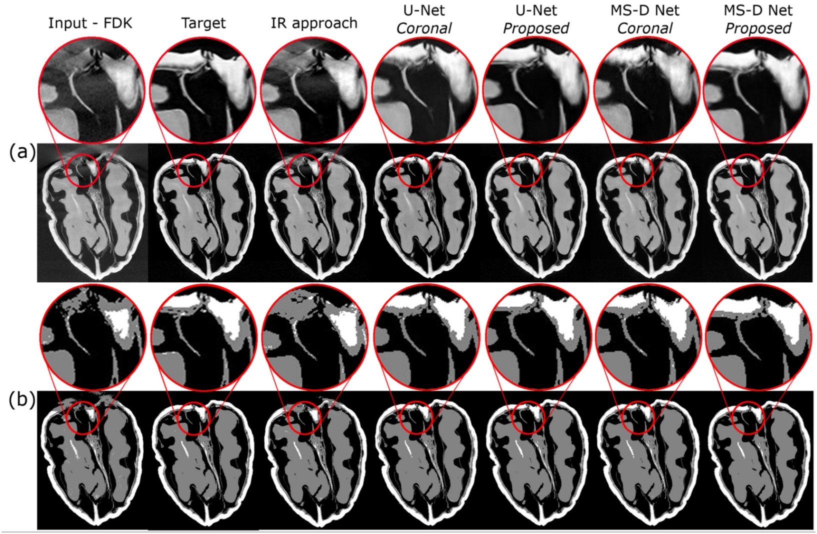

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Deep Learning Challenges in Image Reconstruction

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Conceptual

- scaling - dimensional reduction
- algorithm design / incorporate imaging physics
- un/self supervised
- task-adaptation (end-to-end)

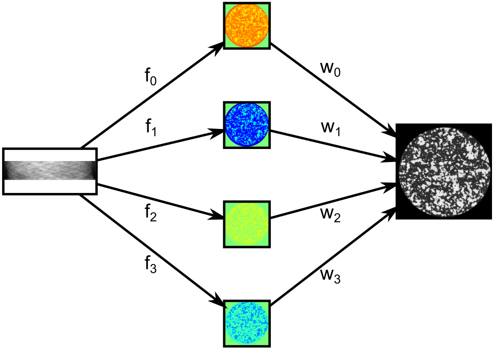
Software

- coupling CI - DL toolboxes
- real-time imaging

Different Route: Neuronal Network Filtered Backprojection

FBP is 1D data filter followed by backprojection: $\hat{x}_{FBP} = A^*(f * y)$

NN-FBP: non-linear combi of FBP for different filters f_i



learn convolution filters and weights from training data

Pelt, Batenburg, 2013. Fast Tomographic Reconstruction from Limited Data Using Artificial Neural Networks, *IEEE Image Processing, 22 (12).*

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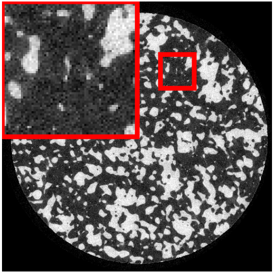
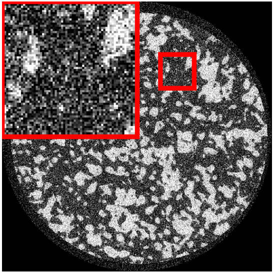
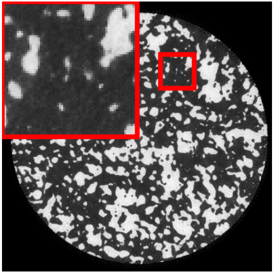


