HTC 2022
HELSINKI TOMOGRAPHY CHALLENGE

Team CIL
CORE IMAGING LIBRARY

3rd place algorithm

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Joint work with

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CIL CORE IMAGING LIBRARY

CCPi TOMOGRAPHIC IMAGING

DTU THE VELUX FOUNDATIONS VILLUM FONDEN VELUX FONDEN

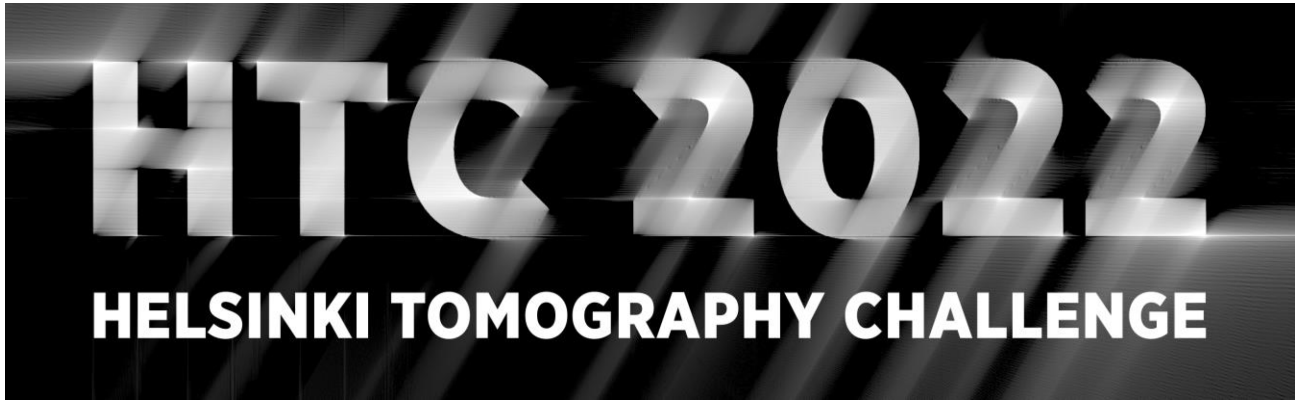
UKRI Science and Technology Facilities Council Scientific Computing

Finden

Core Imaging Library (CIL) - Team

discontinuity

Open challenge on limited-angle reconstruction



https://www.fips.fi/HTC2022.php

CIL team entry finished 3rd
– beaten by two teams using machine learning

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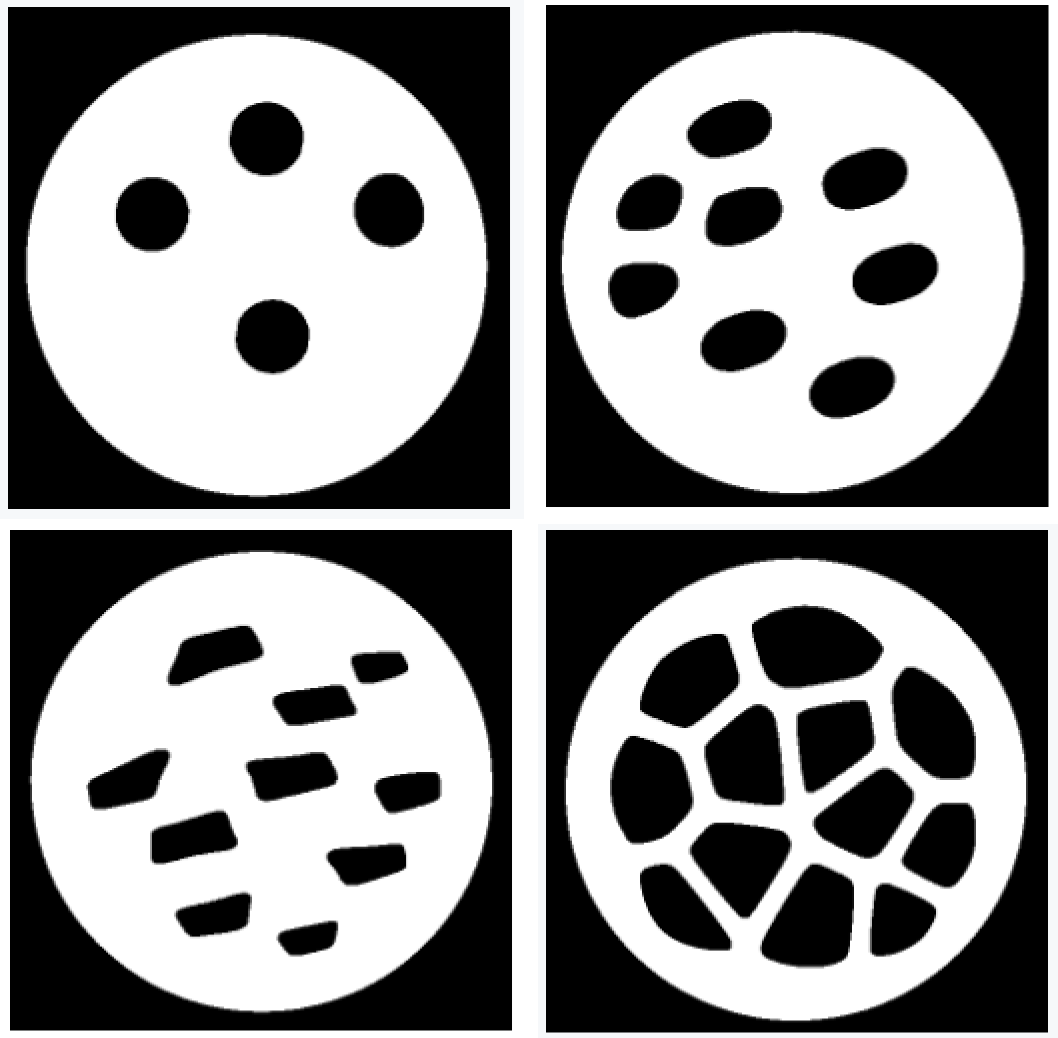
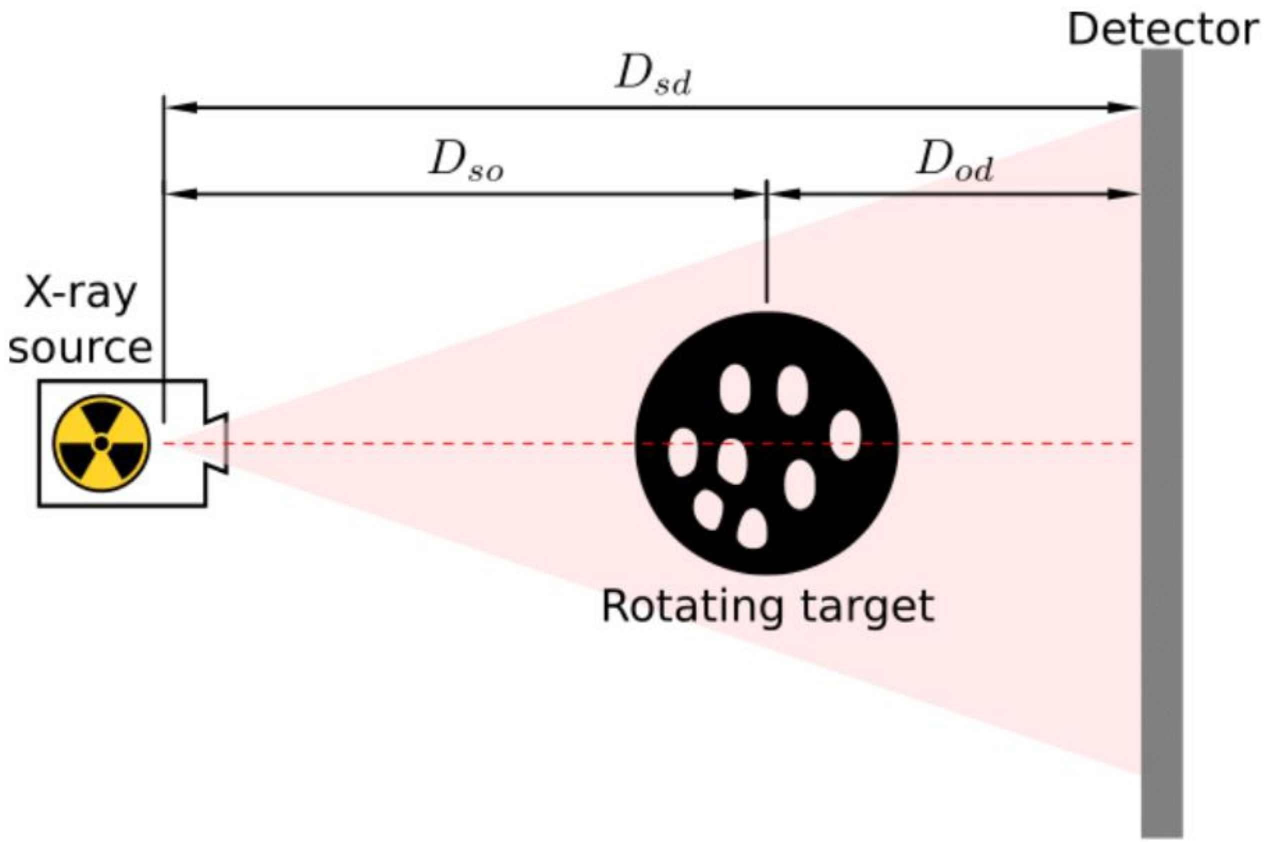
Test data provided and scan setup

- Four 360 degree measured sinogram data sets to generate limited-angle data from
- Reference reconstructions and segmentations





Challenge levels

Table 1: Limited-angle tomography difficulty groups

Group	Angular range	Angular increment	Number of projections
1	90°	0.5°	181
2	80°	0.5°	161
3	70°	0.5°	141
4	60°	0.5°	121
5	50°	0.5°	101
6	40°	0.5°	81
7	30°	0.5°	61

Assessment of (segmented) reconstructions

The reconstructions will be assessed quantitatively, comparing the reconstructed binary image I_r with the ground truth binary image I_t, assigning a numeric score. I_r is assumed to have a dimension of 512 x 512 pixels, otherwise a score 0 will be given to the reconstruction I_r.

