CWI
Centrum Wiskunde & Informatica

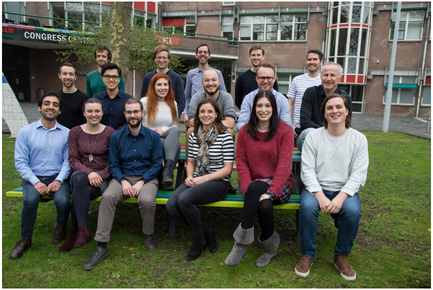
UCL

New Applications and Challenges in X-Ray Tomography

Felix Lucka

International Congress on Industrial and Applied Mathematics
Valencia
17 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:

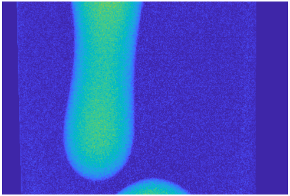
- higher & higher resolution 3D imaging
- spectral/dynamic imaging
- phase/diffraction/scattering contrast

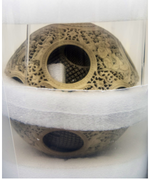
same from less:

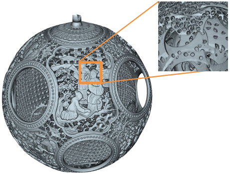
- low-dose, limited view

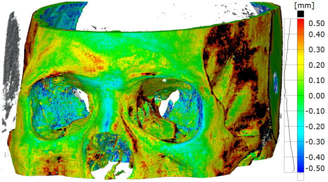
break the routine:

