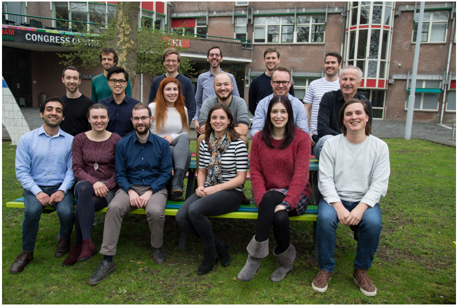
Centrum Wiskunde & Informatica

Deep Learning for Computed Tomography Applications

Felix Lucka for the Computational Imaging Group @ CWI

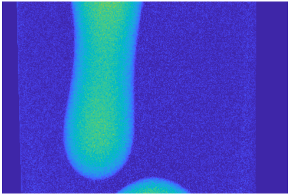
Applied Inverse Problems Conference
Grenoble
11 July 2019

Computational Imaging @ CWI



- headed by **Joost Batenburg**, 18 members
- mathematics, computer science & (medical) physics
- advanced computational techniques for 3D imaging
- 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
- (inter-)national collaborations from science, industry & medicine

Image Reconstruction Challenges



more from more:

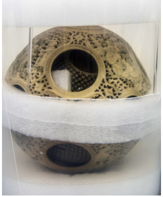
- higher & higher resolution 3D imaging
- spectral / dynamic imaging

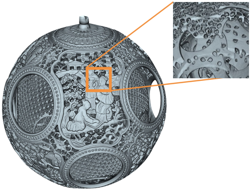
same from less:

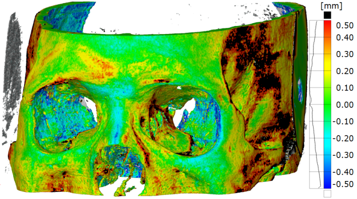
- low-dose, limited view

break the routine:

- real-time 3D imaging
- explorative/adaptive 3D imaging

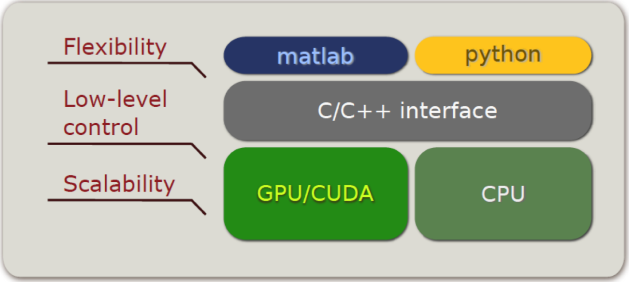






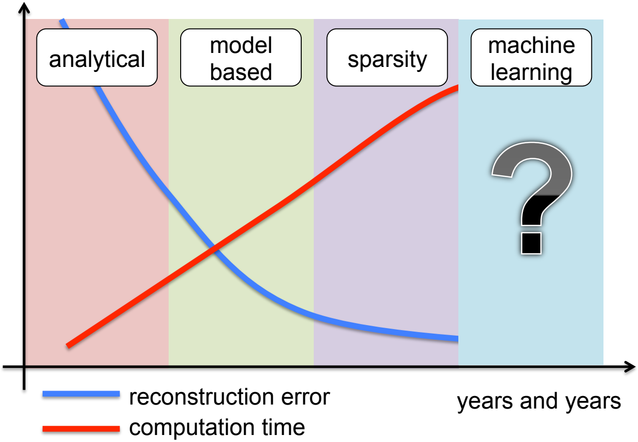
ASTRA Toolbox: HPC Building Blocs for CT

- 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
- next major release autumn 2019!



www.astra-toolbox.com

4 Waves of Image Reconstruction



Ravishankar, Ye, Fessler, 2019. Image Reconstruction: From Sparsity to Data-adaptive Methods and Machine Learning, *arXiv:1904.02816*

! graphic not from the paper !.

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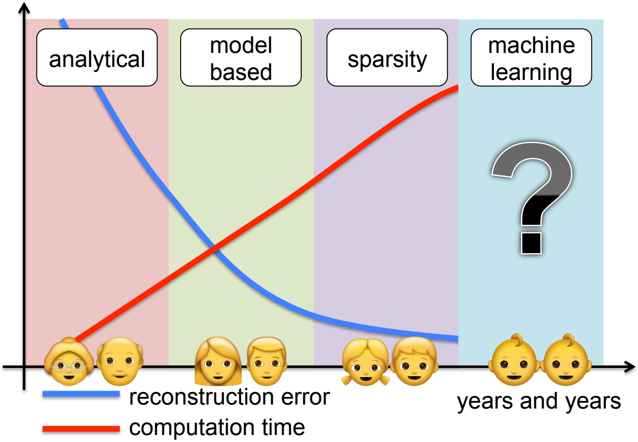