The score is based on the confusion matrix of the classification of the pixels between empty (0) or material (1). The confusion matrix is composed by

$$TP = \sum_{i,j} (I_t \cap I_r)_{ij}$$

$$FP = \sum_{i,j} (\bar{I}_t \cap I_r)_{ij}$$

$$FN = \sum_{i,j} (I_t \cap \bar{I}_r)_{ij}$$

$$TN = \sum_{i,j} (\bar{I}_t \cap \bar{I}_r)_{ij}$$

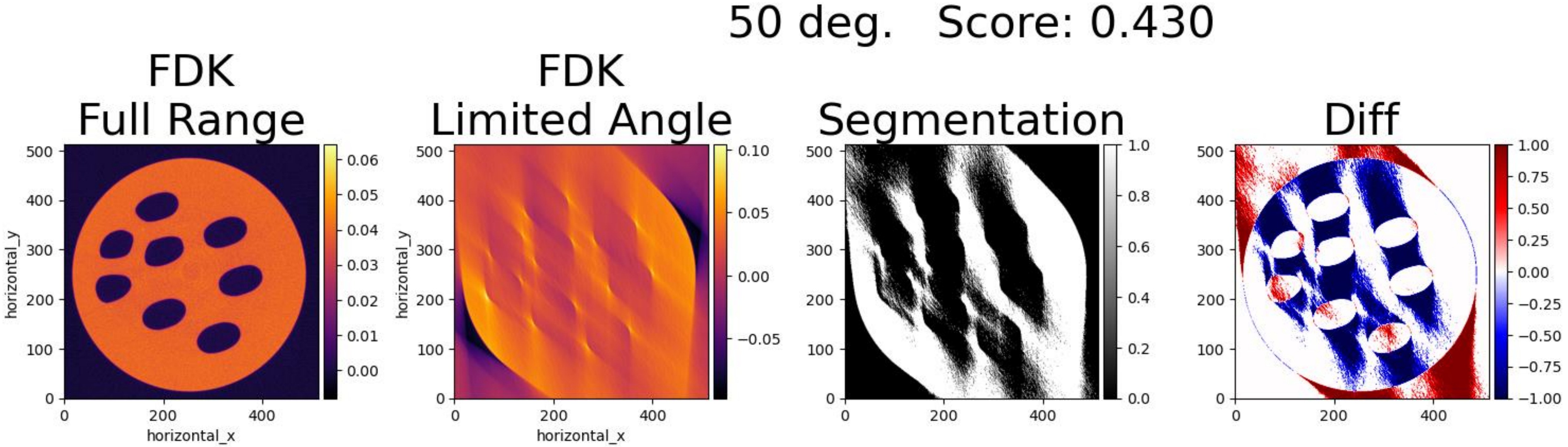
$$\mathbf{M} = \begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix}$$

The score of the reconstruction is given by the Matthews correlation coefficient (MCC)

$$S = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}},$$

where $S \in [-1, 1]$. A score of $+1$ (best) represents a perfect reconstruction, 0 no better than random reconstruction, and -1 (worst) indicates total disagreement between reconstruction and ground truth. A python code that implements the scoring will be provided to the competitors. The same code will be used to assess the algorithms.

Motivation



- See how far "conventional" CT pre-processing plus variational methods could go
- Use existing general purpose CIL tools as much as possible – limited time for new dev

5 submissions, variations of

Preprocessing

Reconstruction

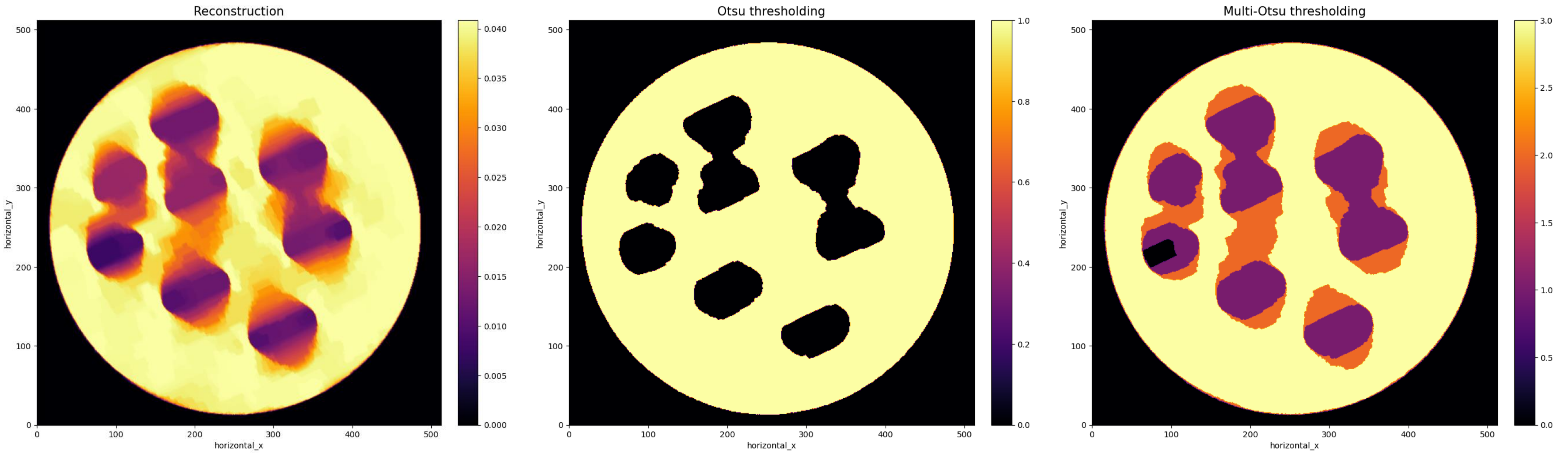
Segmentation

Segmentation

- 'blind' segmentation of the test data
- Not our expertise!
- Otsu triple-threshold worked consistently for the test data at 30 degrees

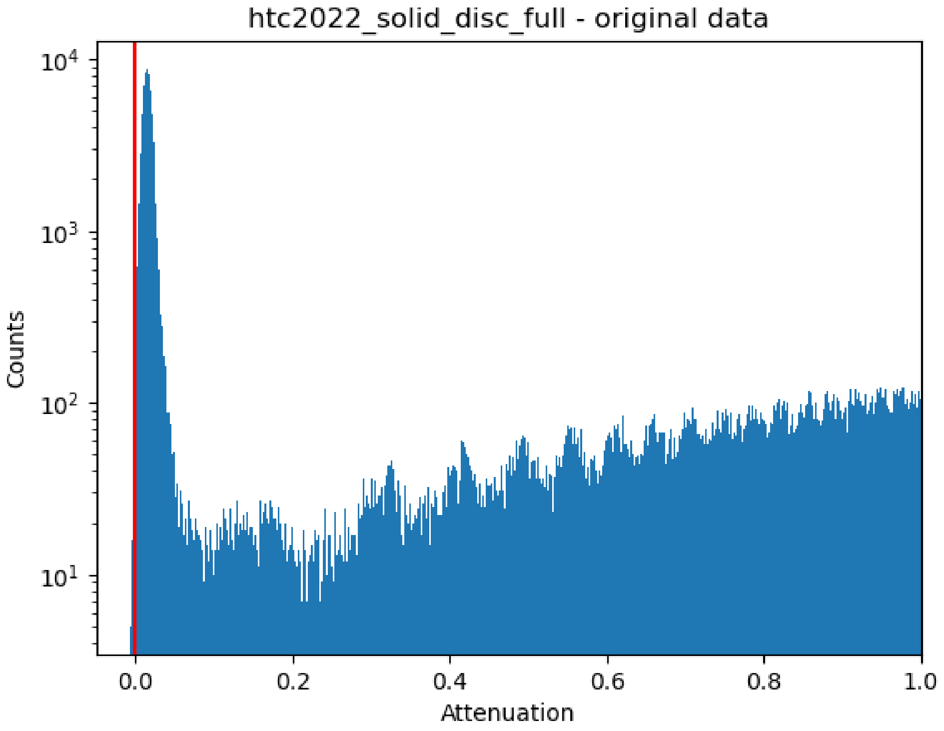
- Otsu thresholded segmentation
  - Identifies signal peak

