Open-Source Python Reconstruction Software for CT and Other Inverse Problems

CORE IMAGING LIBRARY

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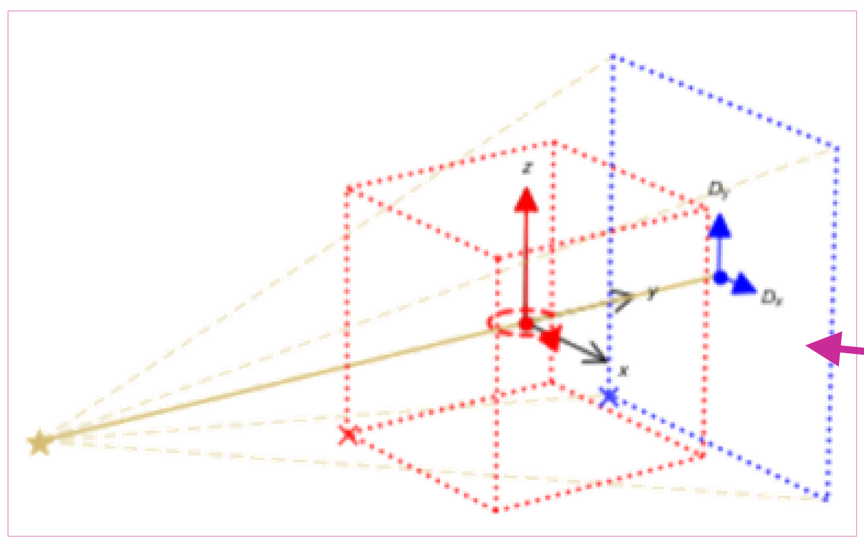
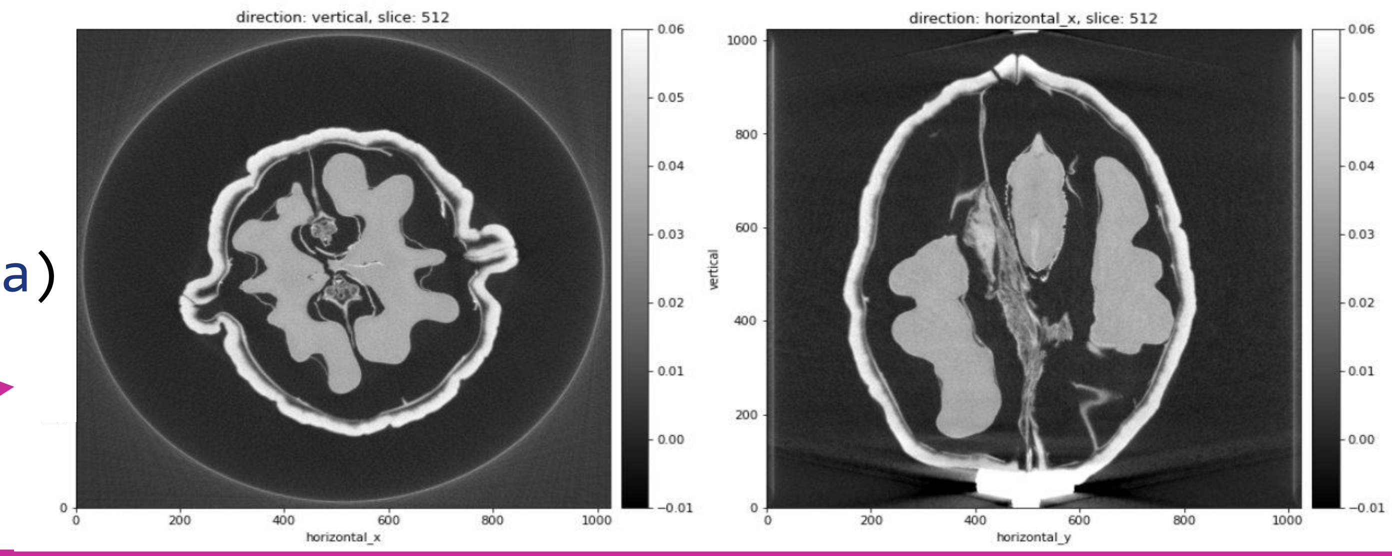
The Core imaging library (CIL) is designed for both imaging scientists and the inverse problems and optimisation mathematical community. Combining **mathematical building blocks** and the **modular design** of CIL enable users to **rapidly implement and experiment** with new reconstruction algorithms and compare them against existing **state-of-the-art methods.**



Data Loading and FDK Example

```
data = ZEISSDataReader(filename).read()
data = TransmissionAbsorptionConverter()(data)
show_geometry(data.geometry)
recon = FDK(data).run()
show2D(recon)
```



Near math syntax – Limited angle CT reconstruction using iterative reconstruction methods

Variational regularization with anisotropic and isotropic TV reconstruction using PDHG.