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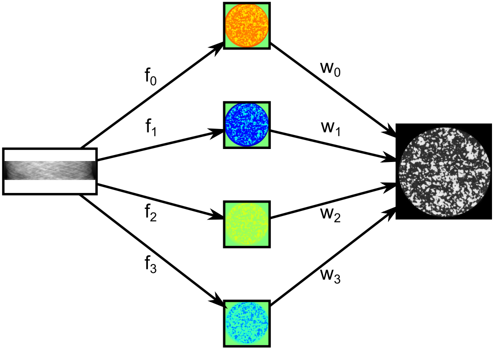
Early Ideas: Neuronal Network FBP

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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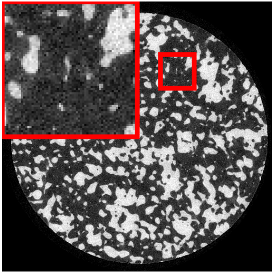
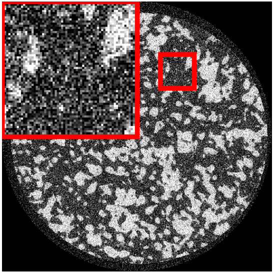
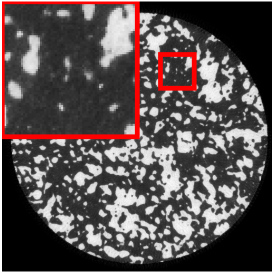


FBP, all projections



FBP, 5%



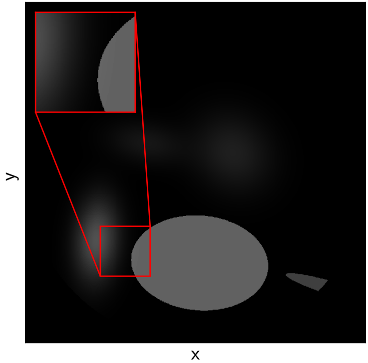
NN-FBP, 5%

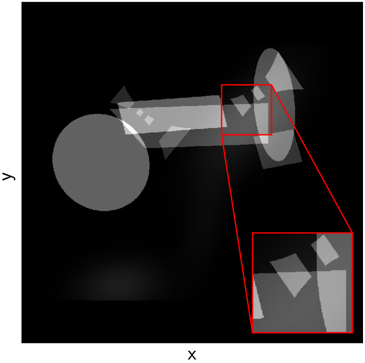
✓comp. efficient ✓few trainable parameters ✓lot's of training data