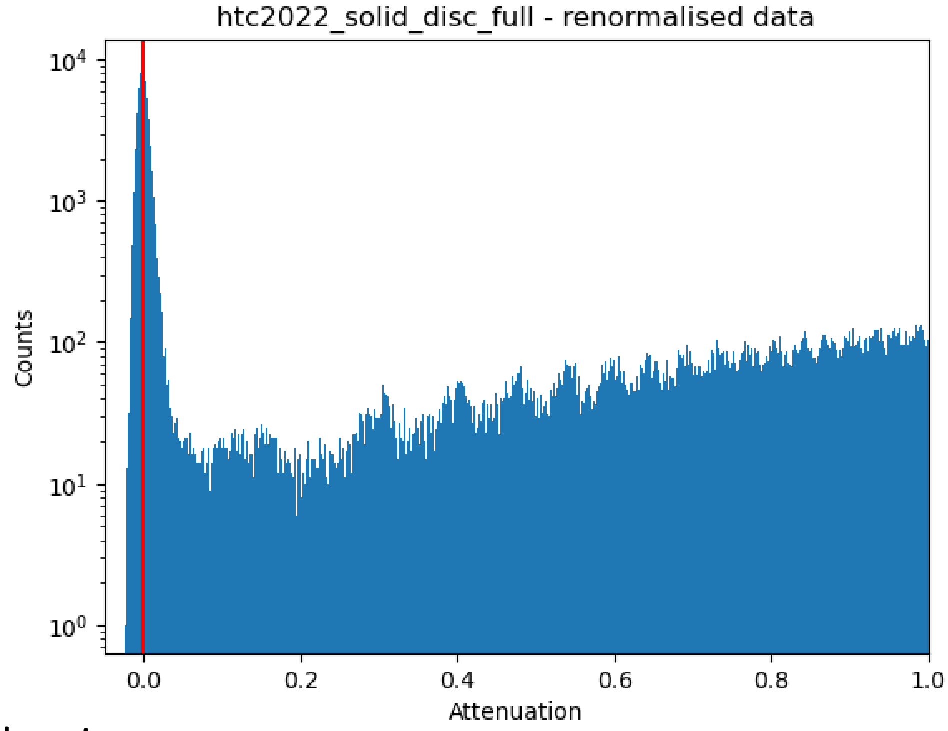
- Otsu triple-thresholded segmentation
  - Strong signal
  - Messy signal
  - Messy background
  - Strong background



Renormalization of sinogram

- Background attenuation should have a mean at zero
- Test data had an offset i.e. the normalization image was brighter than the data
  - Convert data back to I/I0, renormalize for a peak at 1, convert back to absorption

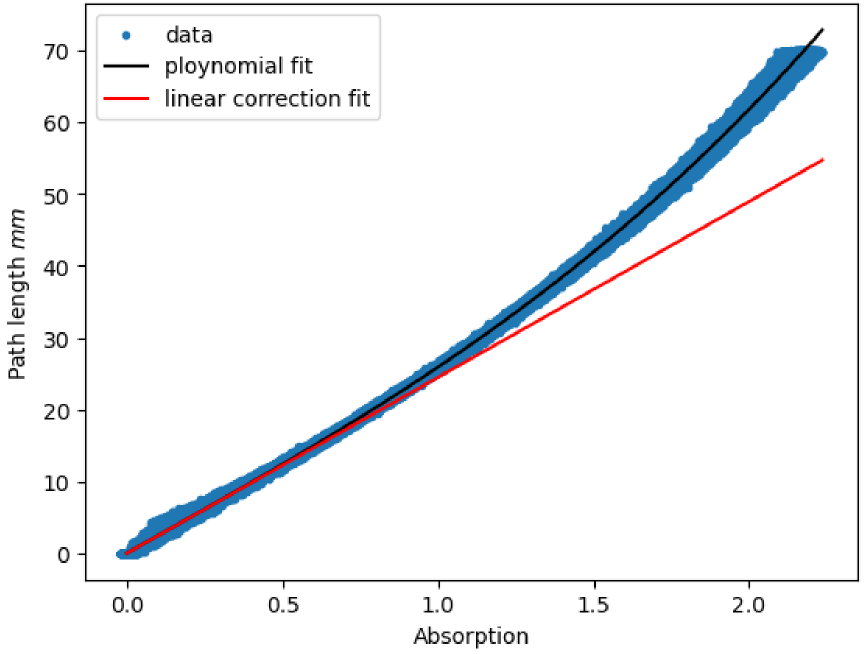


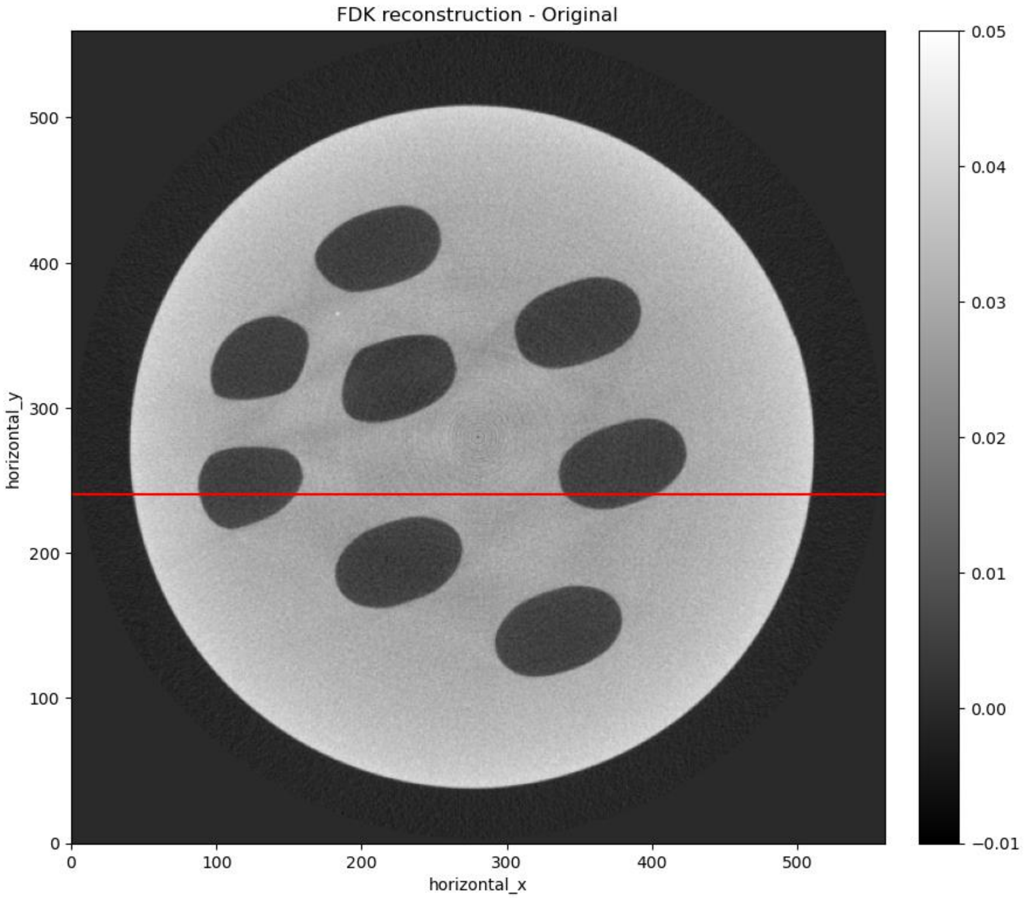


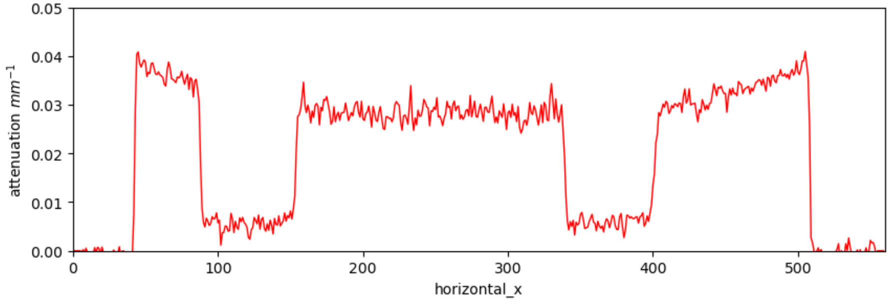
Histograms of the sinogram

Beam hardening correction

- Lower energy rays are preferentially absorbed leading to a non-linear measurement
- Single material scan can be linearised to an effective monochromatic energy
- Correction to the linear attenuation of acrylic at 24.7 KeV, mu = 0.0409 mm^{-1}