- real-time 3D imaging
- explorative/adaptive 3D imaging
- X-ray optics



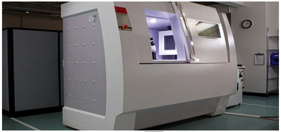






Traditional 3D X-Ray Imaging Work-flow

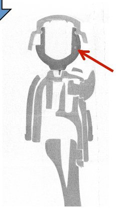
scan first



Scan finished

compute 3D image later

visualize/analyze even later



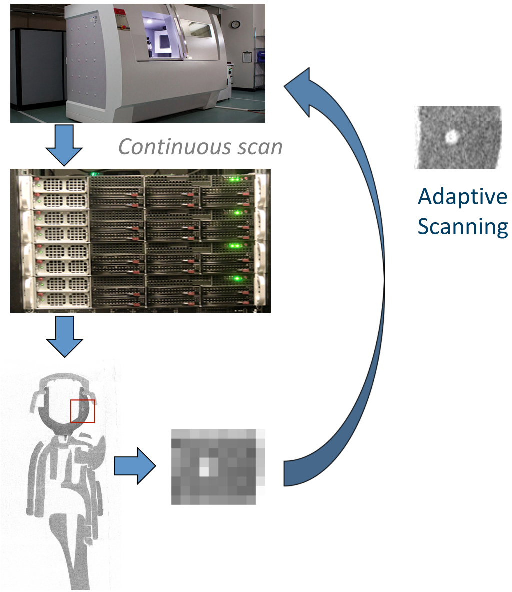
Cross section

Real-Time 3D Imaging Work-flow

scan quickly / continuously

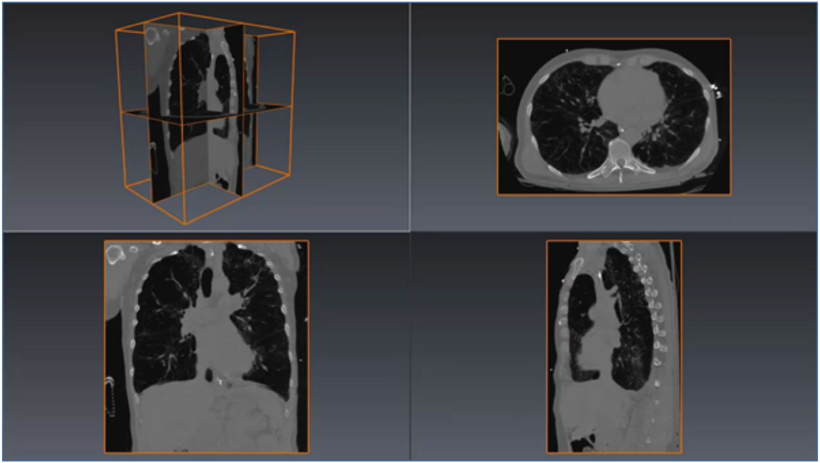
compute 3D image in real-time

analyze/visualize immediately



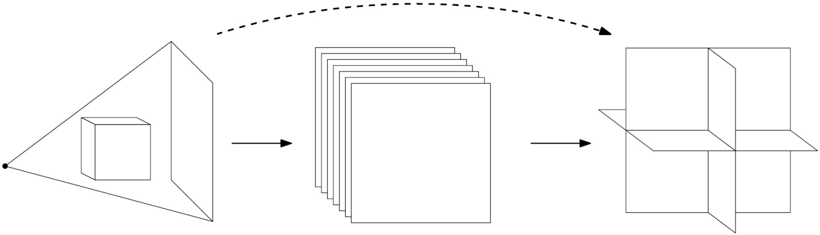
Sliced Visualizations

3D volumes are often visualized using a slicer



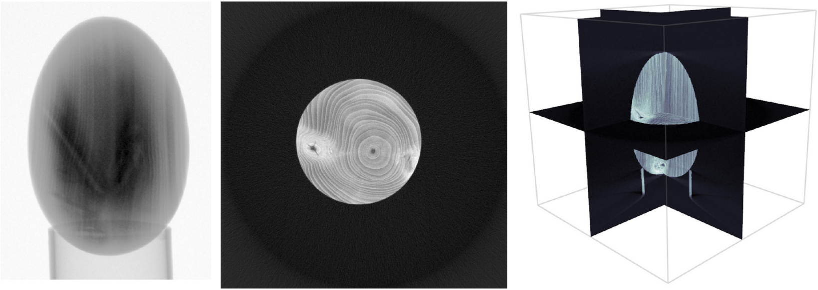
Quasi-3D Imaging

Can we reconstruct arbitrary slices to create the "illusion of having a full 3D volume"?



The **RECAST3D** workflow

RECAST 3D

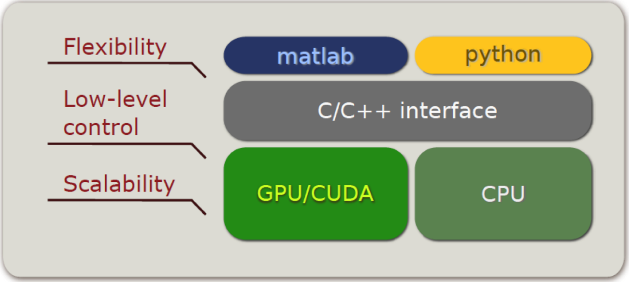


- implemented at PSI, at TOMCAT beam line
- https://github.com/cicwi/RECAST3D

Buurlage, Kohr, Palenstijn, Batenburg, 2018. Real-time quasi-3D tomographic reconstruction, *Meas. Sci. Technol.*.

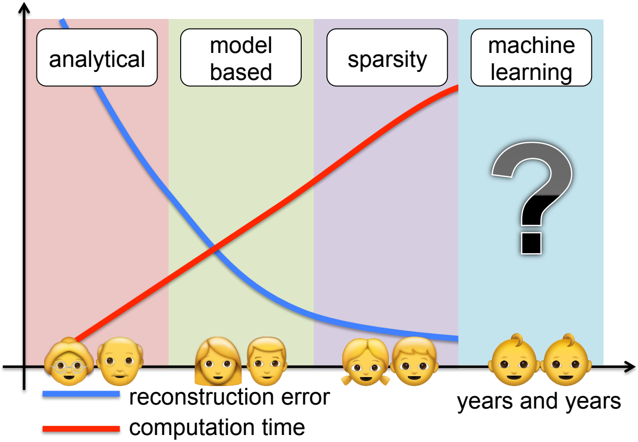
ASTRA Toolbox: HPC Building Blocs for CT

- 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 ODL, TomoPy and others
- next major release autumn 2019: BIG data sets



www.astra-toolbox.com

4 Waves of Image Reconstruction



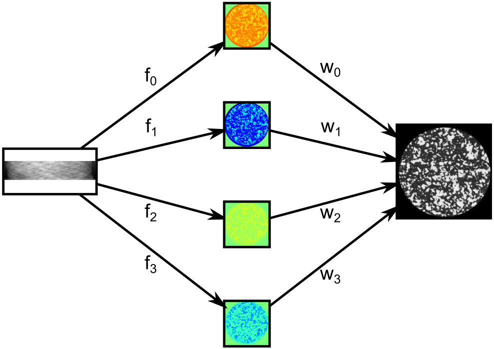
Ravishankar, Ye, Fessler, 2019. Image Reconstruction: From Sparsity to Data-adaptive Methods and Machine Learning, *arXiv:1904.02816*

! graphic not from the paper !.