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

Going 3D: NN-FDK

circular cone beam scanning: Feldkamp-Davis-Kress (FDK) algorithm

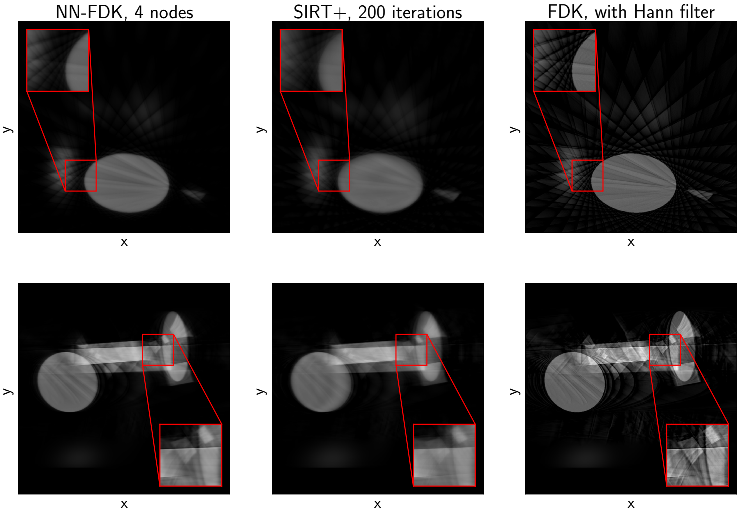




phantoms, size: 1024^3

Going 3D: NN-FDK

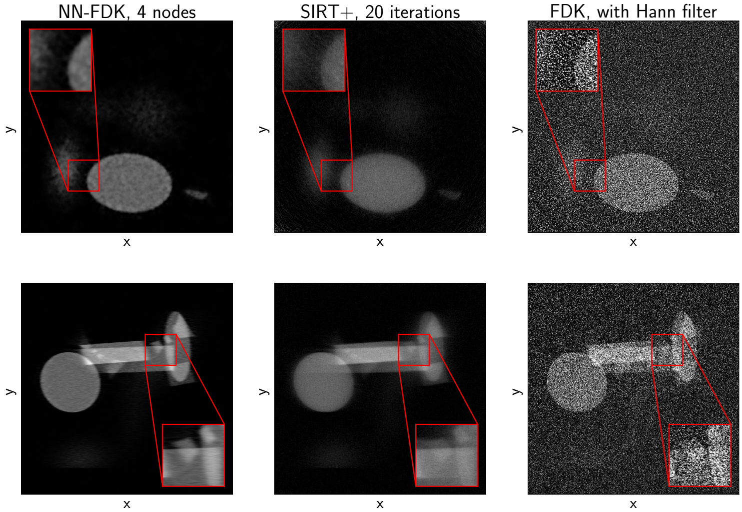
circular cone beam scanning: Feldkamp-Davis-Kress (FDK) algorithm



limited angle scenario

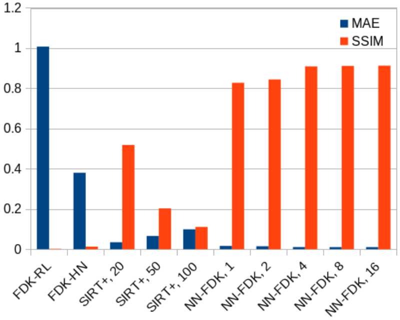
Going 3D: NN-FDK

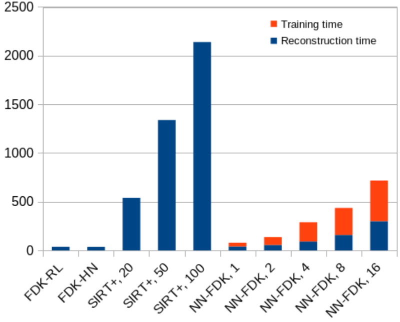
circular cone beam scanning: Feldkamp-Davis-Kress (FDK) algorithm



high noise scenario

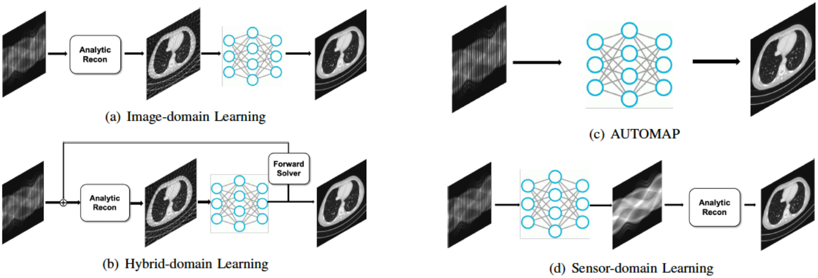
NN-FDK: Quantitative results





Watch out for

Lagerwerf et al., 2019. Neural Network Feldkamp-Davis-Kress algorithm, *in preparation.*



(a) Image-domain Learning

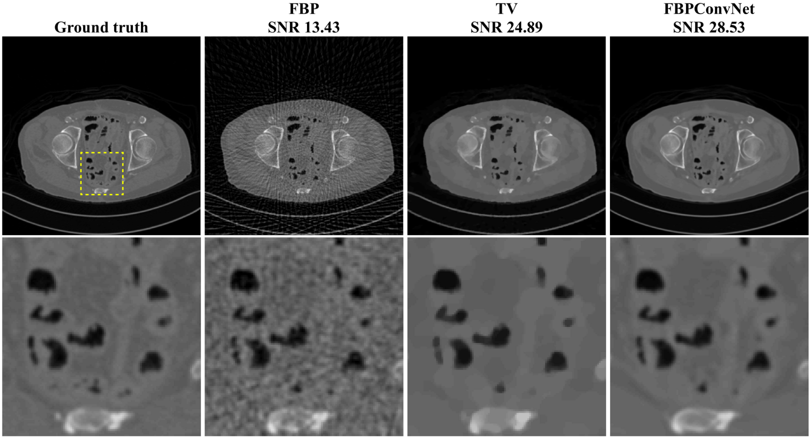
(b) Hybrid-domain Learning

(c) AUTOMAP

(d) Sensor-domain Learning

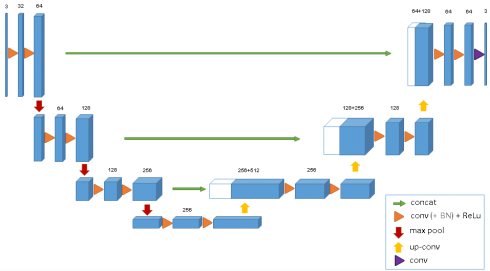
Ravishankar, Ye, Fessler, 2019. Image Reconstruction: From Sparsity to Data-adaptive Methods and Machine Learning, *arXiv:1904.02816.*