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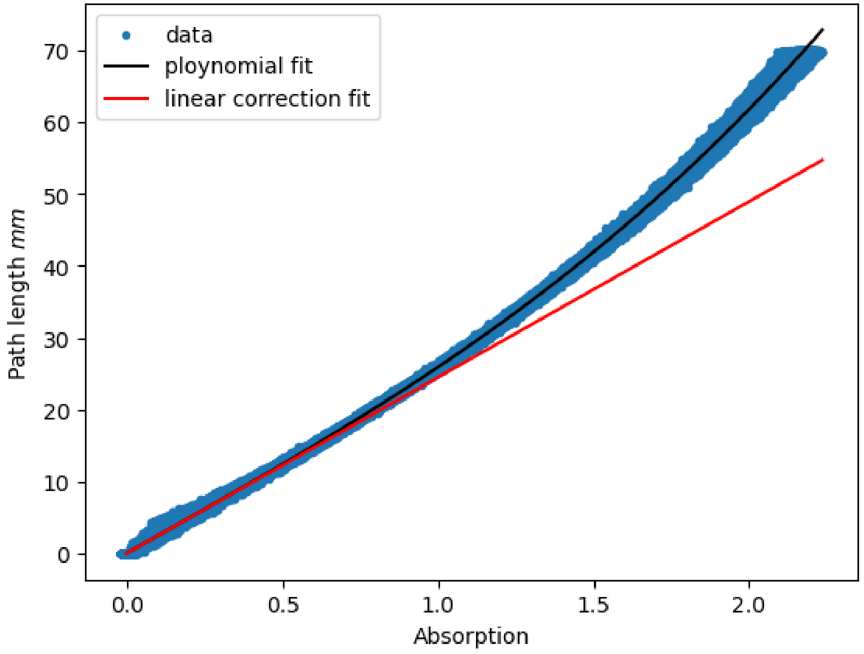
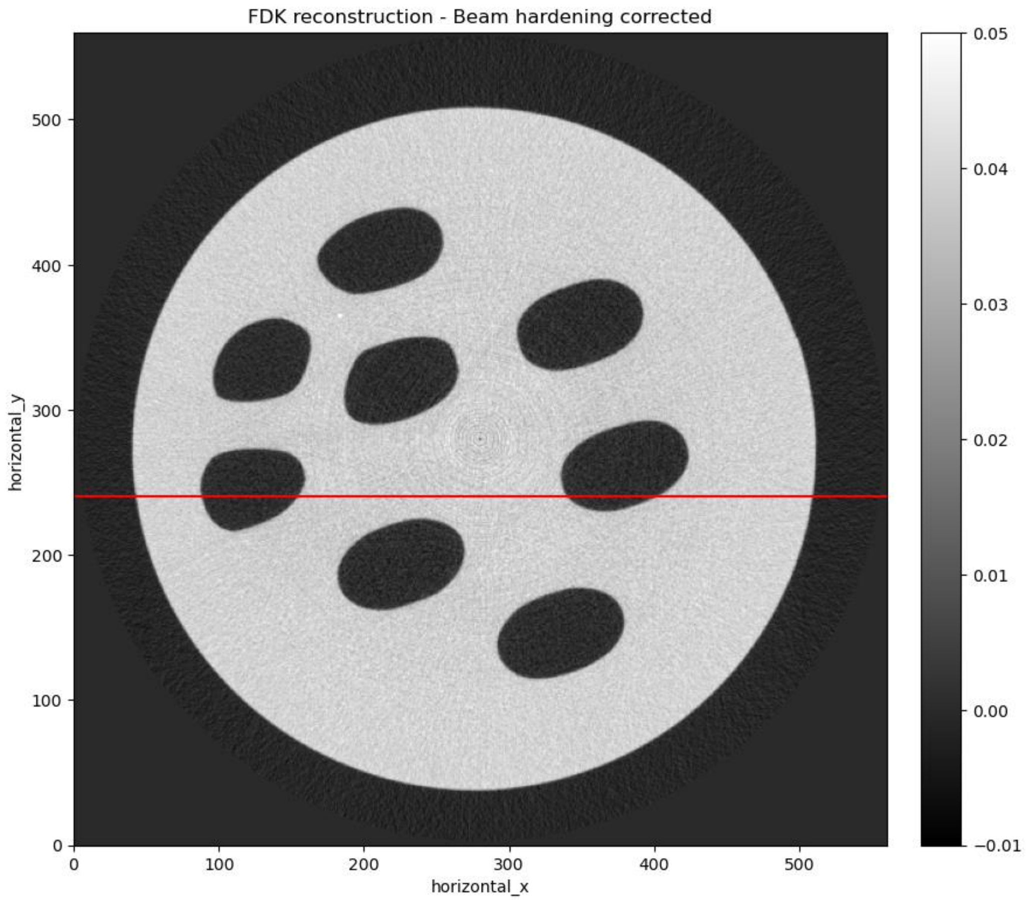
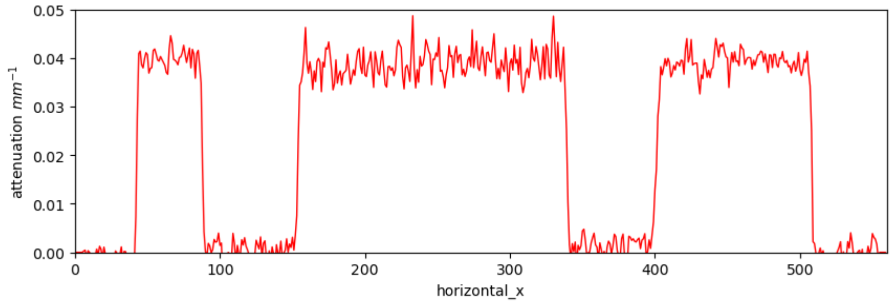
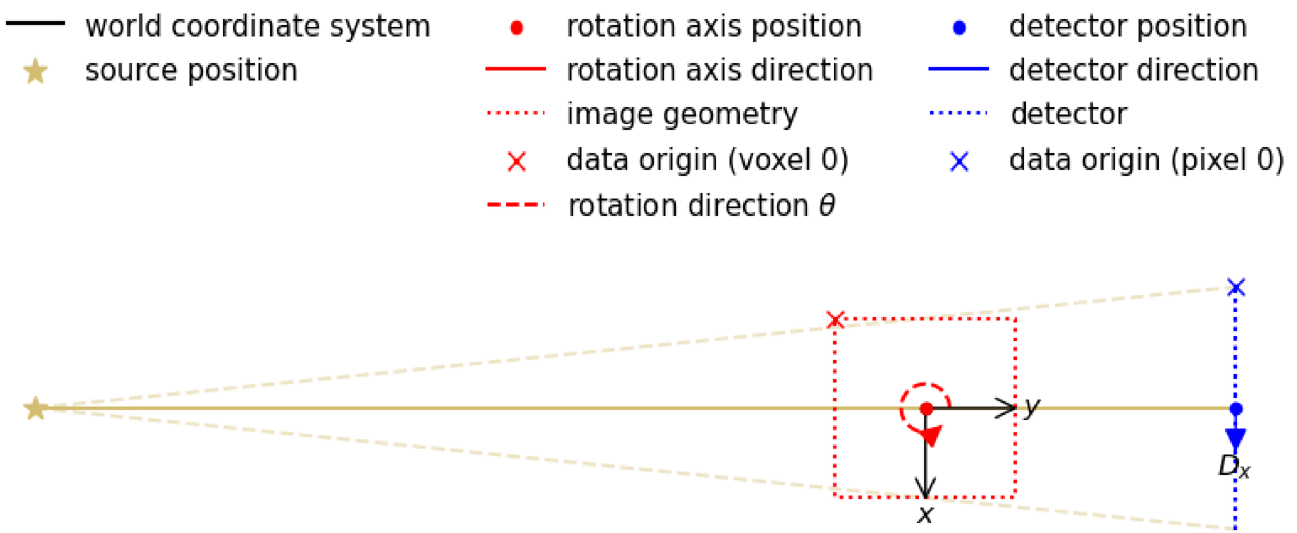


