

Dynamic Imaging

Tomographic reconstruction, object recognition,
classification, tracking...

Daniil Kazantsev

ITT9, 29.01.2019

Diamond Light Source



Two fast imaging examples and data modelling tool

1. Microstructural ice-cream melting/freezing processes

Data collected on I13 beamline of DLS by *E. Guo et al.* [1, 4]

<https://www.diamond.ac.uk/Instruments/Imaging-and-Microscopy/I13.html>

Two fast imaging examples and data modelling tool

1. Microstructural ice-cream melting/freezing processes

Data collected on I13 beamline of DLS by *E. Guo et al.* [1, 4]

<https://www.diamond.ac.uk/Instruments/Imaging-and-Microscopy/I13.html>

2. Microstructural dendritic grain growth in Mg alloys

Data collected on I13 beamline of DLS by *E. Guo et al.* [3, 2, 5]

Two fast imaging examples and data modelling tool

1. Microstructural ice-cream melting/freezing processes

Data collected on I13 beamline of DLS by E. Guo et al. [1, 4]

<https://www.diamond.ac.uk/Instruments/Imaging-and-Microscopy/I13.html>

2. Microstructural dendritic grain growth in Mg alloys

Data collected on I13 beamline of DLS by E. Guo et al. [3, 2, 5]

3. Modelling phantoms and tomographic data with artifacts

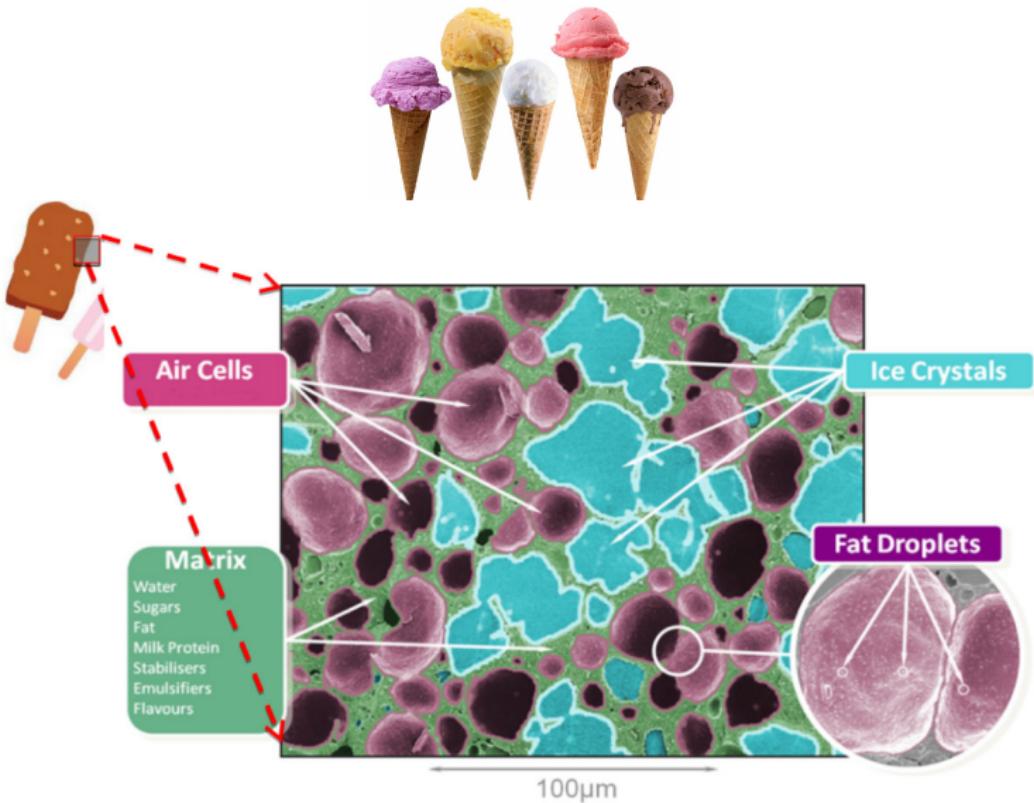
TomoPhantom software is able to model 2D-4D phantoms and their projection data with noise and some common imaging artifacts [6]