Postprocessing via Deep Learning: FBPConvNet



Jin, McCann, Froustey, Unser, 2017. Deep Convolutional Neural Network for Inverse Problems in Imaging, *IEEE TIP.*

U-Net Type Encoder-Decoder Networks



Great results for many applications, but

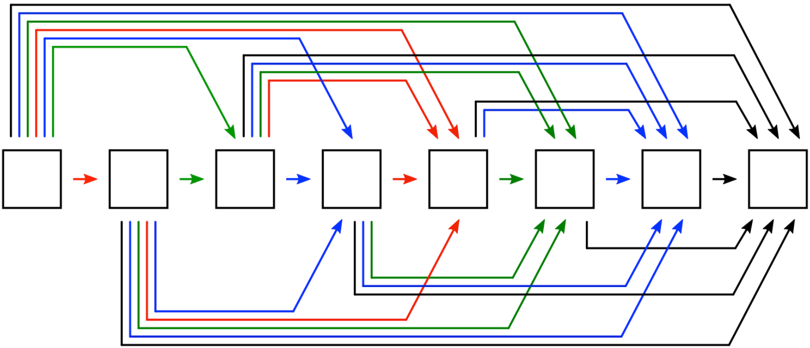
- ! detected features have to be copied to deeper layers
- ! layers are wide, leading to many convolutions
- ! decoder cannot be used to improve encoder

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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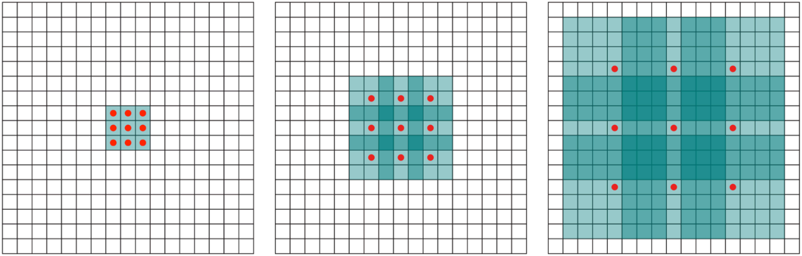
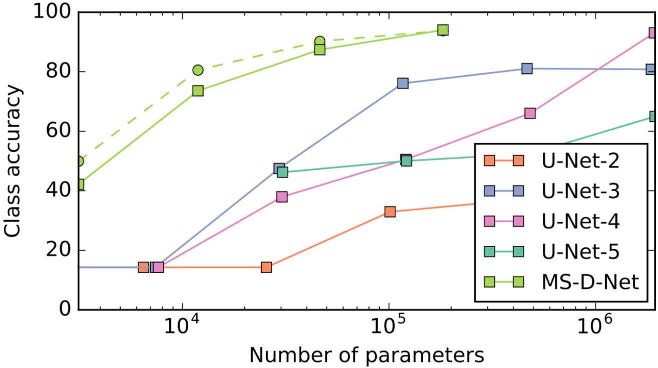


(a) (b) (c)

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

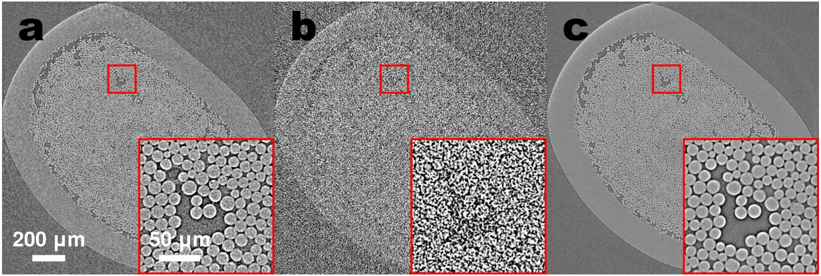
MS-D Net vs U-Net



try it yourself?

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

MS-D-Net Removal of FBP Artefacts

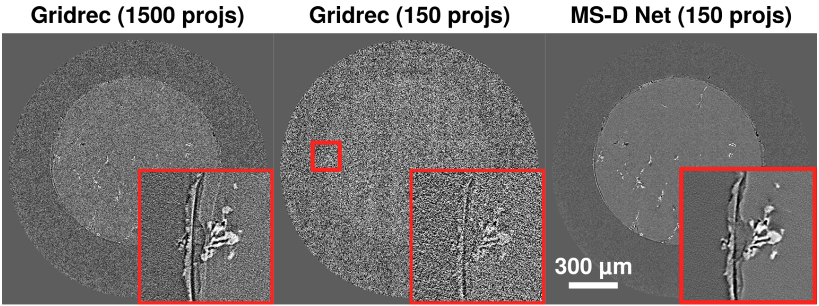


2560x2560 tomography images of fiber composite.