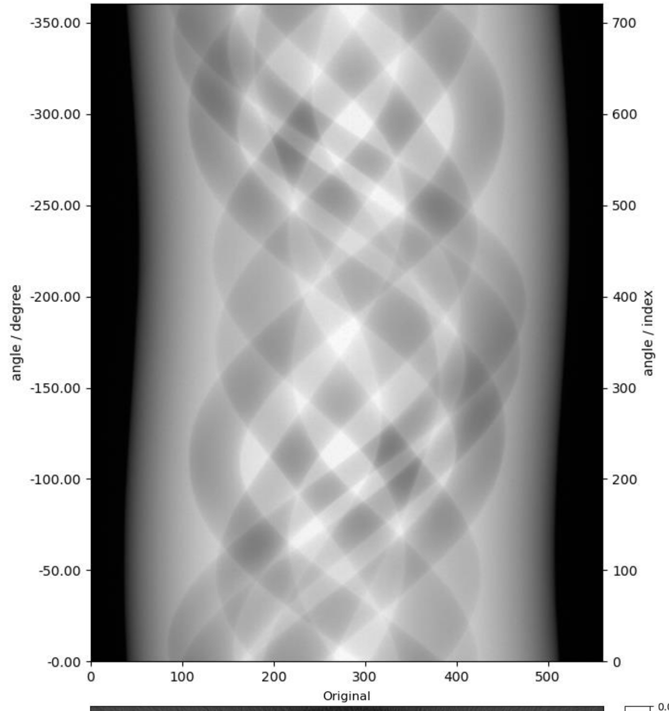


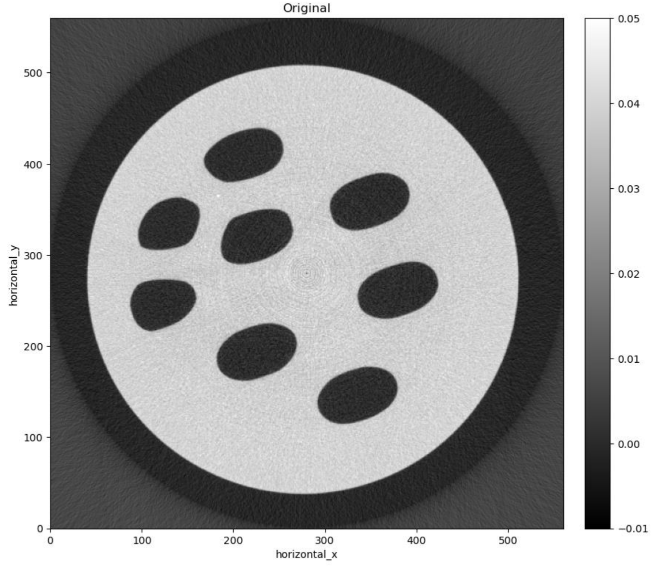


Zero-padding

- The reconstruction window extends outside the field of view
- Causes a non-zero background outside the radius of the detector
- Zero-Padding the acquisition data corrects this







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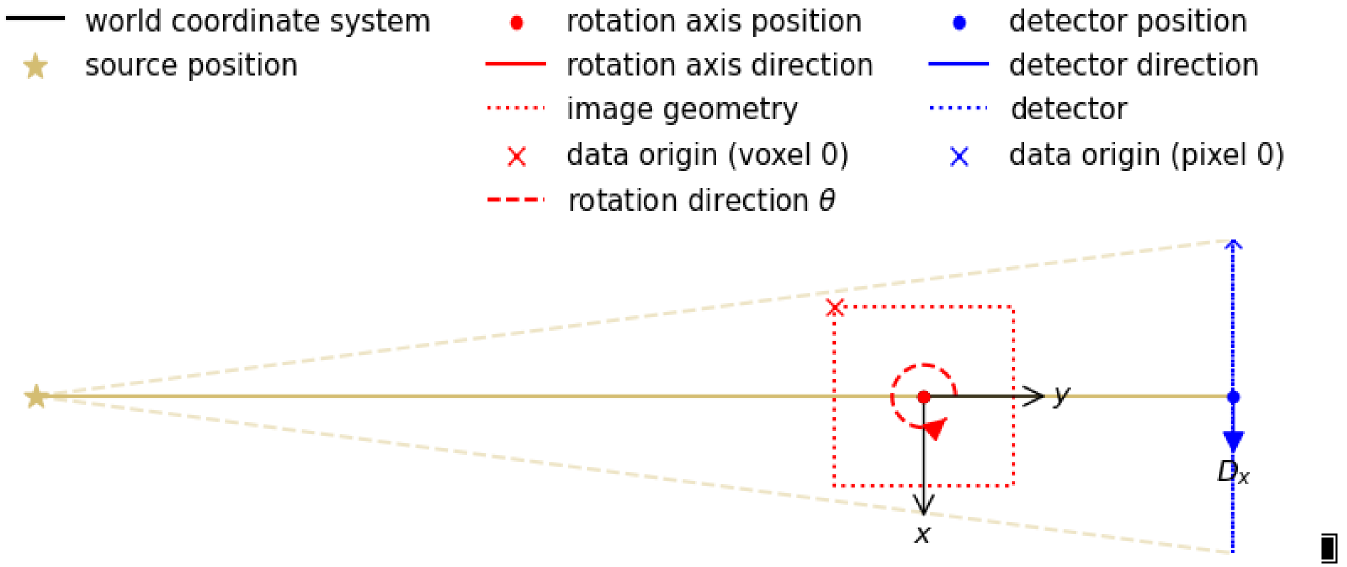
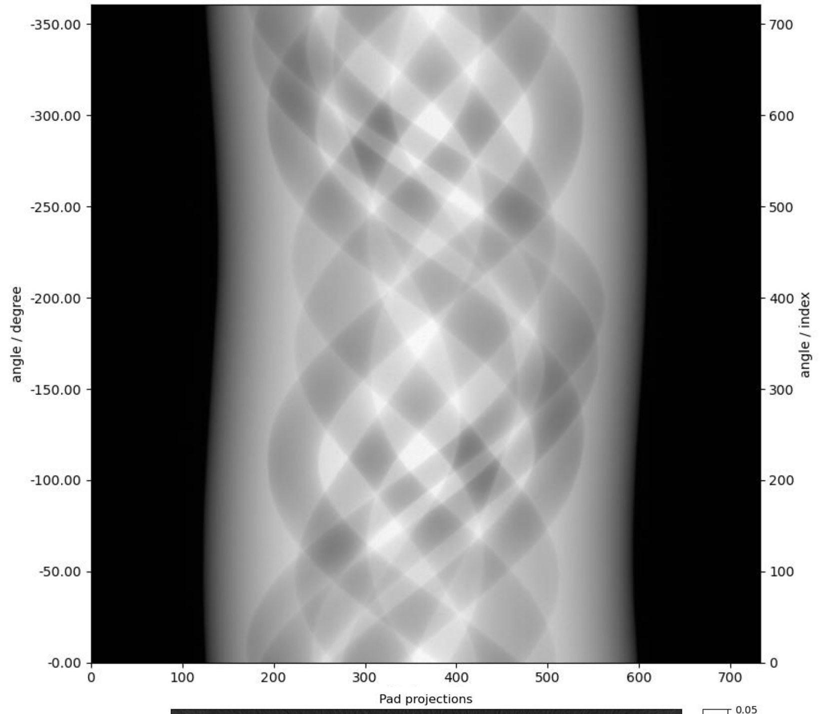
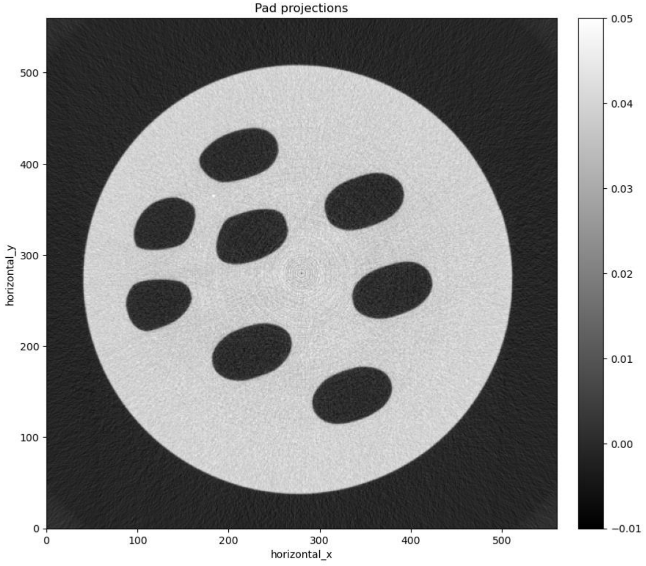






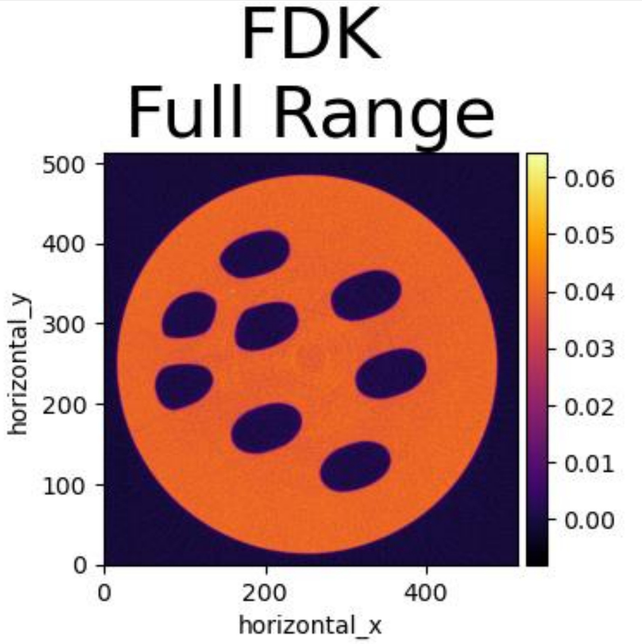
Reconstruction: Exploit prior knowledge

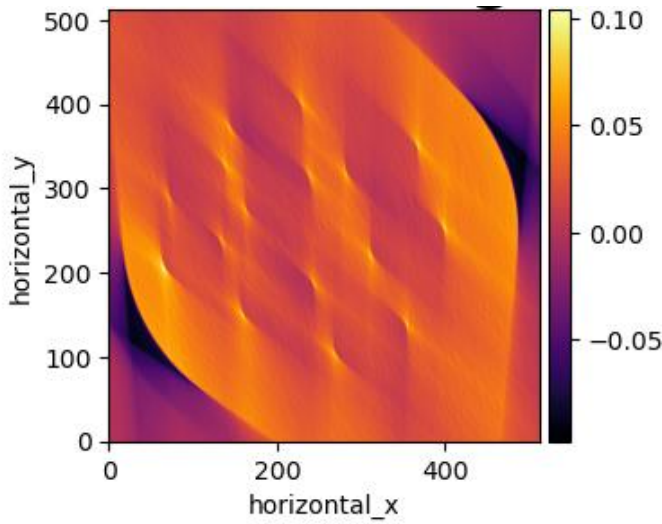
Construct optimization problem to express what we know:

- Single homogeneous material
- Sharp edges

- Object is approximately disk shaped
- Zero attenuation outside the object
- Constant value of 0.0409 mm^{-1} inside the object

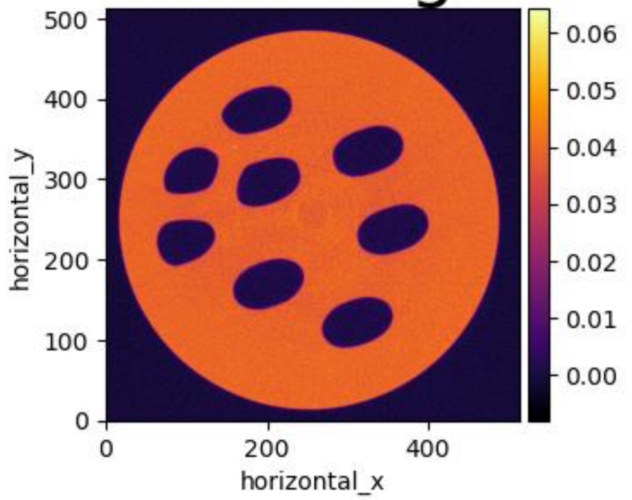
- Edges perpendicular to projection angles are the most difficult (micro-local analysis)





Prior knowledge: homogeneous material with sharp edges

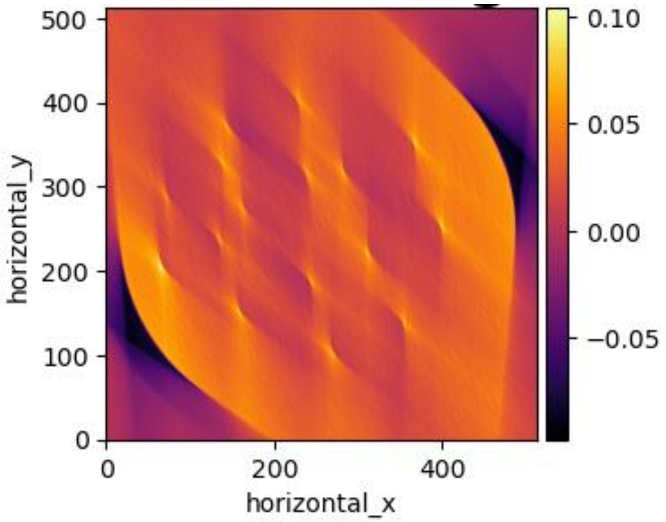
FDK
Full Range

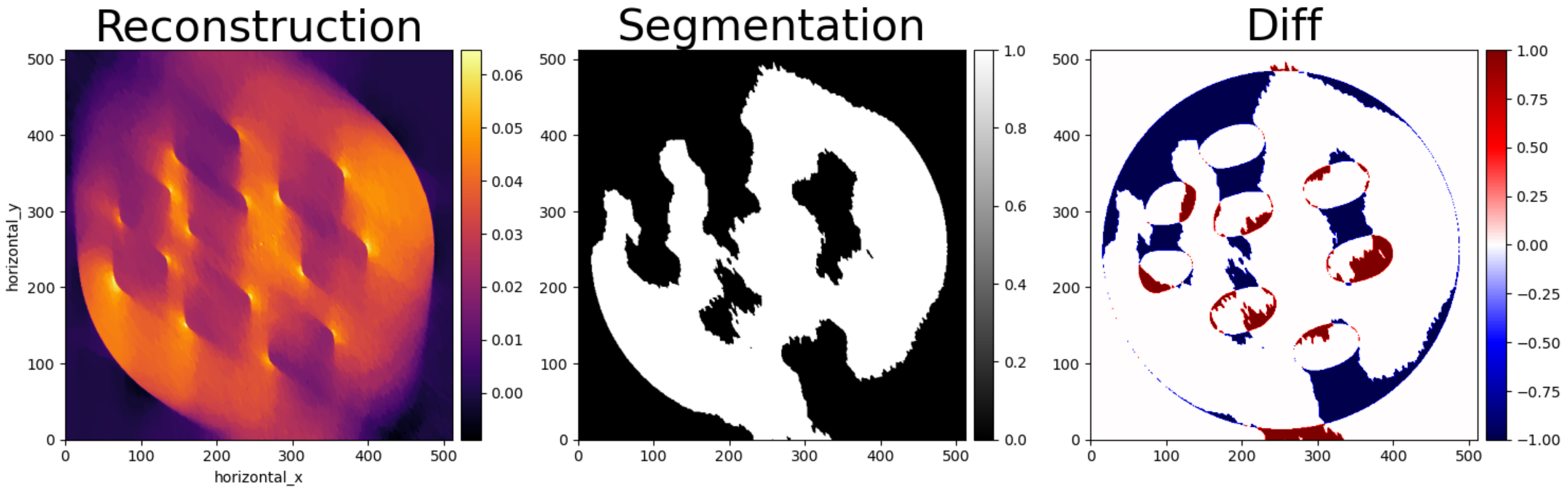


$$\min_{\mathbf{u}} \quad a_1\|\mathbf{A}\mathbf{u}-\mathbf{b}\|_2^2 + a_2\mathrm{ITV}(\mathbf{u})$$

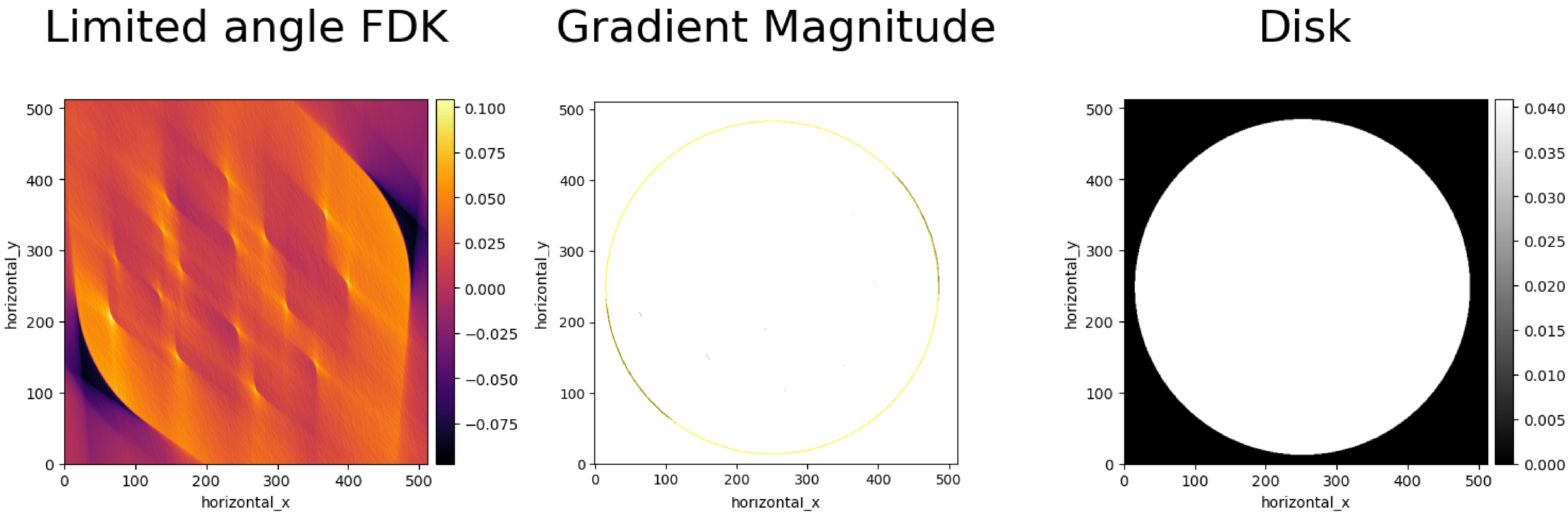
LS + isoTV Mask: none 50 deg. Score: 0.713