FBP, all projections



FBP, 5%



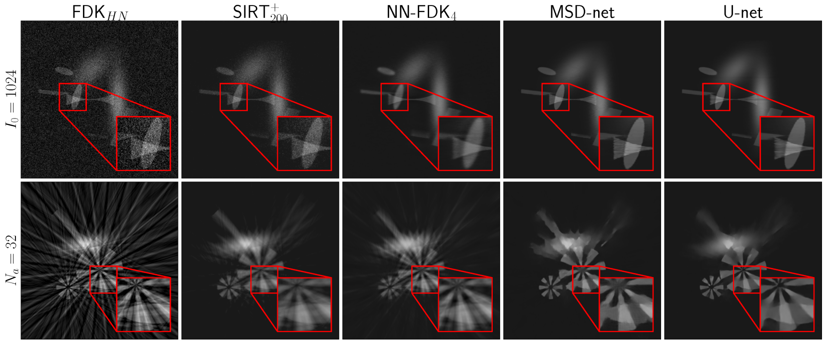
NN-FBP, 5%

✓comp. efficient ✓few trainable parameters ✓lot's of training data

Pelt, Batenburg, 2013. Fast Tomographic Reconstruction from Limited Data Using Artificial Neural Networks, *IEEE Image Processing, 22 (12).*

Going 3D: NN-FDK

volume of $1024 \times 1024 \times 1024$

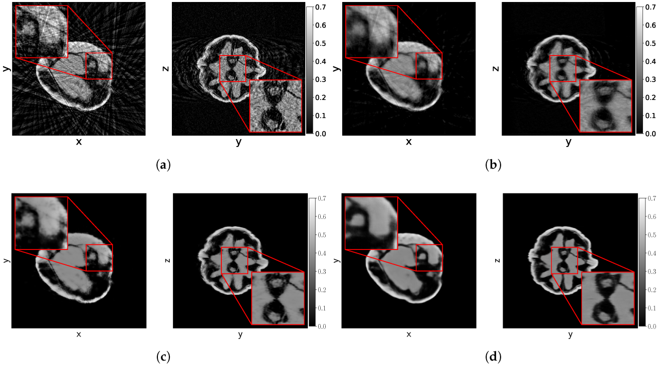


reconstruction time:

28s (FDK) 3225s (SIRT) 76s (NN-FDK) 382s (U-net) 809s (MSD-net)

Lagerwerf, Pelt, Palenstijn, Batenburg, 2020. A Computationally Efficient Reconstruction Algorithm for Circular Cone-Beam Computed Tomography Using Shallow Neural Networks , *J. Imaging 2020, 6(12).*

NN-FDK for High Resolution & High Throughput in 3D

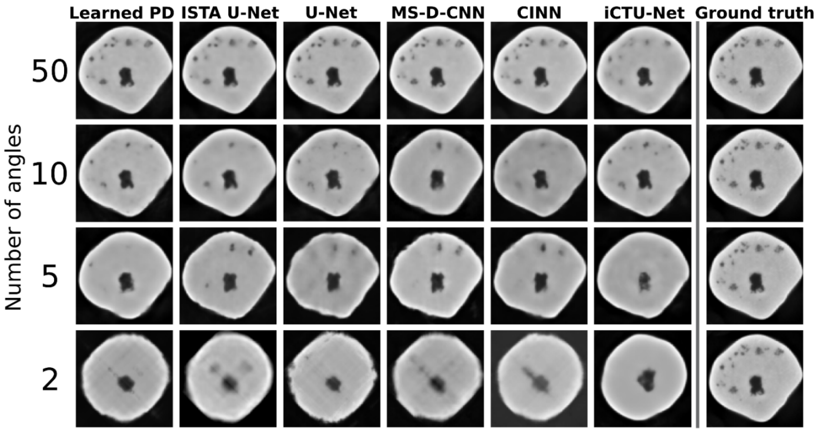


(a) FDK (b) SIRT+, 200 iter (c) NN-FDK, 4 filter (d) MSD-net

similar accuracy as iterative reconstruction at fraction of run time short training time; scales up to 4096^3

Lagerwerf et al., 2020. A Computationally Efficient Reconstruction Algorithm for Circular Cone-Beam Computed Tomography Using Shallow Neural Networks , *J. Imaging 2020, 6(12).*

