

# Dynamic Imaging

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

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Diamond Light Source



## 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>

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## 2. Microstructural dendritic grain growth in Mg alloys

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# Two fast imaging examples and data modelling tool

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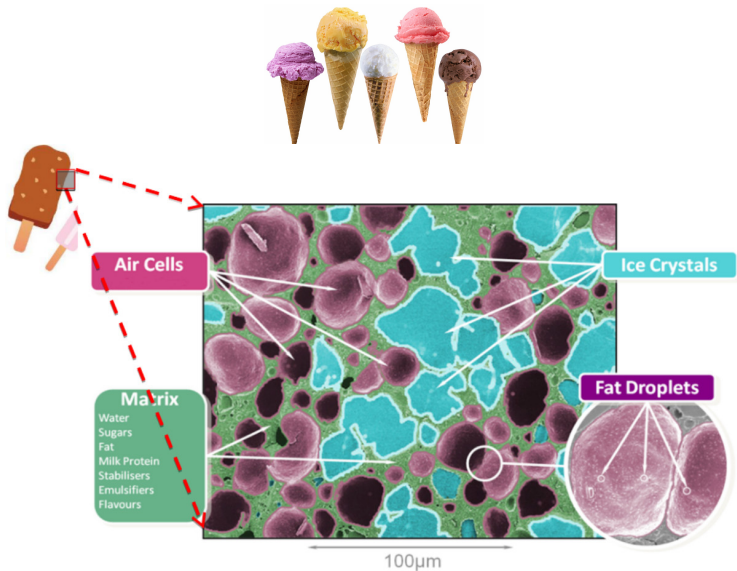
## 3. Modelling phantoms and tomographic data with artifacts

**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>

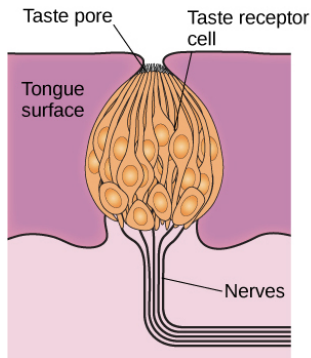
# Looking into ice-cream structure



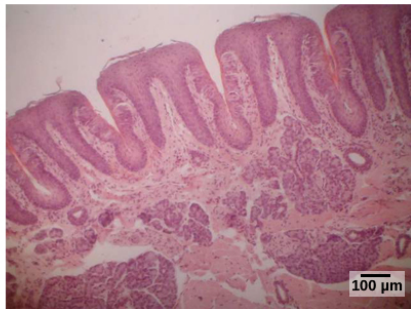
# Looking into ice-cream structure



# 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?



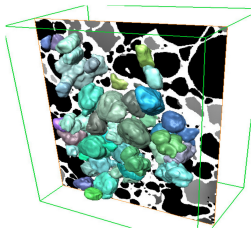
Manufacturer



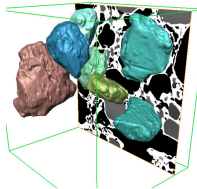
Transportation



Ice Cream  
Seller



Smooth crystals

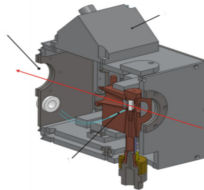
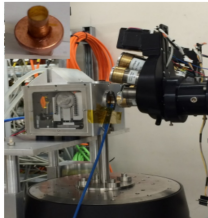
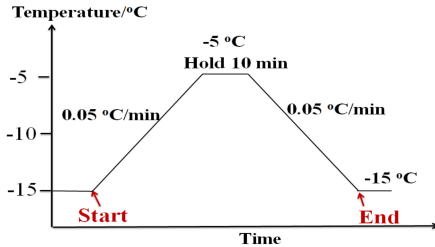