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



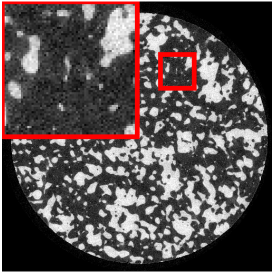
learn convolution filters and weights from training data

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

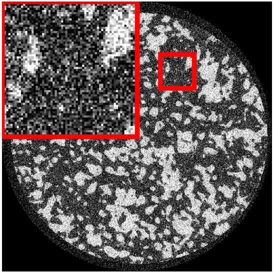
Early Ideas: Neuronal Network FBP

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

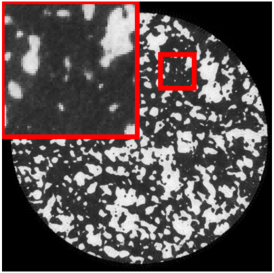
NN-FBP: non-linear combi of FBPs for different filters f_i



FBP, all projections



FBP, 5%



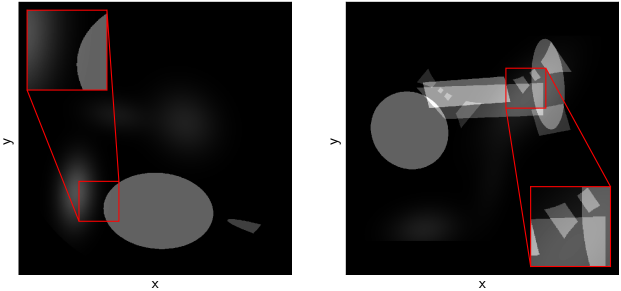
NN-FBP, 5%

✓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

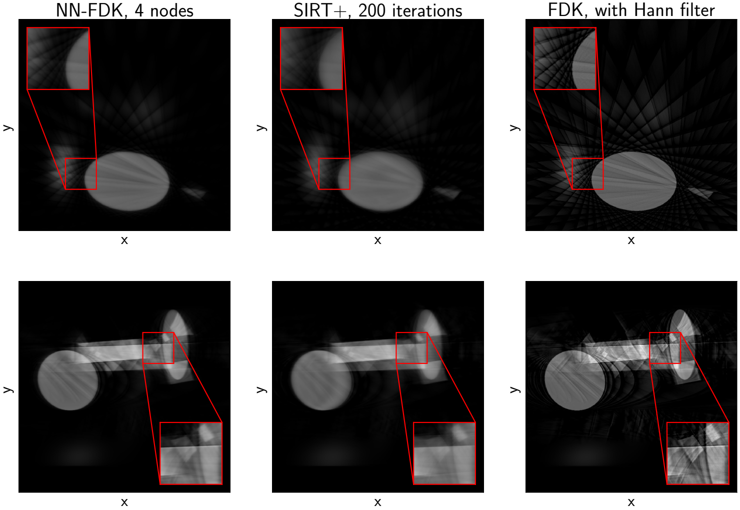


phantoms, size: 1024^3, watch out for

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

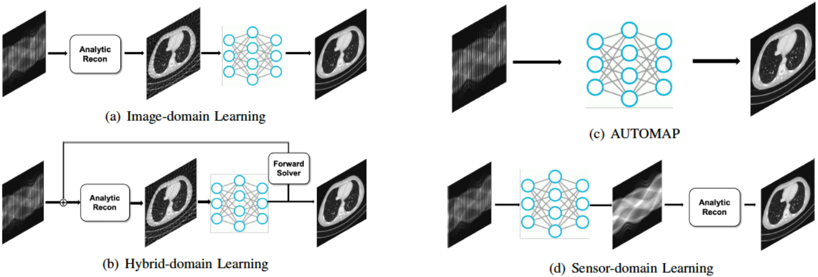
Going 3D: NN-FDK

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



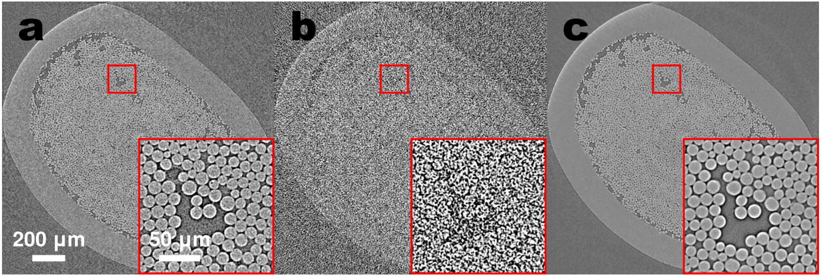
limited angle scenario

Deep Learning in Image Reconstruction



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

Mixed-Scale Dense Nets for Postprocessing



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.*
- **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