Quantitative Evaluation of Deep Learning-Based Image Reconstruction



Leuschner et al., 2021. Quantitative Comparison of Deep Learning-Based Image Reconstruction Methods for Low-Dose and Sparse-Angle CT Applications, *J. Imaging, 7(3).*

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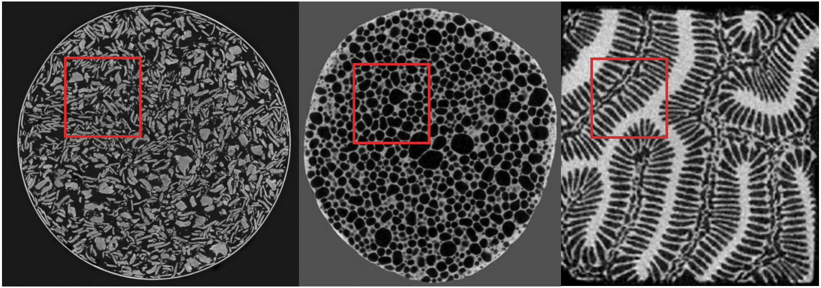
On-the-Fly Machine Learning for Unique Objects



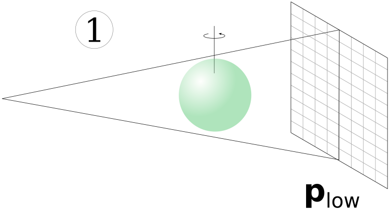
Improve resolution on single object CT reconstruction

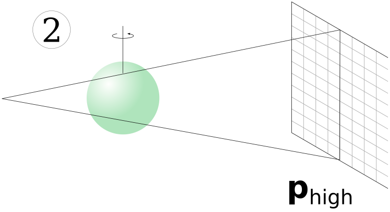
- with same scanner
- with limited increase in computation and scan time

Hendriksen, Pelt, Palenstijn, Coban, Batenburg, 2019. On-the-Fly Machine Learning for Improving Image Resolution in Tomography, *Appl. Sci. 2019.*, 9, 2445

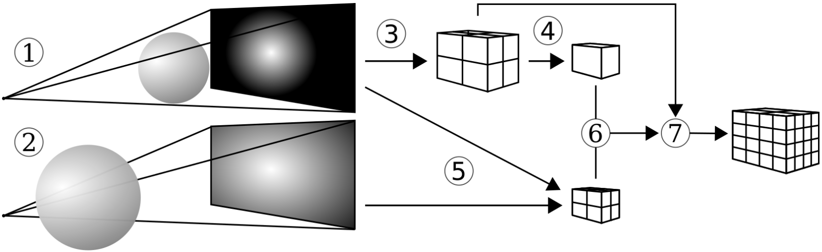
image sources: Saadatfar et al, 2009; Ketcham et al, 2001