Left: 1024 projections, *middle/right*: 128 projections

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

MS-D-Net Removal of Gridrec Artefacts



- Tomobank fatigue-corrosion data (De Carlo et al, MST 2018)
- 2160x2560x2560 voxels
- use first and last scans as training data, eval on intermediate scan

Pelt, Batenburg, Sethian, 2018. Improving Tomographic Reconstruction from Limited Data Using Mixed-Scale Dense Convolutional Neural Networks, *Journal of Imaging 4 (11), 128.*

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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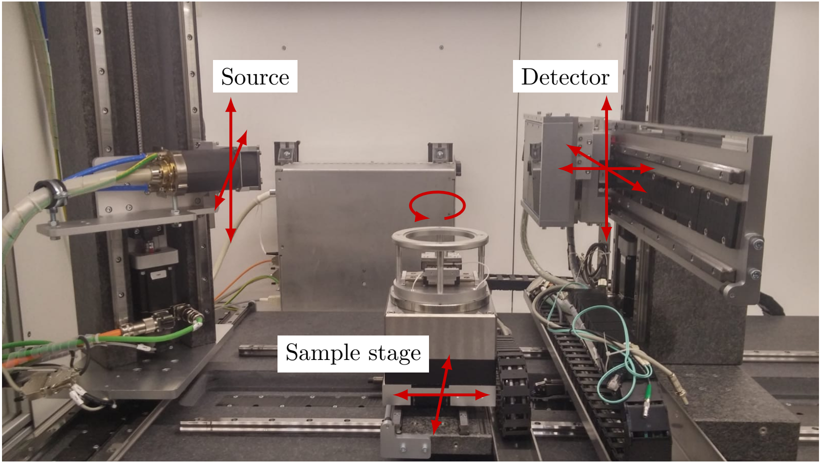
for real applications?

FleX-ray Lab @ CWI

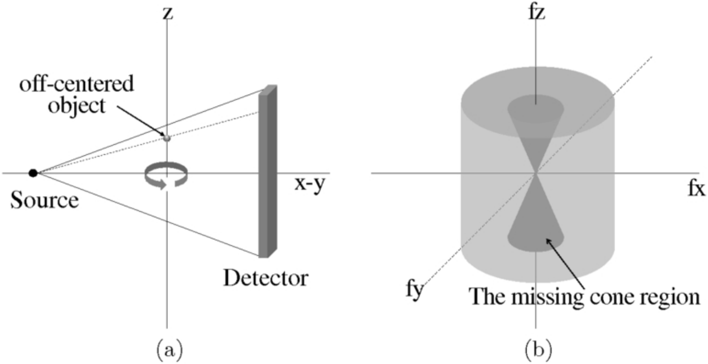


- custom-built (by XRE nv), fully-automated, highly flexible
- linked to large-scale computing hardware
- **Aim: Proof-of-concept** experiments directly accessible to mathematicians and computer scientists.

Cone Beam Computed Tomography (CBCT)

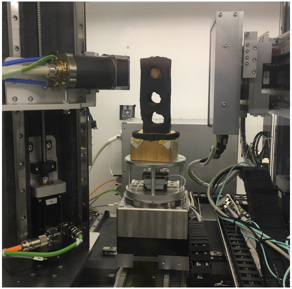
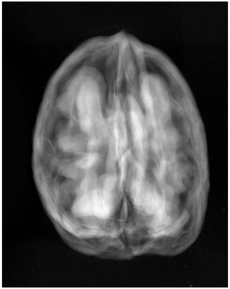
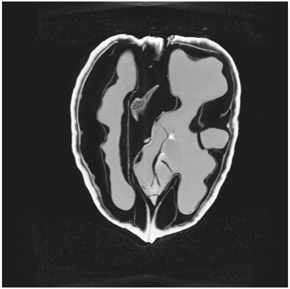
Circular cone beam scanning geometry

- 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.