Rough crystals

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

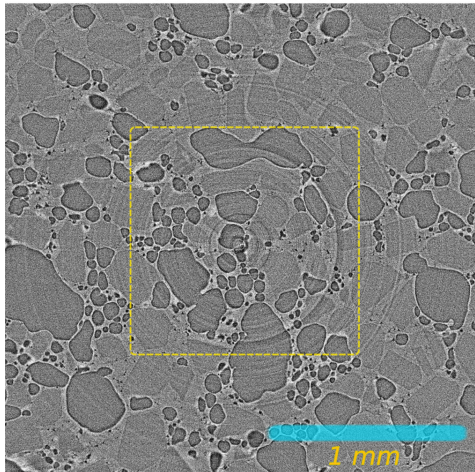


# Using thermal 'abuse' chamber



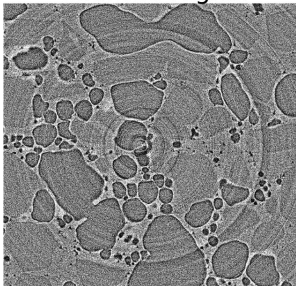
# Direct (FBP) reconstruction

FBP reconstruction



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

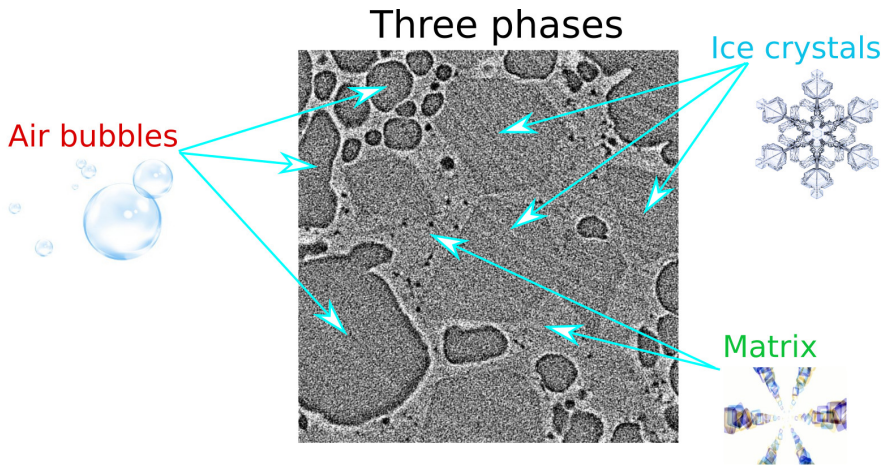
zoomed region



**The list of issues:**

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

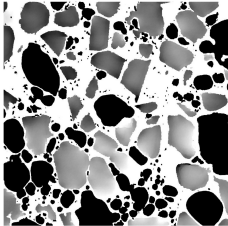
# Three-phases structure



# 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.

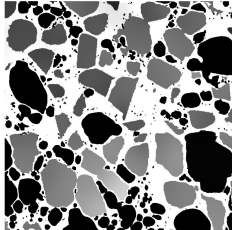
## FISTA-TV-L1(ring)



*Input: cropped volume*

size: 900 x 900 x 650 vox.

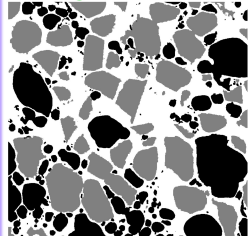
## 3D Constr. Diffusion



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

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

## Segmentation

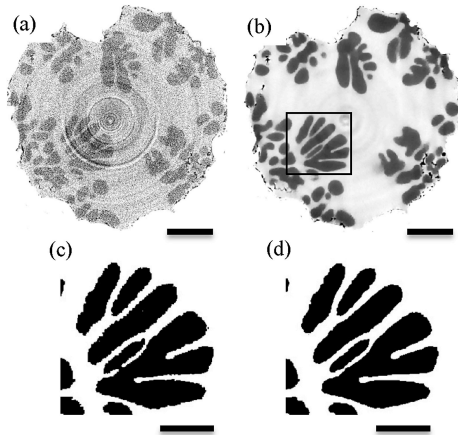


*Result: segmented volume  
with three phases*

3 values thresholding +  
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



CCPI Core Imaging Library (CIL)

D. Kazantsev<sup>1,2</sup>, V. Piskalov<sup>1</sup>, J. Jorgensen<sup>1</sup>, M. Turner<sup>1,2,3</sup>, E. Pasca<sup>1</sup>, P. Withers<sup>1</sup>, B. Lindheart<sup>1</sup>, S. Nagalla<sup>2</sup>

<sup>1</sup> Research Complex at Harwell, <sup>2</sup> Science and Technology Facilities Council, <sup>3</sup> University of Manchester, <sup>4</sup> Rheinisch-Westfälisches Institut für Theoretische und Angewandte Medizinische SB RAS

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### Core Imaging Library CIL:

CIL is a framework for 3D and 4D reconstruction of Computerized Tomographic data, consisting of 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.ccpi.ac.uk>

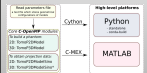
**TomoPhantom** – within CT imaging many novel reconstruction techniques are routinely tested using simplistic numerical phantoms. This package allows quick access to an external library to create advanced modular analytical 2D/3D phantoms with temporal extensions.

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

### 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.



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### Resolution Independent Phantoms:

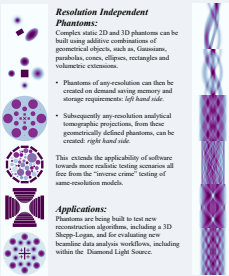
Complex static, 2D and 3D phantoms can be built using additive combinations of geometrical objects, such as, Gaussians, parabolas, cones, ellipses, rectangles and volumetric extensions.

- 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.

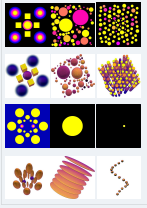
### Applications:

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



### Extensions to 4D:

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



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 CCPI funding under EPSRC (EP/R022986/1) and CofA (13/081303)  
 CCPI Display funding under EPSRC (EP/P012903/1)

Want to know more? [tomophantom@ccpi.ac.uk](mailto:tomophantom@ccpi.ac.uk) [david.kazantsev@ccpi.ac.uk](mailto:david.kazantsev@ccpi.ac.uk) [www.ccpi.ac.uk](http://www.ccpi.ac.uk)



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

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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:

$$\mathbf{b} = \mathbf{A}\mathbf{x} + \boldsymbol{\delta},$$

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)

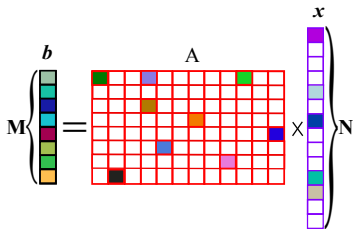
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- For 4D imaging  $M(5.6 \times 10^9) \ll N(1.56 \times 10^{10})$  and  $\mathbf{A}$  is "fat"



## 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.

$$\mathbf{B} = \mathbf{A}\mathbf{X},$$

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.




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

[https://github.com/dkazanc/ITT\\_BATH\\_DLS](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



-  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.

-  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.