FDK Score: 0.430





Prior knowledge: approximately disk shaped

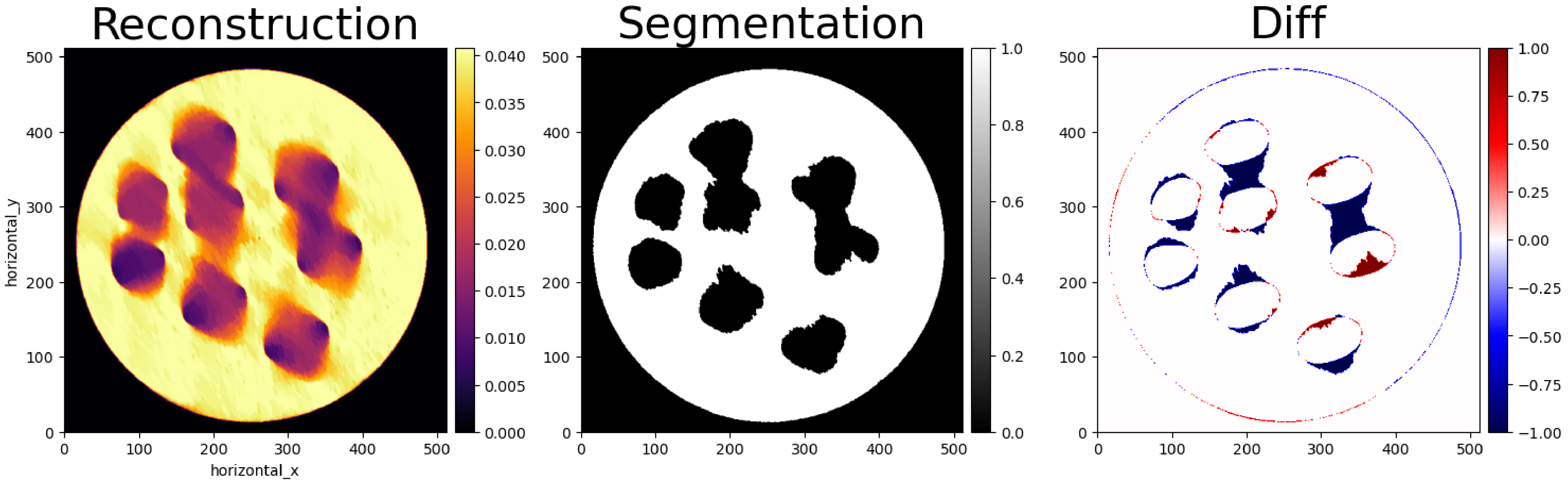


I.D. Coope *Circle fitting by linear and nonlinear least squares in 2D*
`https://link.springer.com/article/10.1007/BF00939613`

Disk shape with known attenuation as constraints

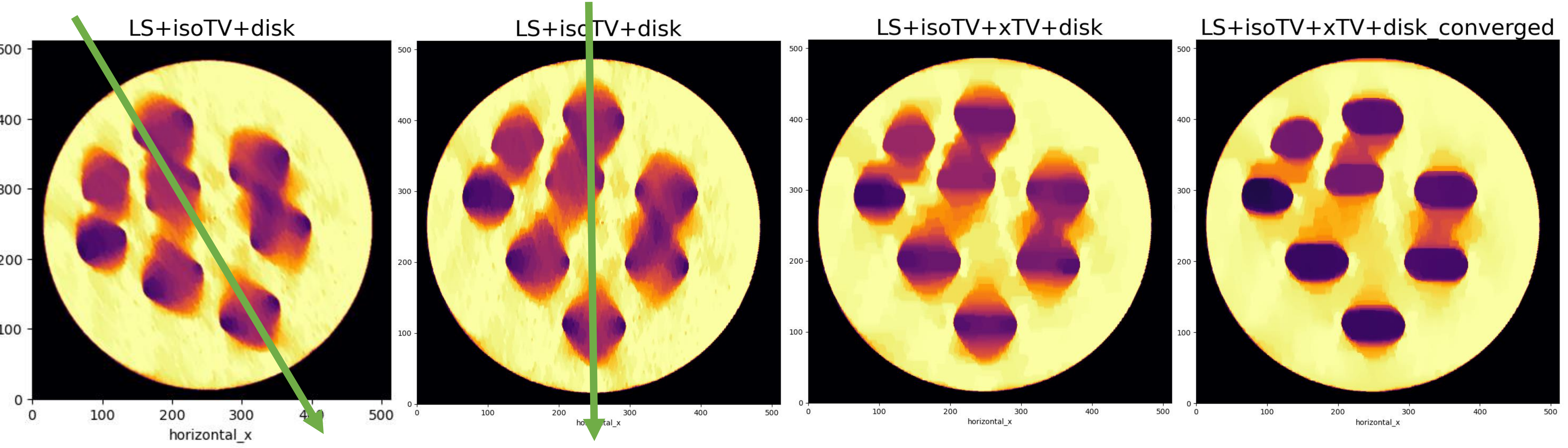
$$\begin{aligned} \min_{\mathbf{u}} \quad & a_1\|\mathbf{A}\mathbf{u}-\mathbf{b}\|_2^2 + a_2\mathrm{ITV}(\mathbf{u}) \\ \text{s.t.} \quad & \mathbf{0} \le \mathbf{u} \le v\mathbf{m} \end{aligned}$$

LS + isoTV   Mask: fitted 50 deg.   Score: 0.919



Anisotropic TV

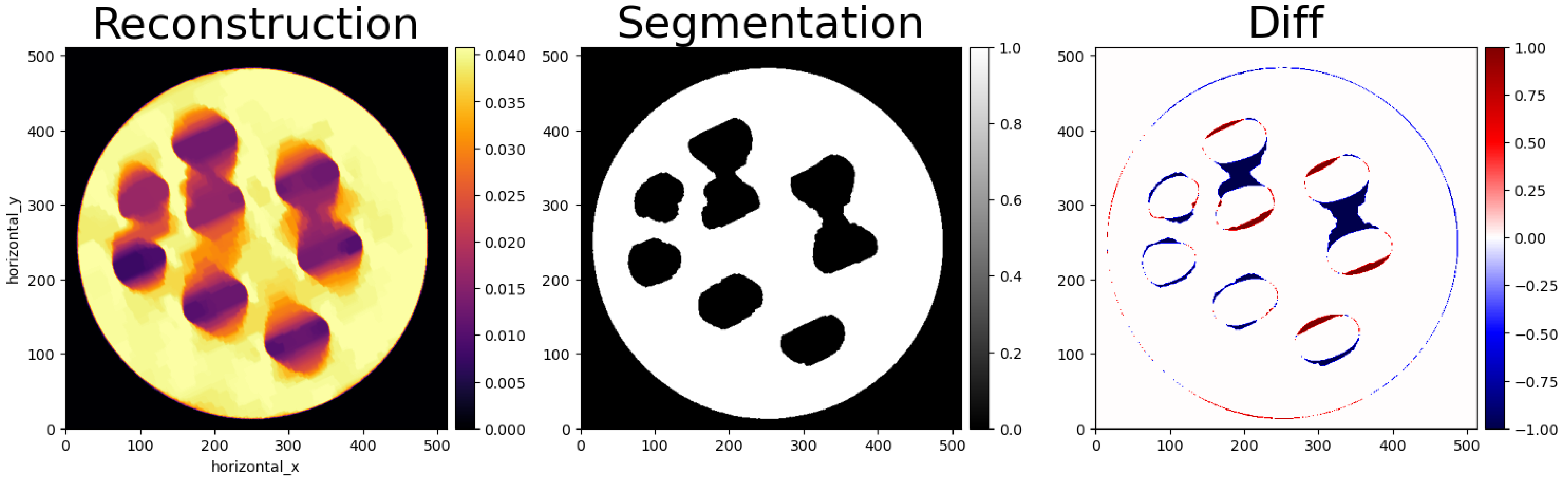
- Blurred edges along central projection direction
- Rotate to align with coordinate axis
- Apply single-directional TV to encourage edges in blurred direction
- Remember to check convergence!
- Rotate back



LS + isoTV + disk + xTV

$$\min_{\mathbf{u}} \quad a_1\|\mathbf{Au}-\mathbf{b}\|_2^2 + a_2\mathrm{ITV}(\mathbf{u}) + a_3\mathrm{ATV}_x(\mathbf{u})$$
$$\text{s.t.} \quad \mathbf{0} \leq \mathbf{u} \leq v\mathbf{m}$$