<https://github.com/dkazanc/TomoPhantom>

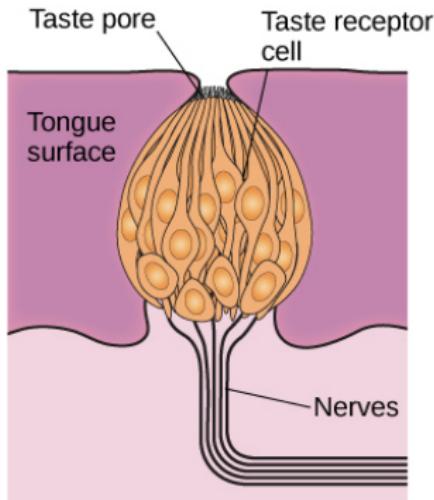
Looking into ice-cream structure



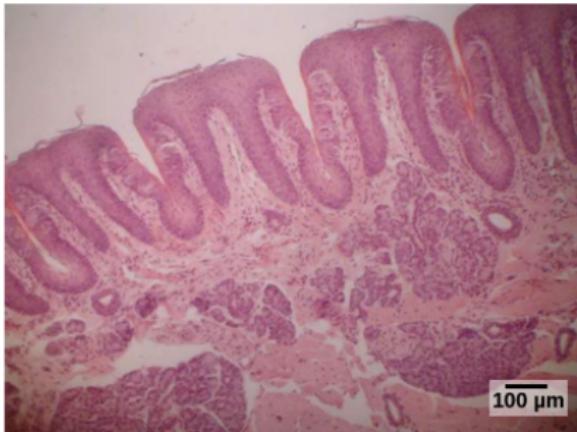
Looking into ice-cream structure



Why ice-cream doesn't always taste good?



(a)



(b)

Figure 1: (a) a taste bud; (b) The micrograph shows a close-up view of tongue's surface

What causes the shape of ice-crystals to change?



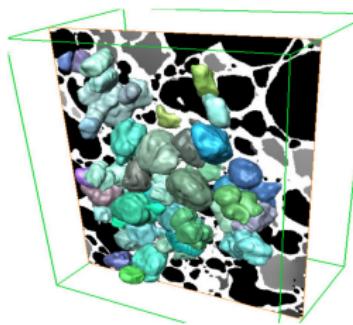
Manufacturer



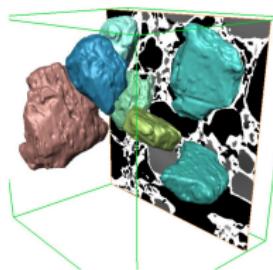
Transportation



Ice Cream Seller



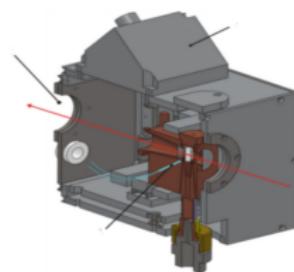
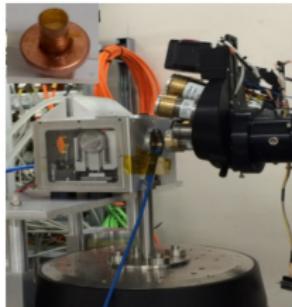
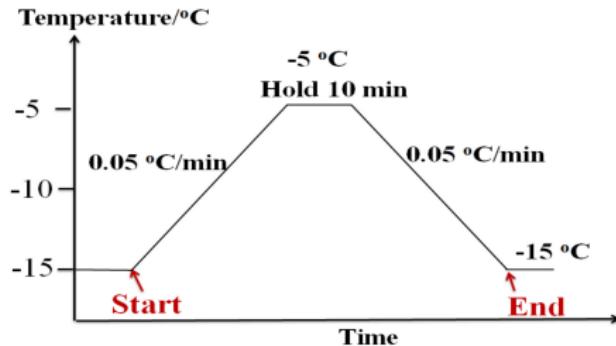
Smooth crystals