Zooming & Region of Interest Tomography



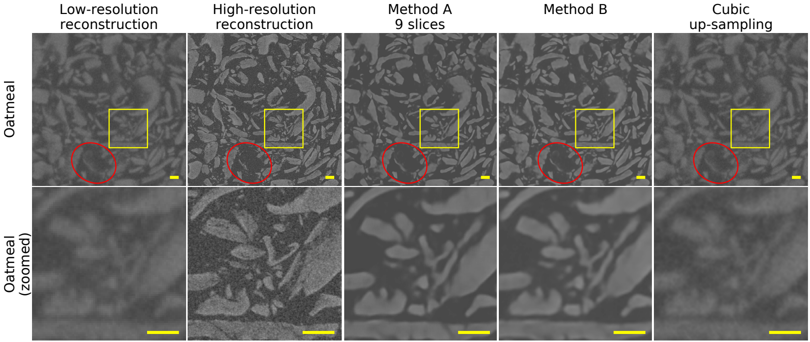


On-the-Fly Resolution Improvement Pipeline

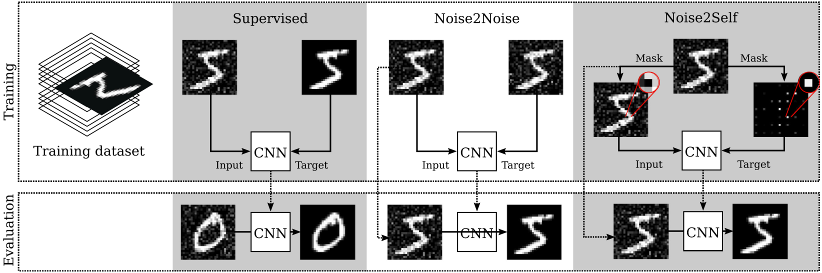


- full view (1) and ROI acquisition (2)
- image reconstruction (3), (5)
- preparing training data (4)
- training (6)
- improving resolution (7)

On-the-Fly Image Improvement Results



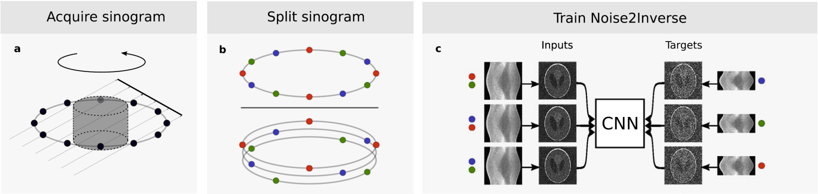
Self-Supervised Image Denoising



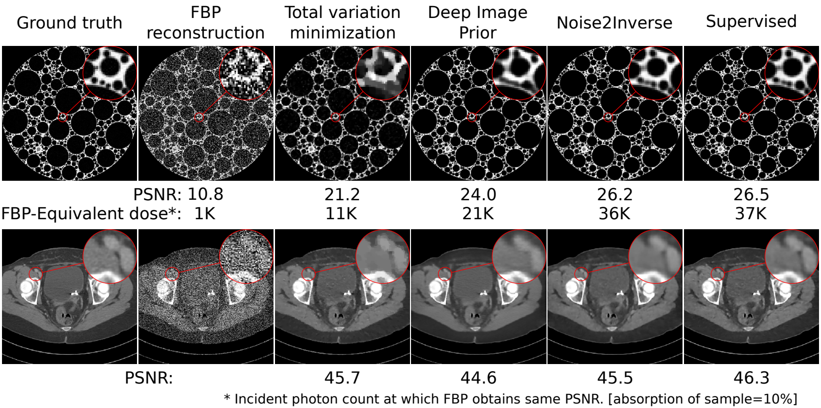
Lehtinen, Munkberg, Hasselgren, Laine, Karras, Aittala, Aila, 2018. Noise2Noise: Learning image restoration without clean data, *Proc 35th Int Conf Mach Learn 80, PMLR.*

Batson and Royer, 2019. Noise2Self: Blind denoising by self-supervision, *Proc 36th Int Conf Mach Learn 97, PMLR.*

Self-Supervised Learning for Tomography: Noise2Inverse

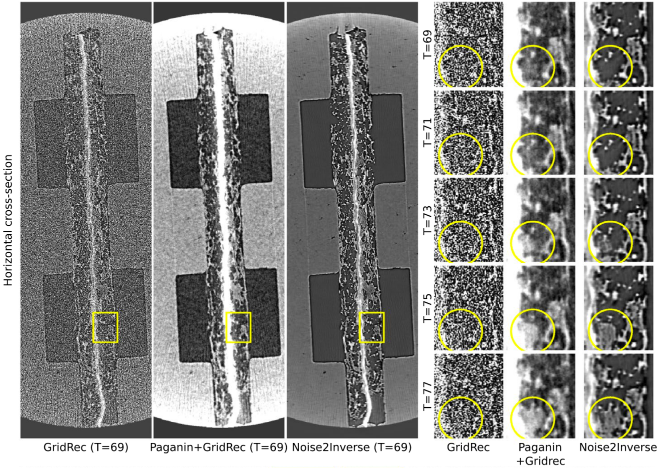


Hendriksen, Pelt, Batenburg, 2020. Noise2inverse: Self-supervised deep convolutional denoising for tomography, *IEEE TCI.*