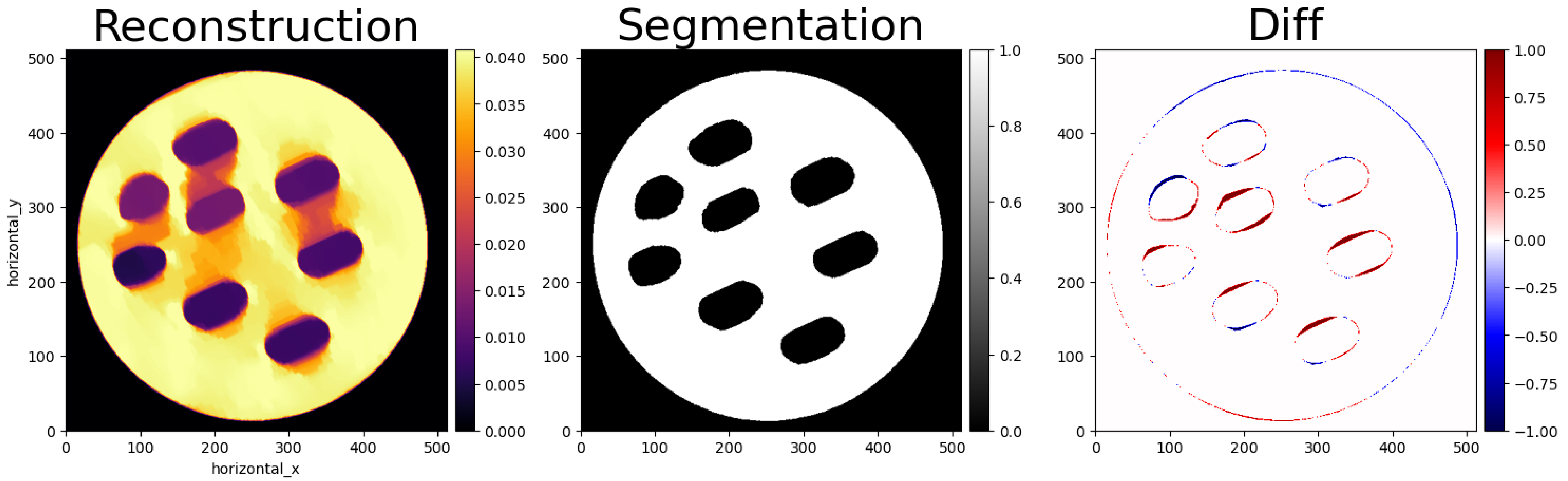
LS + isoTV + xTV   Mask: fitted 50 deg.   Score: 0.934



LS + isoTV + disk + xTV (converged)

$$\begin{aligned} \min_{\mathbf{u}} \quad & a_1\|\mathbf{A}\mathbf{u}-\mathbf{b}\|_2^2 + a_2\mathrm{ITV}(\mathbf{u}) + a_3\mathrm{ATV}_x(\mathbf{u}) \\ \text{s.t.} \quad & \mathbf{0} \leq \mathbf{u} \leq v\mathbf{m} \end{aligned}$$

Converged LS + isoTV + xTV Mask: fitted 50 deg. Score: 0.973



Primal Dual Hybrid Gradient (PDHG) method in CIL

CIL offers a range of optimization algorithms, incl GD, FISTA, ADMM and **PDHG:**

$$\min_{\mathbf{u}} \qquad f(\mathbf{Ku}) + g(\mathbf{u})$$

$$\text{where} \qquad f(\mathbf{Ku}) = \sum_i f_i(\mathbf{K}_i\mathbf{u})$$

Rewrite our optimization problem for PDHG:

$$\min_{\mathbf{u}} \quad a_1\|\mathbf{Au}-\mathbf{b}\|_2^2 + a_2\|\mathbf{Du}\|_{2,1} + a_3\|\mathbf{D_x u}\|_1 + \chi_{[\mathbf{0},v\mathbf{m}]}(\mathbf{u})$$

$$f = \begin{pmatrix} a_1\|\cdot - \mathbf{b}\|_2^2 \\ a_2\|\cdot\|_{2,1} \\ a_3\|\cdot\|_1 \end{pmatrix} \quad \mathbf{K} = \begin{pmatrix} \mathbf{A} \\ \mathbf{D} \\ \mathbf{D_x} \end{pmatrix} \qquad g = \chi_{[\mathbf{0},v\mathbf{m}]}$$

Solving with CIL – "near-math" syntax

$$f = \begin{pmatrix} a_1 \|\cdot - \mathbf{b}\|_2^2 \\ a_2 \|\cdot\|_{2,1} \\ a_3 \|\cdot\|_1 \end{pmatrix}$$

```
F = BlockFunction( a1*L2NormSquared(data),
                   a2*MixedL21Norm(),
                   a3*L1Norm() )
```

$$\mathbf{K} = \begin{pmatrix} \mathbf{A} \\ \mathbf{D} \\ \mathbf{D_x} \end{pmatrix}$$

```
K = BlockOperator( ProjectionOperator(ig, ag),
                   GradientOperator(ig),
                   FiniteDifferenceOperator(ig,'horizontal_x') )
```

$$g = \chi_{[\mathbf{0}, v\mathbf{m}]}$$

```
G = IndicatorBoxPixelwise( lower=0.0,
                           upper=v*m )
```

$$\min_{\mathbf{u}} \quad f(\mathbf{Ku}) + g(\mathbf{u})$$

```
algo = PDHG( initial=ig.allocate(0.0),
             f=F,
             g=G,
             operator=K,
             max_iteration=2000 )
algo.run()
```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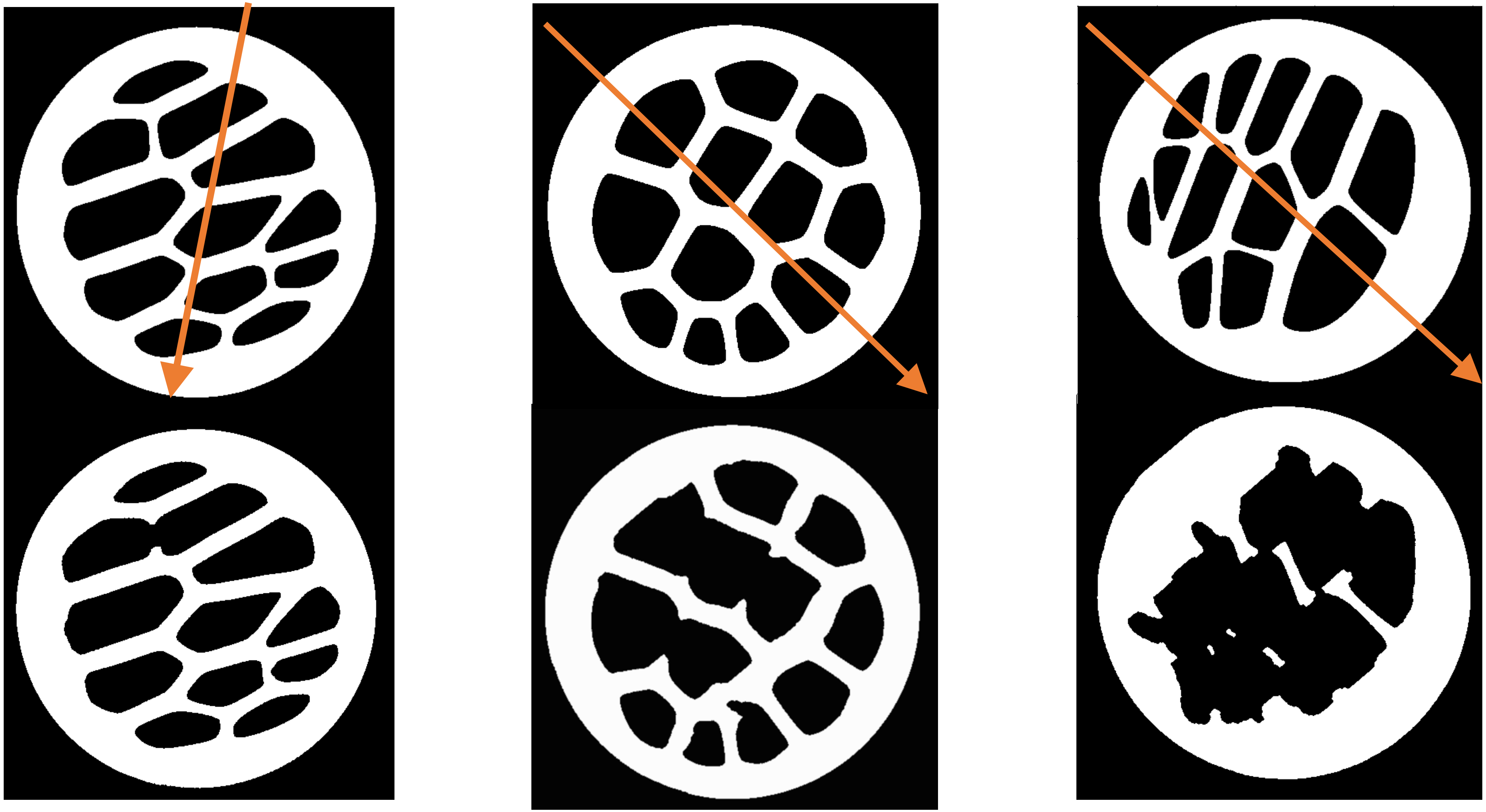
Mesh type sample – orientation matters!

60° "easy" | 60° "hard" | 40° "very hard"

Ground truth

Result



Conclusions

- Thanks to organizers – hope to see more challenges!
- CIL
  - HTC submission: github.com/TomographicImaging/CIL-HTC2022-Algo2
  - Main site: ccpi.ac.uk/cil
  - Discord community: discord.gg/9NTWu9MEGq
- Job opening(s) at UKRI Science and Technology Facilities Council Scientific Computing
- CIL Training course & Hackathon - March 20-24, Cambridge, UK
  - "Bring your data",
  - nonlinear problems,
  - deep learning

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