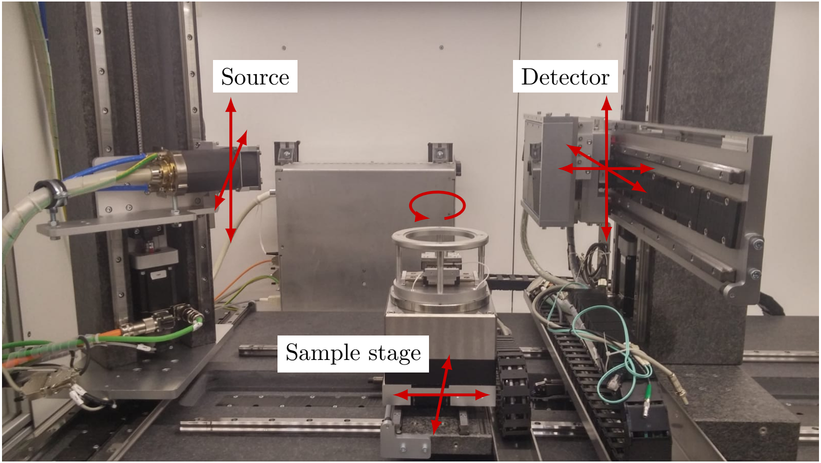
Training Data for Deep Learning

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

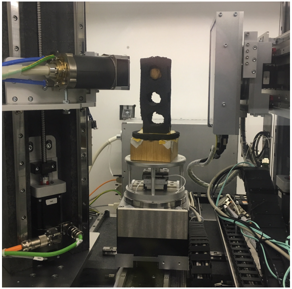
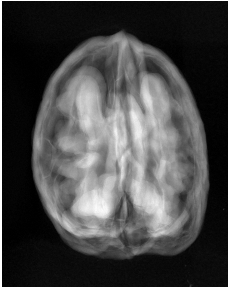
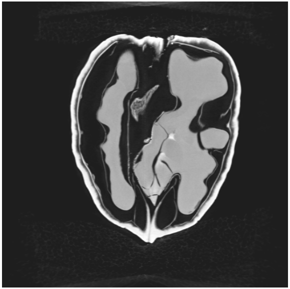
for real applications?

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.

CBCT Data Collection for Machine Learning

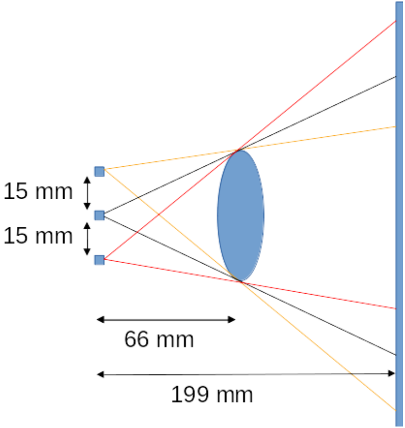




42 Walnuts:

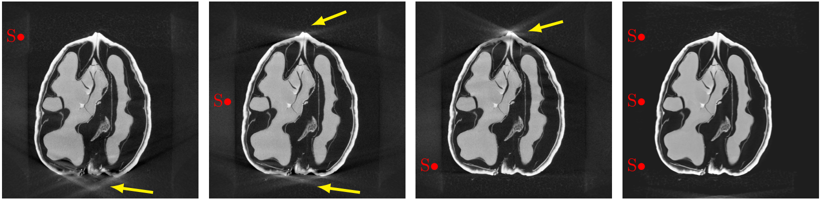
- natural inter-population variability
- hard shell, a softer inside, air filled cavities
- variety of large-to-fine-scale features
- proxy for human head details
- 42 3D samples = a lot of 2D data

CBCT Data Acquisition

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



CBCT Data Collection for Machine Learning



we provide

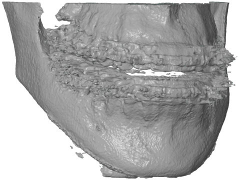
- this (and other) data sets on zenodo.org, community "CI-CWI"
- MATLAB and Python scripts for reading, pre-processing and image reconstruction on github.com/cicwi/WalnutReconstructionCodes

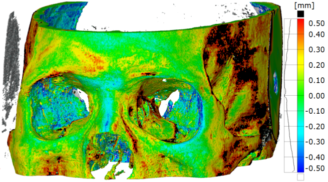
Der Sarkissian, L, van Eijnatten, Colacicco, Coban, Batenburg, 2019.
A Cone-Beam X-Ray CT Data Collection Designed for Machine Learning,
arXiv:1905.04787, in revision.