Rough crystals

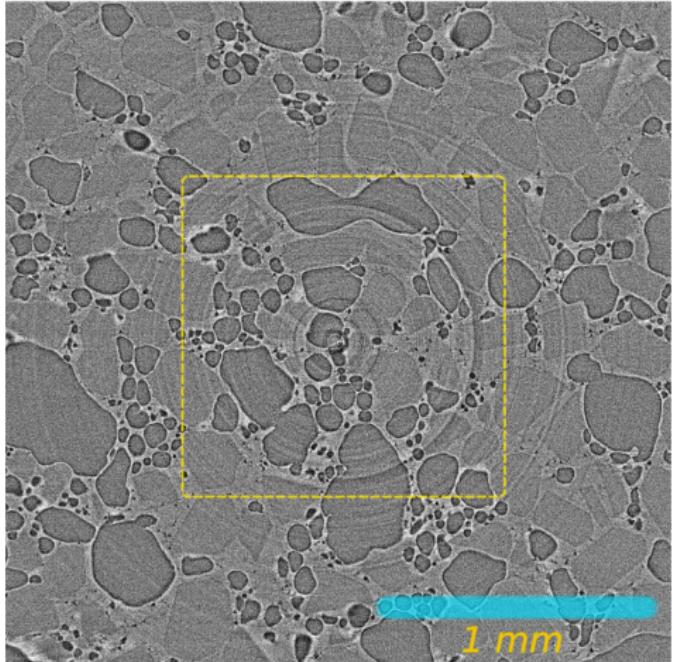
The goal is to establish various morphological relationships in ice-cream microstructure as a function of time and temperature

Using thermal 'abuse' chamber



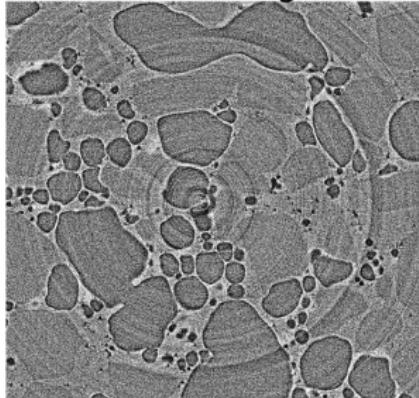
Direct (FBP) reconstruction

FBP reconstruction



Cropped $1.5k^2$ pixels region, 900 proj.

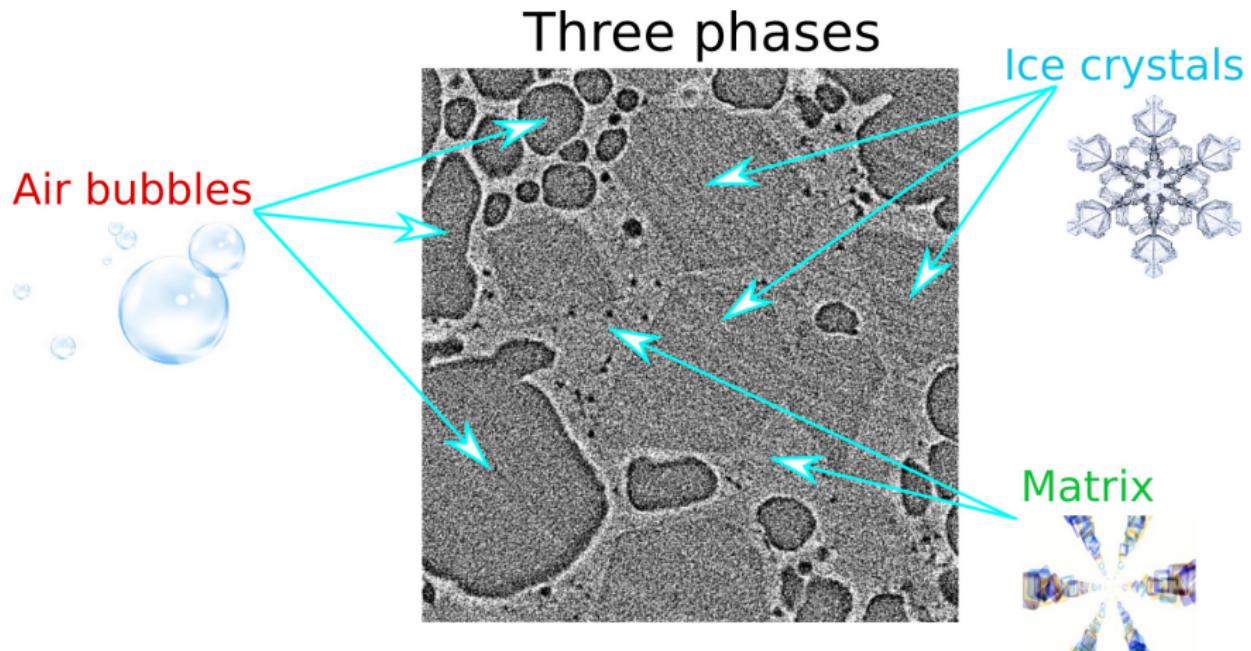
zoomed region



The list of issues:

- low contrast
- noise levels
- ring artifacts
- motion artifacts
- big data ($2k^3 \times 100$)

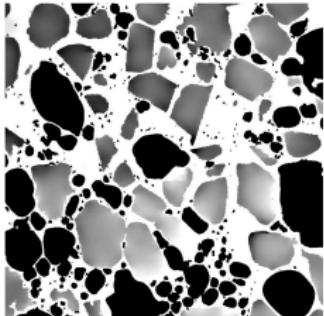
Three-phases structure



One solution to reach segmentable quality

We equalized intensity within separate phases by means of gradient-constrained 3D non-linear diffusion. Here we use the advantage of very sharp and clear boundaries of IR ice-matrix.

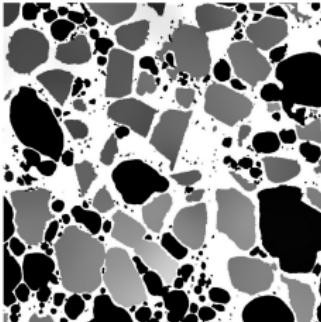
FISTA-TV-L1(ring)



Input: cropped volume

size: 900 x 900 x 650 vox.

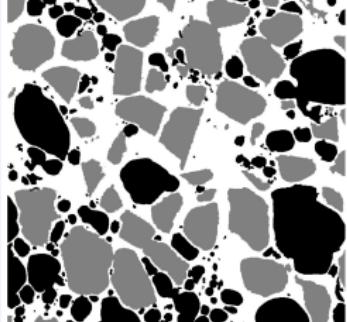
3D Constr. Diffusion



*Output: processed volume
with equalized intensities
within each phase*

GPU time: 1 hour
CPU time (24 cores) = 60h!

Segmentation

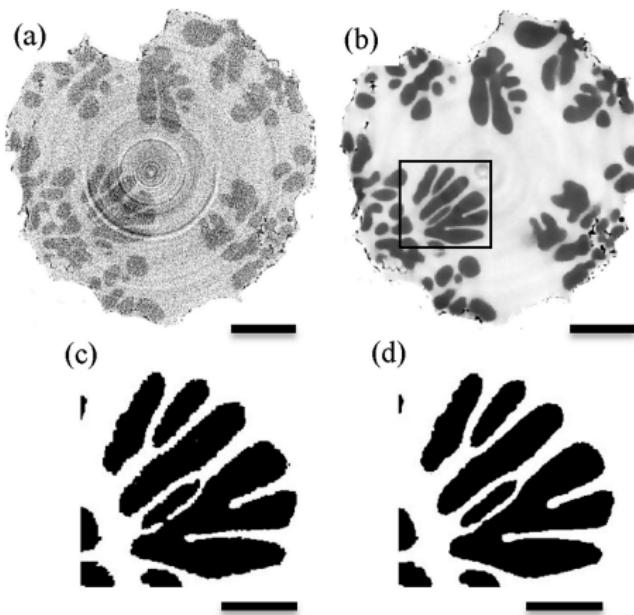


*Result: segmented volume
with three phases*

3 values threhsolding +
some spots cleaning

Segmented 3-phases time-lapse

Dendritic growth experiments



Reconstructed time-lapse dendritic data

80 time-frames reconstructed with FBP (left) and iteratively (right).

TomoPhantom: software package to generate 2D–4D phantoms for CT image reconstruction algorithm benchmarks

TomoPhantom: software package to generate 2D–4D phantoms for CT image reconstruction algorithm benchmarks

D. Kazancı^{1,2}, V. Pickalov¹, J. Jorgensen¹, M. Turner^{2,3}, E. Pasci¹, P. Withers¹, B. Linnemann¹, S. Nagel²
1 Research Complex at Harwell, Science and Technology Facilities Council, 2 University of Manchester, 3 Karlsruhe Institute of Chemical and Applied Mechanics (KI)

CCPI Core Imaging Library (CIL)

Core Imaging Library CIL:
CIL is a framework for 3D and 4D reconstruction of Computed Tomographic data, containing a set of modules for each process involved in the data analysis workflow. This is part of the Collaborative Computational Project in Tomographic Imaging (CCPI) for the UK tomography community – with over 370 registered.