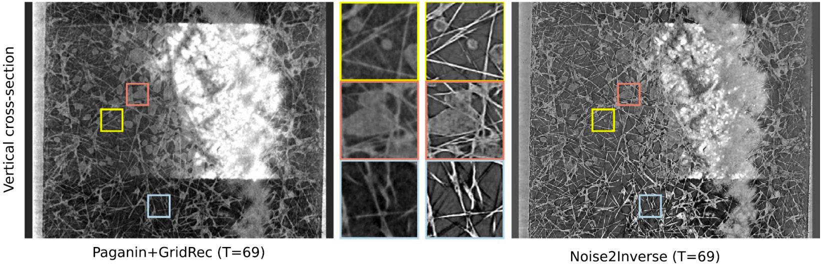
Hendriksen, Pelt, Batenburg, 2020. Noise2inverse: Self-supervised deep convolutional denoising for tomography, *IEEE TCI.*

Noise2Inverse on Dynamic Synchrotron Data



Hendriksen et al., 2021. Deep denoising for multi-dimensional synchrotron X-ray tomography without high-quality reference data, *Scientific Reports.*

Noise2Inverse on Dynamic Synchrotron Data



Hendriksen et al., 2020. Deep denoising for multi-dimensional synchrotron X-ray tomography without high-quality reference data, *Scientific Reports.*

Reflectivity-Based Ultrasonic Imaging

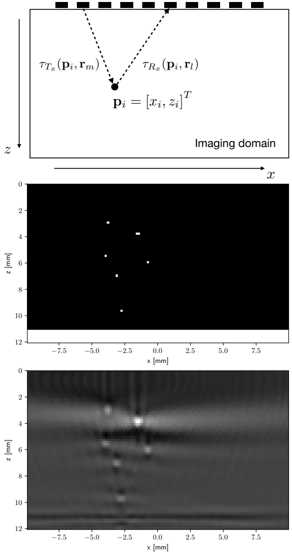
Public Private Partnership with ApplusRTD

2D US imaging with linear arrays:

- ✓ non-ionizing radiation, mobile, low operating costs
- ! non-linear problem, low image quality, interpretation

Typical workflow:

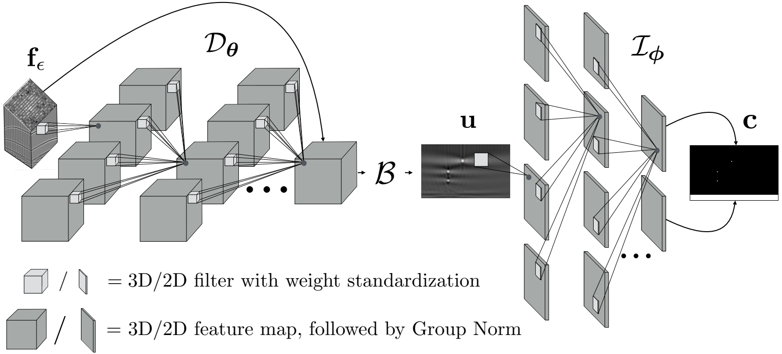
1. data pre-processing (denoising, filtering, deconvolution)
2. image formation via beamforming (Delay-And-Sum)
3. image post-processing (e.g. image enhancement or segmentation)



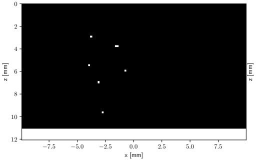
Ultrasonic Imaging Using End-To-End Deep Learning

Key ideas:

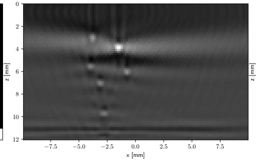
- Mapping from acoustic properties to data is non-linear and include complicated wave-matter interactions
- Delay-And-Sum is localizing linear back-projection approximating underlying wave physics
- DNNs can correct it and exploit data information end-to-end



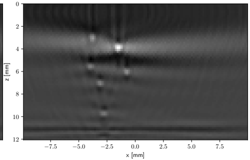
Ultrasonic Imaging Using End-To-End Deep Learning



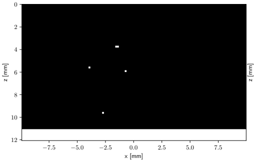
(a) target



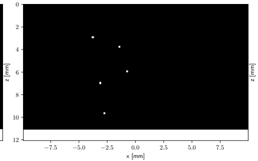
(b) DAS clean



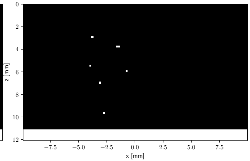
(c) DAS noisy sub-sampled



(d) three-step



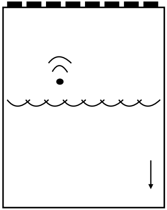
(e) two-step



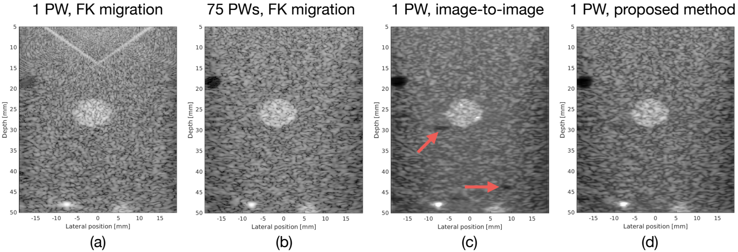
(f) end-to-end

Pilikos, Horchens, Batenburg, van Leeuwen, L, 2020. Fast ultrasonic imaging using end-to-end deep learning, *IEEE International Ultrasonics Symposium.*

Single Plane-Wave Imaging Using End-To-End Deep Learning



- **ultrafast ultrasound imaging** via plane waves
- Embed Stolt's FK migration end-to-end



Pilikos, de Korte, van Leeuwen, L, 2021. Single Plane-Wave Imaging using Physics-Based Deep Learning, *IEEE International Ultrasonics Symposium, arXiv:2109.03661.*

Deep Learning Challenges in Image Reconstruction

Application

- training data
- evaluation
- robustness

Conceptual

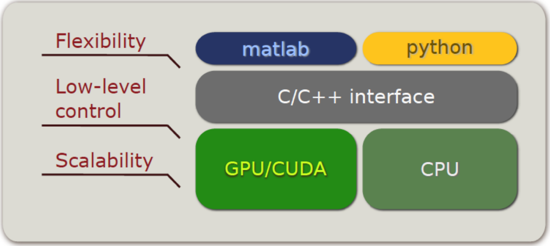
- scaling - dimensional reduction
- algorithm design / incorporate imaging physics
- un/self supervised
- task-adaptation (end-to-end)

Software

- coupling CI - DL toolboxes
- real-time imaging

ASTRA Toolbox: HPC Building Blocs for CT

- open source software, developed by CWI and Univ. Antwerp
- provides scalable, high-performance GPU primitives for tomography
- flexible with respect to projection geometry
- back-end in the Operator Discretization Library (ODL) software



Integration into Deep Learning frameworks via

- Operator Discretization Library (ODL) software
- Tomosipo

Summary & Outlook

- computational imaging will always keep us busy
- deep learning can help us to keep up
- translation is not trivial
- getting training data for real applications is hard work
- self/un-supervised training maybe viable alternative
- combining analytical methods with data or image domain CNNs
- integrating image formation end-to-end

Thanks for your attention!