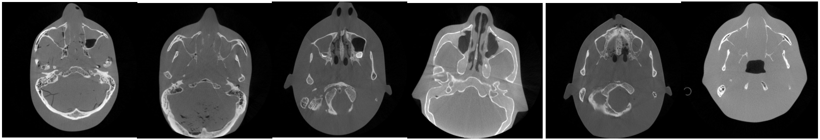
Cone Beam in Action

Public Private Partnership with Planmeca

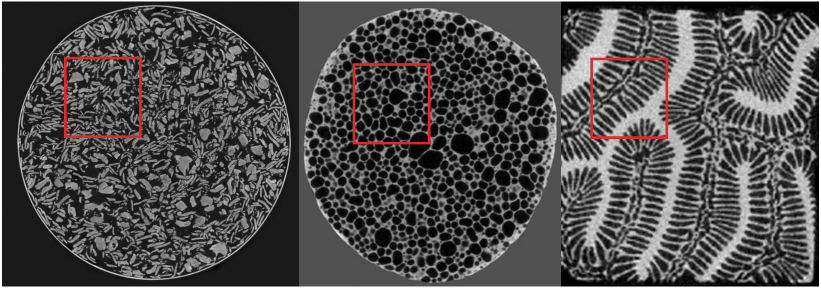
- CBCT increasingly important in clinical applications
- artifacts impair usability compared to conventional CT
- most tedious and time-consuming task in many medical imaging pipelines: **segmentation**
- most challenging: **training data acquisition**







On-the-Fly Machine Learning for Unique Objects



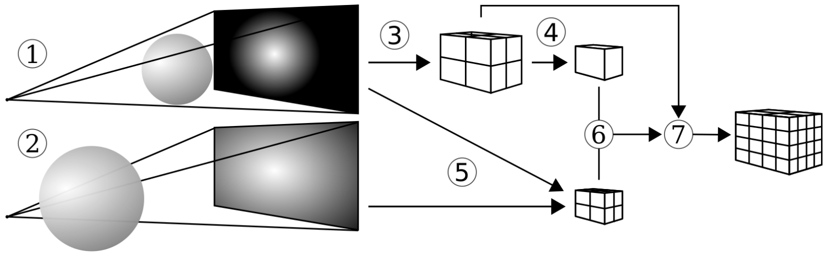
Improve resolution on single object CT reconstruction

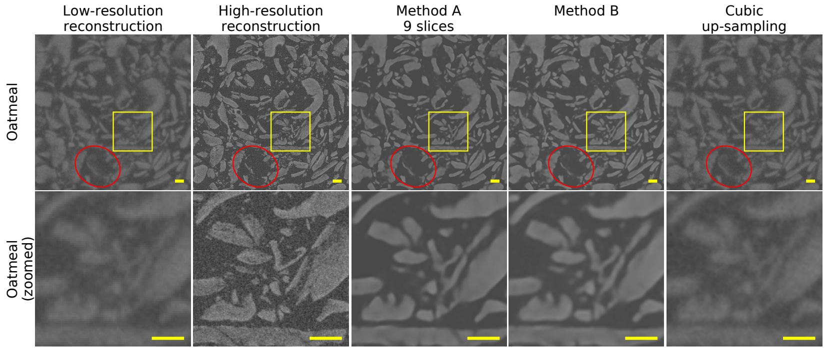
- with same scanner
- with limited increase in computation and scan time

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

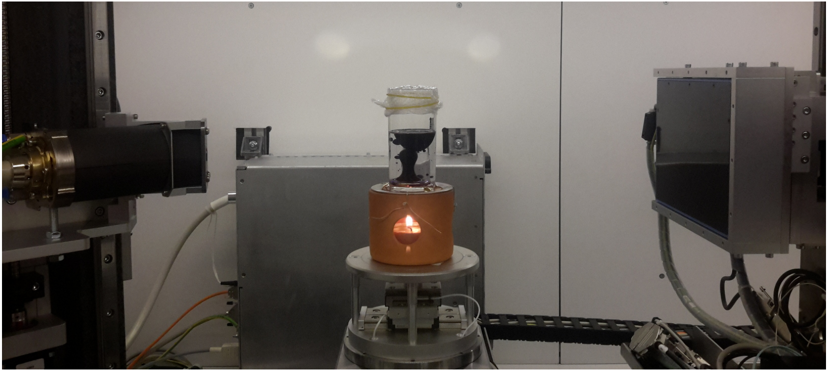
image sources: Saadatfar et al, 2009; Ketcham et al, 2001