<https://www.ccp1.ac.uk>

TomoPhantom: – within CT imaging many novel reconstruction techniques are routinely tested using simplistic numerical phantoms. This package allows quick access to an external library to create advanced modular analytical 2D/3D phantoms with temporal extensions.

<https://github.com/dkazanc/TomoPhantom>

Resolution Independent Phantoms:
Complex static 2D and 3D phantoms can be built using additive combinations of geometrical objects, such as, Gaussians, parabolas, cones, ellipses, rectangles and volumetric extensions.

- Phantoms of any resolution can then be created on demand saving memory and storage requirements: *left hand side*.
- Subsequently any-resolution analytical tomographic projections from these geometrically defined phantoms, can be created: *right hand side*.

This extends the applicability of software towards more realistic testing scenarios all free from the “inverse crime” testing of same-resolution models.

Applications:
Phantoms are being built to test new reconstruction algorithms, including a 3D Shepp-Logan, and for evaluating new beamline data analysis workflows, including within the Diamond Light Source.

Core Modules:
Package is written in the C-OpenMP language with wrappers for Python and MATLAB providing easy access and portability.

C-based multi-threaded implementation, means volumetric phantoms of high spatial resolution can be obtained with computational efficiency.

High level interfaces:

- Read or generate raw projection data
- Create a phantom
- 3D Tomogram
- 3D Volumetric
- 3D Time-varying

Cython

C-MEX

Python

MATLAB

Extensions to 4D:
Temporally extending this to 3D + time; so 4D, is now a trivial procedural process.

Admiregments:
CCPI funding under EPSRC (EP/M012601/1) and Colci (UKRI-STFC)
EPSRC funding under EP/R022825/1

Fast tomographic imaging challenges

Very low signal-to-noise ratio, various errors in projections resulting in inaccurate reconstructions, motion artifacts.

1. Advanced image reconstruction techniques: mathematical methodology, practical challenges

Fast tomographic imaging challenges

Very low signal-to-noise ratio, various errors in projections resulting in inaccurate reconstructions, motion artifacts.

1. Advanced image reconstruction techniques: mathematical methodology, practical challenges
2. Better segmentation methods, object recognition, feature tracking, clustering and labeling

Fast tomographic imaging challenges

Very low signal-to-noise ratio, various errors in projections resulting in inaccurate reconstructions, motion artifacts.

1. Advanced image reconstruction techniques: mathematical methodology, practical challenges
2. Better segmentation methods, object recognition, feature tracking, clustering and labeling
3. Machine learning approaches using data simulated by TomoPhantom, application to real data

Fast tomographic imaging challenges

Very low signal-to-noise ratio, various errors in projections resulting in inaccurate reconstructions, motion artifacts.

1. Advanced image reconstruction techniques: mathematical methodology, practical challenges
2. Better segmentation methods, object recognition, feature tracking, clustering and labeling
3. Machine learning approaches using data simulated by **TomoPhantom**, application to real data
4. Development of more advanced physical models to replicate real data errors/artifacts

Example of SLAE for tomography

Let's consider a set of linear equations:

$$\mathbf{b} = \mathbf{Ax} + \boldsymbol{\delta},$$

where

- $\mathbf{b} \in \mathbb{R}^M$ - vectorized sinogram; $M = P(2.5k^2) \times \theta(0.9k)$
- $\mathbf{x} \in \mathbb{R}^N$ - seeking volume; $N = 2.5k^3$ voxels
- $\boldsymbol{\delta} \in \mathbb{R}^M$ - random noise
- $\mathbf{A} : \mathbb{R}^N \rightarrow \mathbb{R}^M$ - system projection matrix (discrete approximation of the continuous Radon transform for parallel beam geometry)