CBCT Data Collection for Machine Learning

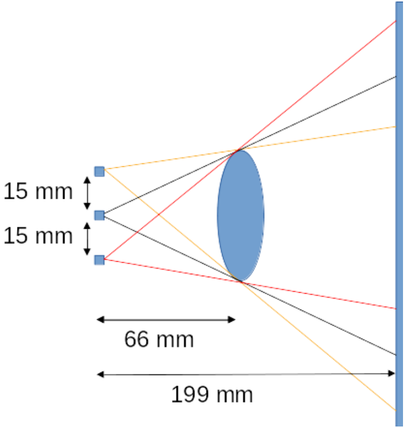
  

42 Walnuts:

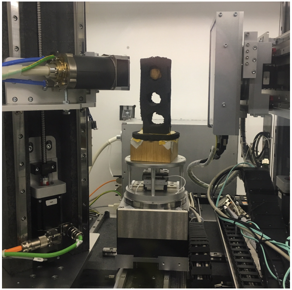
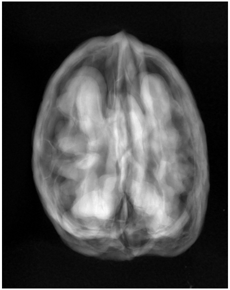
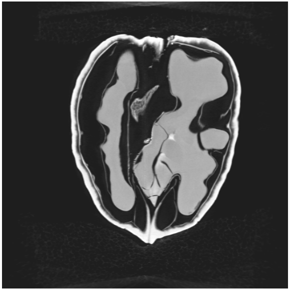
- natural inter-population variability
- hard shell, a softer inside, air filled cavities
- variety of large-to-fine-scale features
- proxy for human head details
- 42 3D samples = a lot of 2D data

CBCT Data Acquisition

- three different source orbits
- cone angles comparable to dental / head imaging
- 1200 projections per orbit
- 768 $\times$ 972 pixels (size 150nm).



CBCT Data Collection for Machine Learning

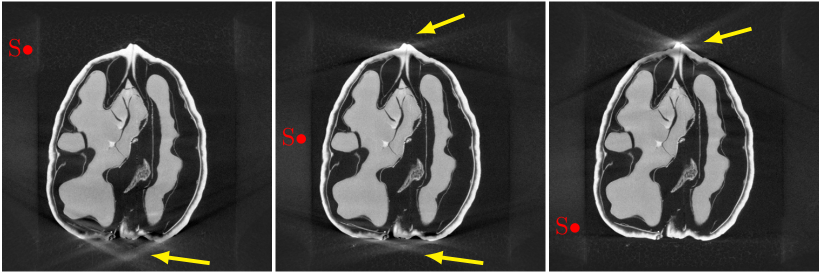




we provide

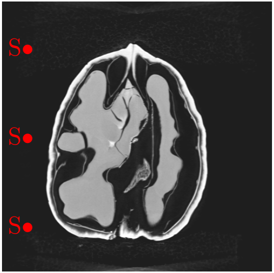
- this (and other) data sets on zenodo.org, community "CI-CWI"
- MATLAB and Python scripts for reading, pre-processing and image reconstruction on github.com/cicwi/WalnutReconstructionCodes

Der Sarkissian, L, van Eijnatten, Colacicco, Coban, Batenburg, 2019.
A Cone-Beam X-Ray CT Data Collection Designed for Machine Learning,
arXiv:1905.04787, in revision.

High Cone Angle Artefacts

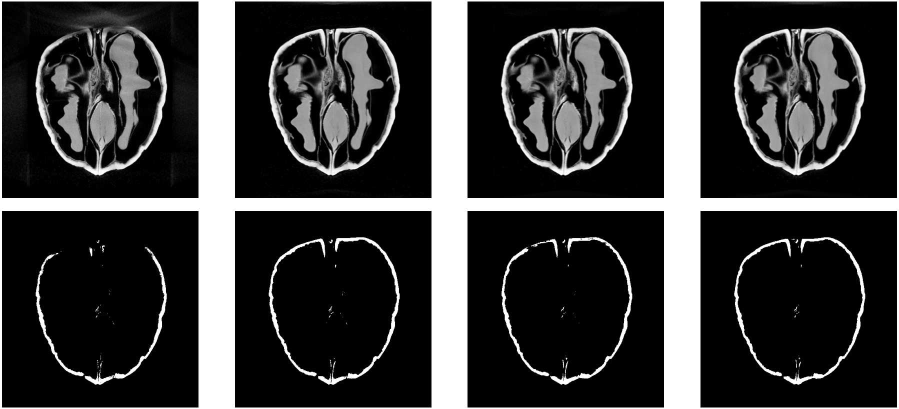


Caused by combination of Tuy's condition not fulfilled (missing data) and FDK algorithm's geometric approximations



High Cone Angle Artifact Reduction

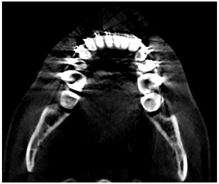
FDK	Gold standard	MS-D correction axial slicing	MS-D correction radial slicing