On-the-Fly Resolution Improvement Pipeline



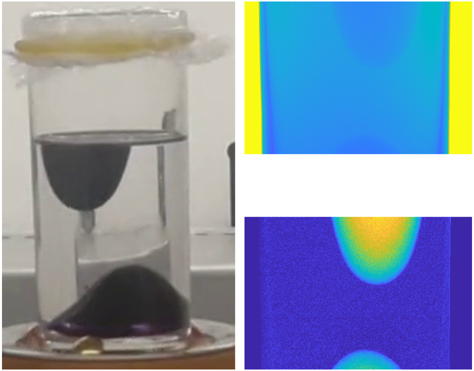


X-Ray Scan of Dynamic Object



- canonical example of temperature-driven **two-phase flow instability**
- 120 projections per rotation $\rightarrow$ each projection averaged over 3°
- 40ms exposure per projection $\rightarrow$ 4.8s per rotation

X-Ray Scan of Dynamic Object



- canonical example of temperature-driven **two-phase flow instability**
- 120 projections per rotation → each projection averaged over 3°
- 40ms exposure per projection → 4.8s per rotation

Joint Image Reconstruction and Motion Estimation

reconstruct image sequence x and motion fields v as

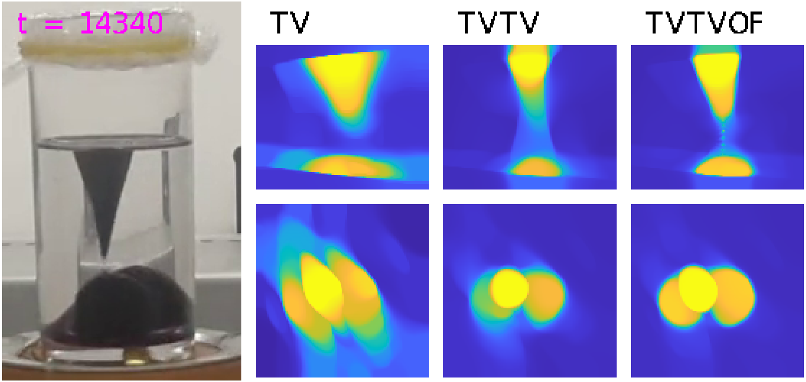
$$\min_{x,v} \sum_t \| W_t\, x_t - p_t \|_2^2 + \mathcal{J}(x_t) + \mathcal{M}(x, v) + \mathcal{H}(v)$$

- data discrepancy
- spatial assumptions on image
- motion model (PDE)
- spatial assumptions on motion

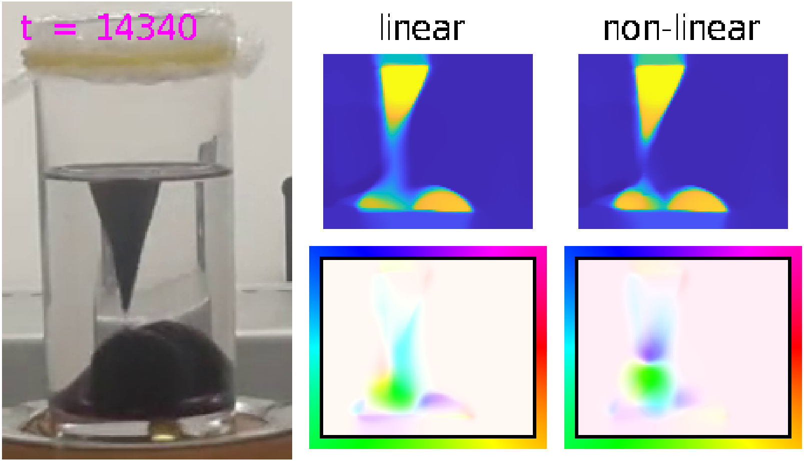
numerical optimization

- alternate between image reconstruction and motion estimation
- image reconstruction **convex but non-smooth**
  primal-dual ("Chambolle-Pock"), augmented Lagrangian ("ADMM")
- motion estimation difficult, **non-convex, non-smooth**
  multi-resolution schemes (pyramids) with linearizations