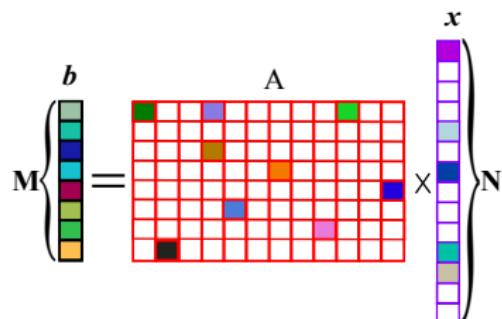
Example of SLAE for tomography

Let's consider a set of linear equations:

$$\mathbf{b} = \mathbf{Ax} + \boldsymbol{\delta},$$

where

- $\mathbf{b} \in \mathbb{R}^M$ - vectorized sinogram; $M = P(2.5k^2) \times \theta(0.9k)$
- $\mathbf{x} \in \mathbb{R}^N$ - seeking volume; $N = 2.5k^3$ voxels
- $\boldsymbol{\delta} \in \mathbb{R}^M$ - random noise
- $\mathbf{A} : \mathbb{R}^N \rightarrow \mathbb{R}^M$ - system projection matrix (discrete approximation of the continuous Radon transform for parallel beam geometry)
- For 4D imaging $M(5.6 \times 10^9) \ll N(1.56 \times 10^{10})$ and \mathbf{A} is “fat”



Adding temporal dimension

We have $K > 100$ time frames and for each frame, data \mathbf{b} can be regarded as it were obtained from the stationary object.

$$\mathbf{B} = \mathbf{AX},$$

where $\mathbf{X} := (\mathbf{x}_1^T, \dots, \mathbf{x}_K^T)^T$, $\mathbf{X} \in \mathbb{R}^{N \times K}$ is a vector containing all \mathbf{x} instances of time lapse series and $\mathbf{B} := (\mathbf{b}_1^T, \dots, \mathbf{b}_K^T)^T$, $\mathbf{B} \in \mathbb{R}^{M \times K}$ is a measured projections vector. The block diagonal matrix $\mathbf{A} \in \mathbb{R}^{M \times K \times N \times K}$ is given as:

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & 0 & \dots & 0 \\ 0 & \mathbf{A}_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{A}_K \end{bmatrix}$$

We can assume that \mathbf{A} is time-invariant, that is, $\mathbf{A}_1 = \mathbf{A}_2 = \dots = \mathbf{A}_K$ or $\mathbf{A} = \mathbf{I} \otimes \mathbf{A}_1$, where \otimes is the Kronecker product.

Access to data and software dependencies

Get python scripts, presentations, installation recommendations and related papers from:

https://github.com/dkazanc/ITT_BATH_DLS

- Ice-cream data can be accessed using the script
ITT_BATH_DLS/DynamicImaging/ICE_CREAM/ITT_IceCreamData.py
- Dendritic data can be accessed using the script
ITT_BATH_DLS/DynamicImaging/Dendrites/ITT_dendrites.py
- **TomoPhantom** package for data modelling
- **TomoRec** package for image reconstruction

References i

-  E. GUO, D. KAZANTSEV, J. MO, J. BENT, G. VAN DALEN, P. SCHUETZ, P. ROCKETT, D. STJOHN, AND P. D. LEE, *Revealing the microstructural stability of a three-phase soft solid (ice cream) by 4d synchrotron x-ray tomography*, Journal of Food Engineering, (2018).
-  E. GUO, A. PHILLION, B. CAI, S. SHUAI, D. KAZANTSEV, T. JING, AND P. D. LEE, *Dendritic evolution during coarsening of mg-zn alloys via 4d synchrotron tomography*, Acta Materialia, 123 (2017), pp. 373–382.
-  E. GUO, S. SHUAI, D. KAZANTSEV, S. KARAGADDE, A. PHILLION, T. JING, W. LI, AND P. D. LEE, *The influence of nanoparticles on dendritic grain growth in mg alloys*, Acta Materialia, 152 (2018), pp. 127–137.

References ii

-  E. GUO, G. ZENG, D. KAZANTSEV, P. ROCKETT, J. BENT, M. KIRKLAND, G. VAN DALEN, D. S. EASTWOOD, D. STJOHN, AND P. D. LEE, *Synchrotron x-ray tomographic quantification of microstructural evolution in ice cream—a multi-phase soft solid*, Rsc Advances, 7 (2017), pp. 15561–15573.
-  D. KAZANTSEV, E. GUO, A. PHILLION, P. J. WITHERS, AND P. D. LEE, *Model-based iterative reconstruction using higher-order regularization of dynamic synchrotron data*, Measurement Science and Technology, 28 (2017), p. 094004.
-  D. KAZANTSEV, V. PICKALOV, S. NAGELLA, E. PASCA, AND P. J. WITHERS, *Tomophantom, a software package to generate 2d–4d analytical phantoms for ct image reconstruction algorithm benchmarks*, SoftwareX, 7 (2018), pp. 150–155.