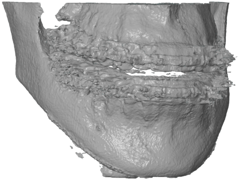


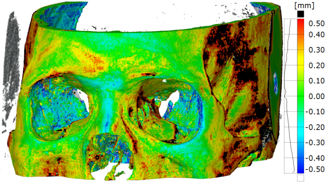
Cone Beam in Action

Public Private Partnership with Planmeca

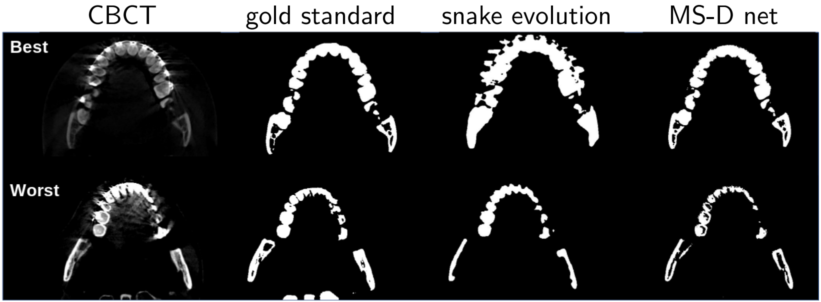
- CBCT increasingly important in clinical applications
- artifacts impair usability compared to conventional CT
- most tedious and time-consuming task in many medical imaging pipelines: **segmentation**







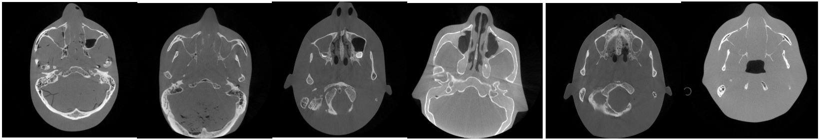
Applications: Dental Imaging



Minnema, van Eijnatten, Hendriksen, Liberton, Batenburg, Forouzanfar, Wolff, 2019. Bone segmentation of dental cone-beam CT scans affected by metal artefacts using a mixed-scale dense convolutional neural network, *in revision.*

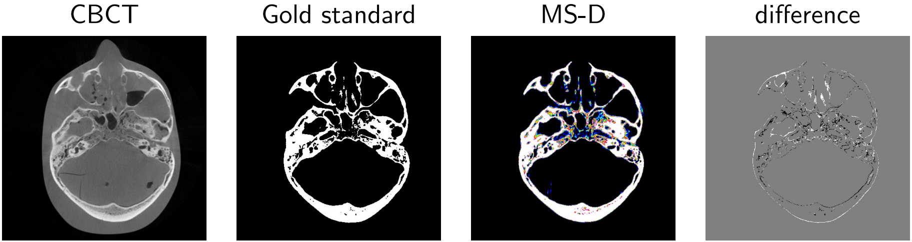
Applications: Skull Segmentation from CBCT

- cone beam artifacts impair skull segmentation
- 7 cadaver heads, skull extracted, phantoms fabricated
- scanned with CTCT, μCT, MDCT
- registration of volumes
- semi-manual segmentation as ground truth
- clinical data set collected at the moment

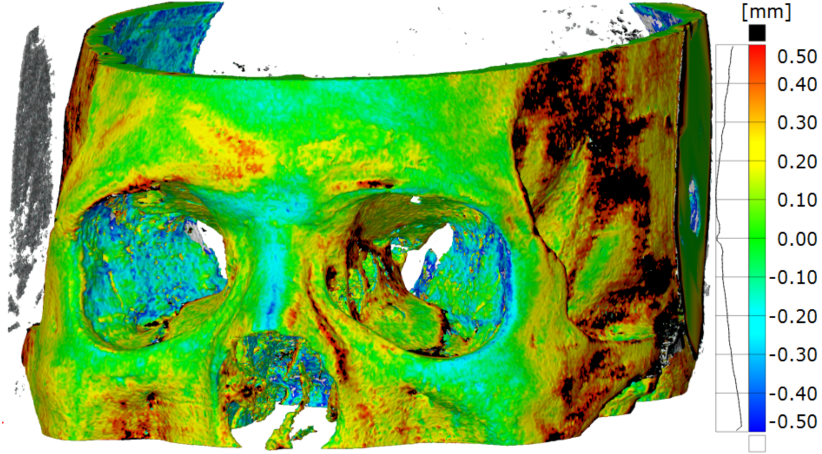


van Eijnatten, van Dijk, Dobbe, Streekstra, Wolf, 2018. CT image segmentation methods for bone used in medical additive manufacturing, *Medical Engineering & Physics.*