Lava Lamp: Spatio-Temporal Reconstruction

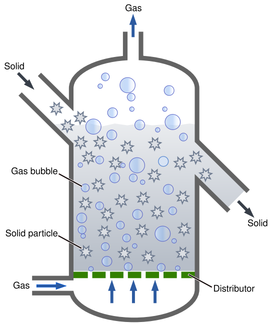


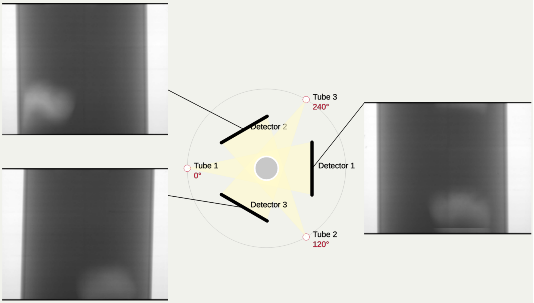
Lava Lamp: Image and Motion Estimation



Example: Fluidized Bed Reactors

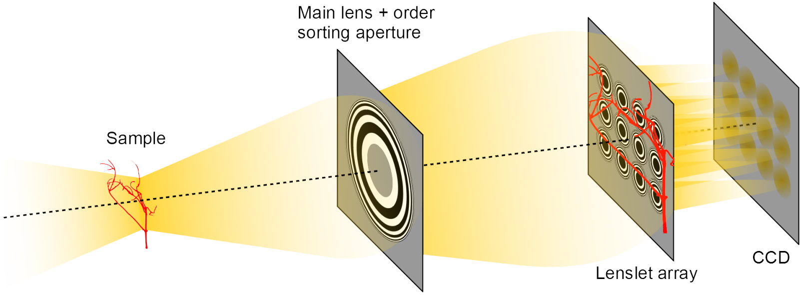
Collaboration with the Transport Phenomena group at TU Delft.

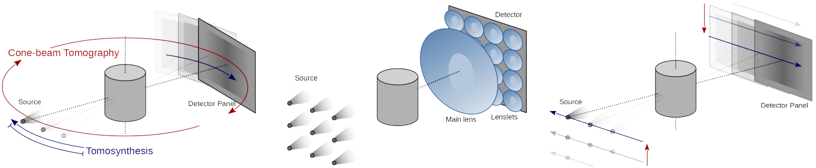




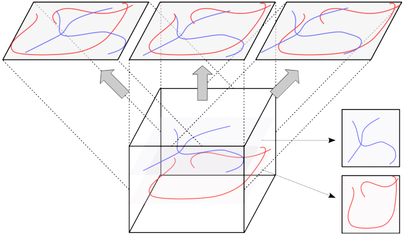
! fast but extremely sparse angle acquisition !

X-Ray Lightfield Imaging

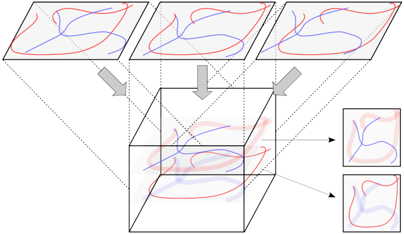




X-Ray Lightfield Imaging

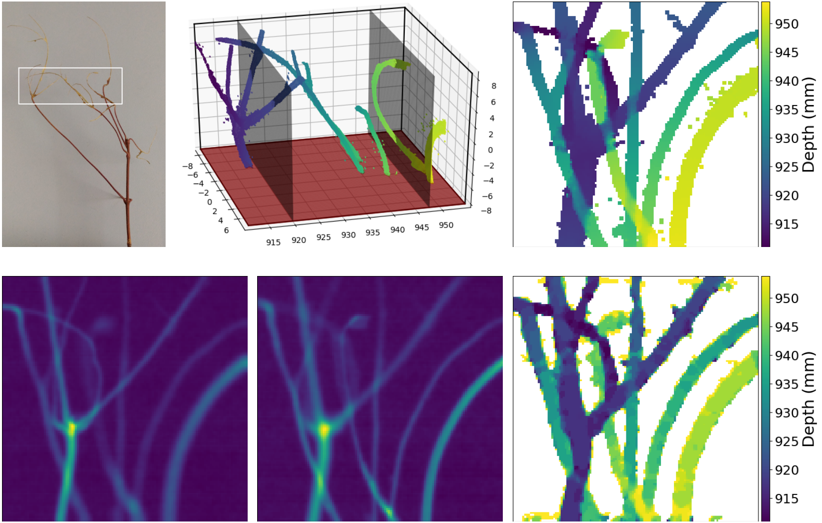


acquisition



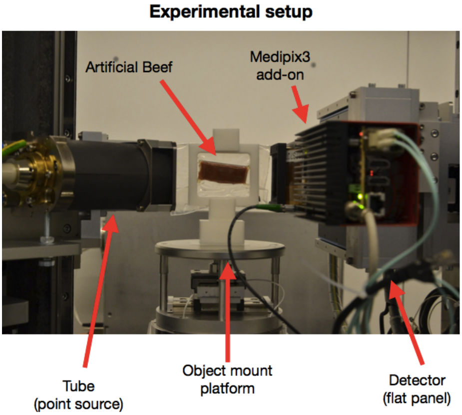
reconstruction

X-Ray Lightfield Imaging: Results



Viganò, Coban, Lucka, van Liere, Batenburg, 2019. X-ray light-field imaging, *in preparation.*