- computational imaging will always keep us busy
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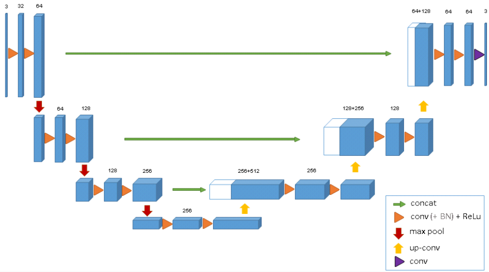
U-Net Type Encoder-Decoder Networks



Great results for many applications, but

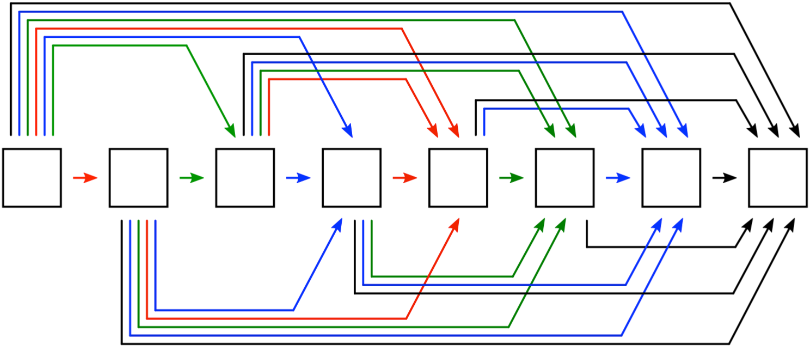
- ! detected features have to be copied to deeper layers
- ! layers are wide, leading to many convolutions
- ! decoder cannot be used to improve encoder

Better: reuse features, fewer convolutions, mix decoder and encoder

Ronneberger, Fischer, Brox, 2015. U-Net: Convolutional Networks for Biomedical Image Segmentation, *MICCAI.*

Mixed Scale Dense Network (MS-D-Net)

- densely connected conv layers
- differently dilated convolutions to mix spatial scales



Pelt, Sethian, 2018. Mixed-scale dense network for image analysis, *PNAS 115 (2) 254-259.*

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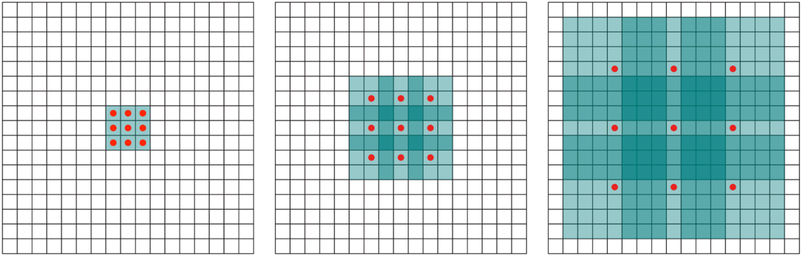
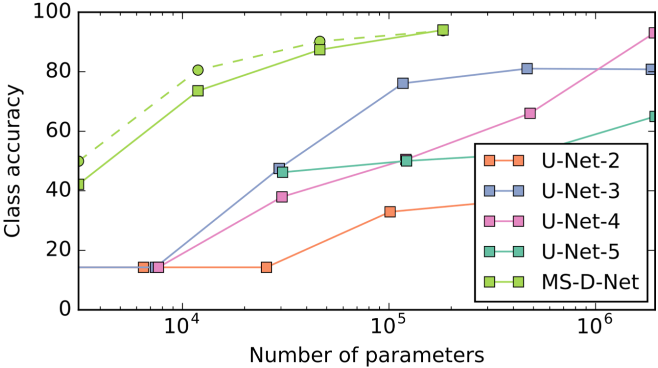


(a) (b) (c)

Pelt, Sethian, 2018. Mixed-scale dense network for image analysis, *PNAS 115 (2) 254-259.*

MS-D Net vs U-Net



try it yourself?

- pyTorch implementation: https://github.com/ahendriksen/msd_pytorch
- stand-alone python implementation coming soon!