Skull Segmentation Results

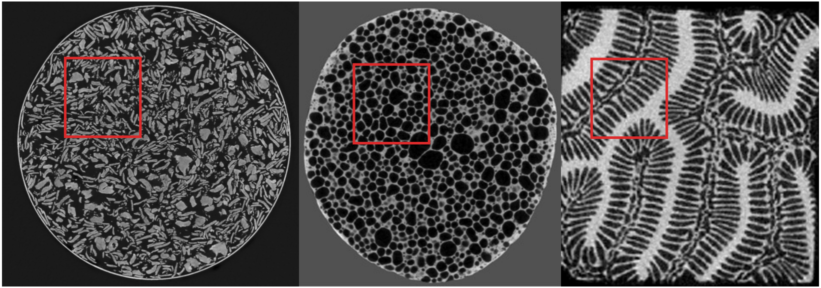


Skull Segmentation



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

On-the-Fly Machine Learning for Unique Objects



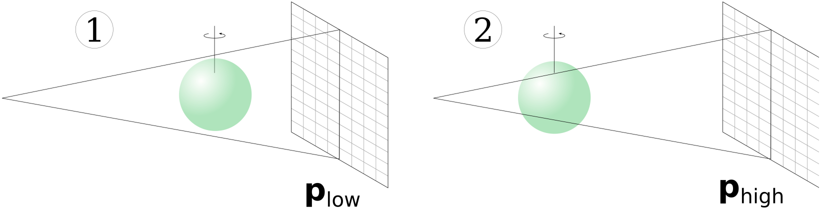
Improve resolution on single object CT reconstruction

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

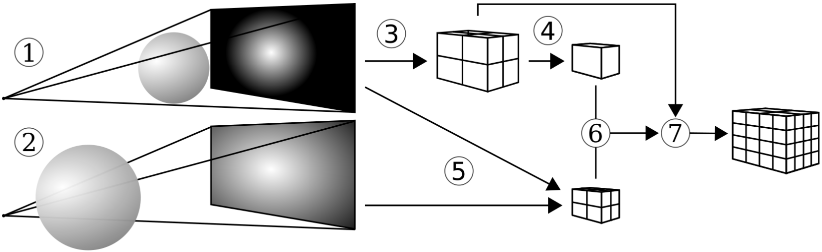
Hendriksen, Pelt, Hendriksen, Palenstijn, Coban, Batenburg, 2019. On-the-Fly Machine Learning for Improving Image Resolution in Tomography, *Appl. Sci. 2019.*, 9, 2445

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

Zooming & Region of Interest Tomography

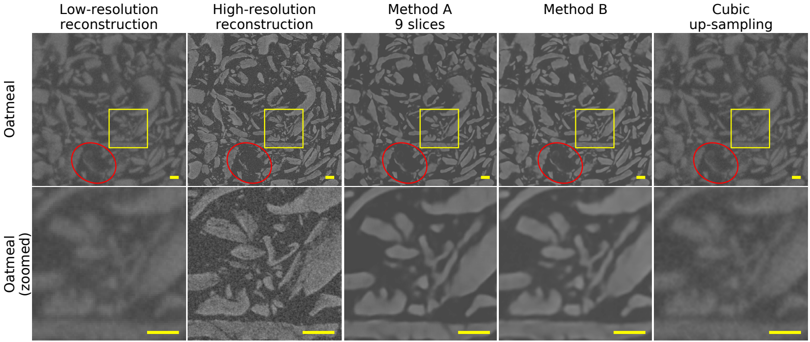


On-the-Fly Resolution Improvement Pipeline



- 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



Summary & Outlook

- tomographic image reconstruction will always keep us busy
- machine learning can help us to keep up
- combining analytical methods with data or image domain CNNs
- network architectures for scientific/clinical applications?
  - small training data sizes
  - over-fitting
- translation is not trivial
- getting training data for real applications is hard work

References

- **Pelt, Batenburg, 2013.** Fast Tomographic Reconstruction from Limited Data Using Artificial Neural Networks, *IEEE Image Processing, 22 (12).*
- **Pelt, Batenburg, Sethian, 2018.** Improving Tomographic Reconstruction from Limited Data Using Mixed-Scale Dense Convolutional Neural Networks, *Journal of Imaging 4 (11), 128.*
- **Pelt, Sethian, 2018.** Mixed-scale dense network for image analysis, *PNAS 115 (2) 254-259.*
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Thanks for your attention!

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