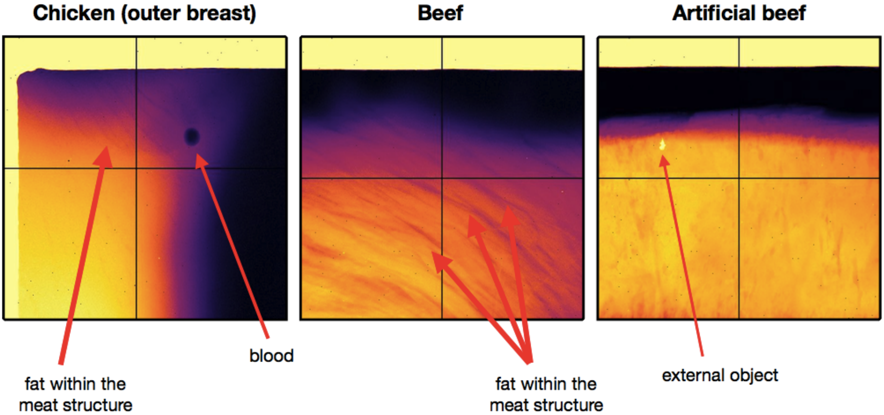
High-Throughput Foreign Object Detection with Spectral CT



Samples included chicken breasts, thighs, skin, beef and pork meat and artificial meat

- template for many industry applications
- low quality data, high throughput

High-Throughput Foreign Object Detection with Spectral CT



- template for many industry applications
- low quality data, high throughput

Summary & Outlook

- tomographic image reconstruction will always keep us busy :
  - higher & higher resolutions
  - dynamic / spectral imaging
  - multidimensional tomography
- HPC & machine learning can help us to keep up
- new workflows need to be developed
- deep learning 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 et al., 2013.** Fast Tomographic Reconstruction from Limited Data Using Artificial Neural Networks, *IEEE Image Processing, 22 (12).*
- **Pelt et al., 2018.** Improving Tomographic Reconstruction from Limited Data Using Mixed-Scale Dense Convolutional Neural Networks, *Journal of Imaging 4 (11), 128.*
- **Der Sarkissian et al., 2019.** A Cone-Beam X-Ray CT Data Collection Designed for Machine Learning, *arXiv:1905.04787, in revision.*
- **Hendriksen et al., 2019.** On-the-Fly Machine Learning for Improving Image Resolution in Tomography, *Appl. Sci. 2019.*, 9, 2445
- **Lucka et al., 2019.** Dynamic Tomography of Rapid Deformations with Sequential Scanning, *in preparation.*
- **Lucka et al., 2018.** Enhancing Compressed Sensing Photoacoustic Tomography by Simultaneous Motion Estimation, *SIAM Imaging Sciences 11 (4).*
- **Viganò et al., 2019.** X-ray light-field imaging, *in preparation.*

Thanks for your attention!

- **Pelt et al., 2013.** Fast Tomographic Reconstruction from Limited Data Using Artificial Neural Networks, *IEEE Image Processing, 22 (12).*
- **Pelt et al., 2018.** Improving Tomographic Reconstruction from Limited Data Using Mixed-Scale Dense Convolutional Neural Networks, *Journal of Imaging 4 (11), 128.*
- **Der Sarkissian et al., 2019.** A Cone-Beam X-Ray CT Data Collection Designed for Machine Learning, *arXiv:1905.04787, in revision.*
- **Hendriksen et al., 2019.** On-the-Fly Machine Learning for Improving Image Resolution in Tomography, *Appl. Sci. 2019.*, 9, 2445
- **Lucka et al., 2019.** Dynamic Tomography of Rapid Deformations with Sequential Scanning, *in preparation.*
- **Lucka et al., 2018.** Enhancing Compressed Sensing Photoacoustic Tomography by Simultaneous Motion Estimation, *SIAM Imaging Sciences 11 (4).*
- **Viganò et al., 2019.** X-ray light-field imaging, *in preparation.*