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

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

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

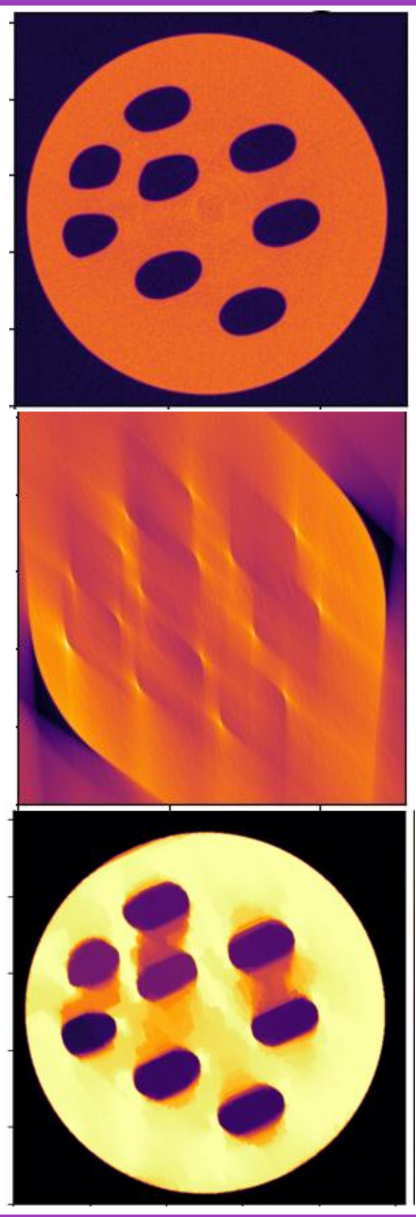
$$\mathbf{K} = \begin{pmatrix} \mathbf{A} \\ \mathbf{D} \\ \mathbf{D_x} \end{pmatrix}$$

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

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

```
algo = PDHG( initial=ig.allocate(0.0), f=F, g=G, operator=K)
algo.run(500)
```

$$\min_u f\left(\mathbf{K}u\right) + g(u)$$



Ground truth

FDK

CIL

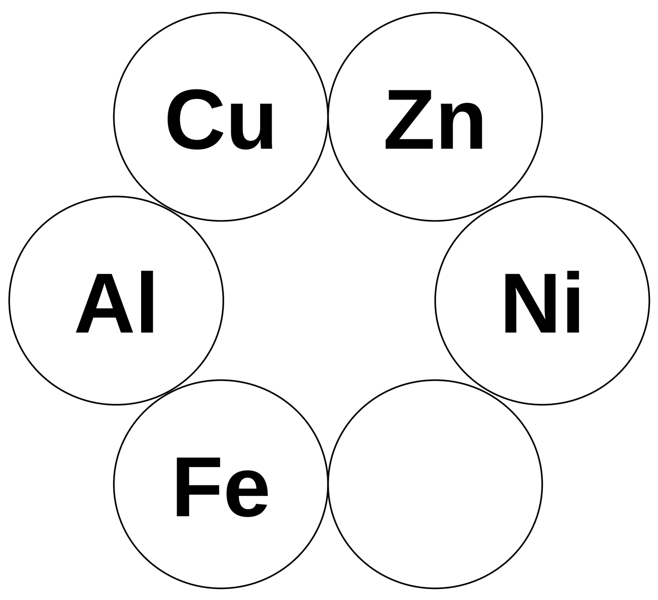
Jørgensen et al., 2023. A directional regularization method for the limited-angle Helsinki Tomography Challenge using the Core Imaging Library (CIL). *Applied Mathematics for Modern Challenges, doi:10.3934/ammc.2023011*

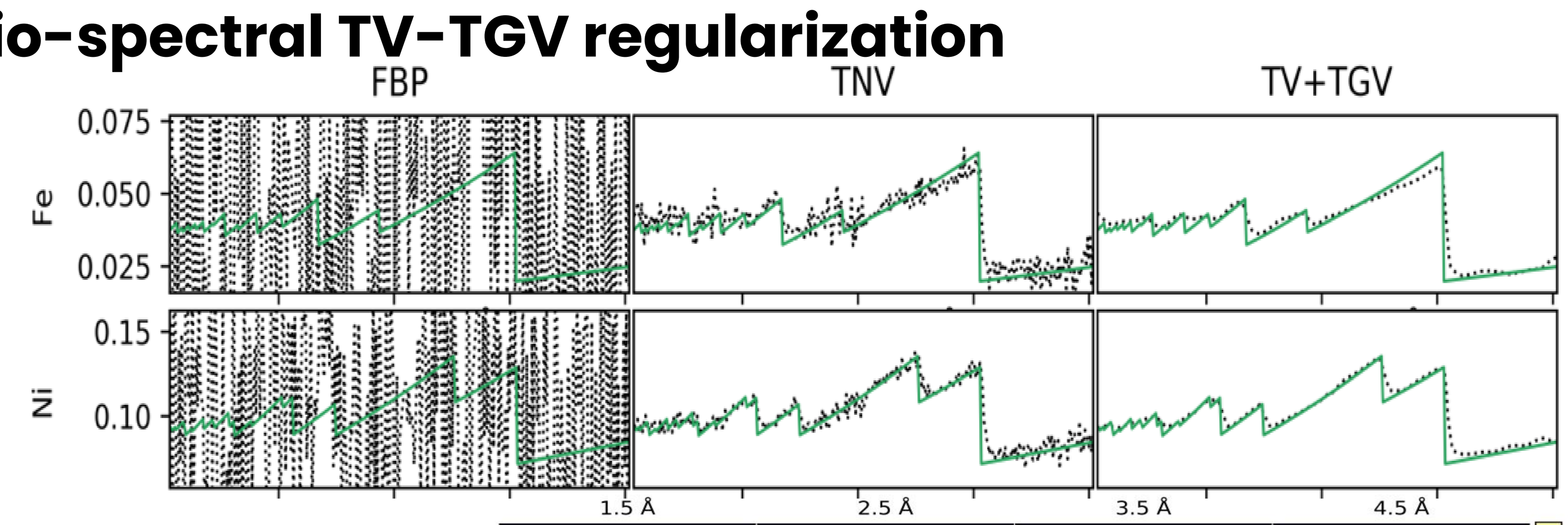
Hyperspectral Bragg-edge neutron tomography with spatio-spectral TV-TGV regularization

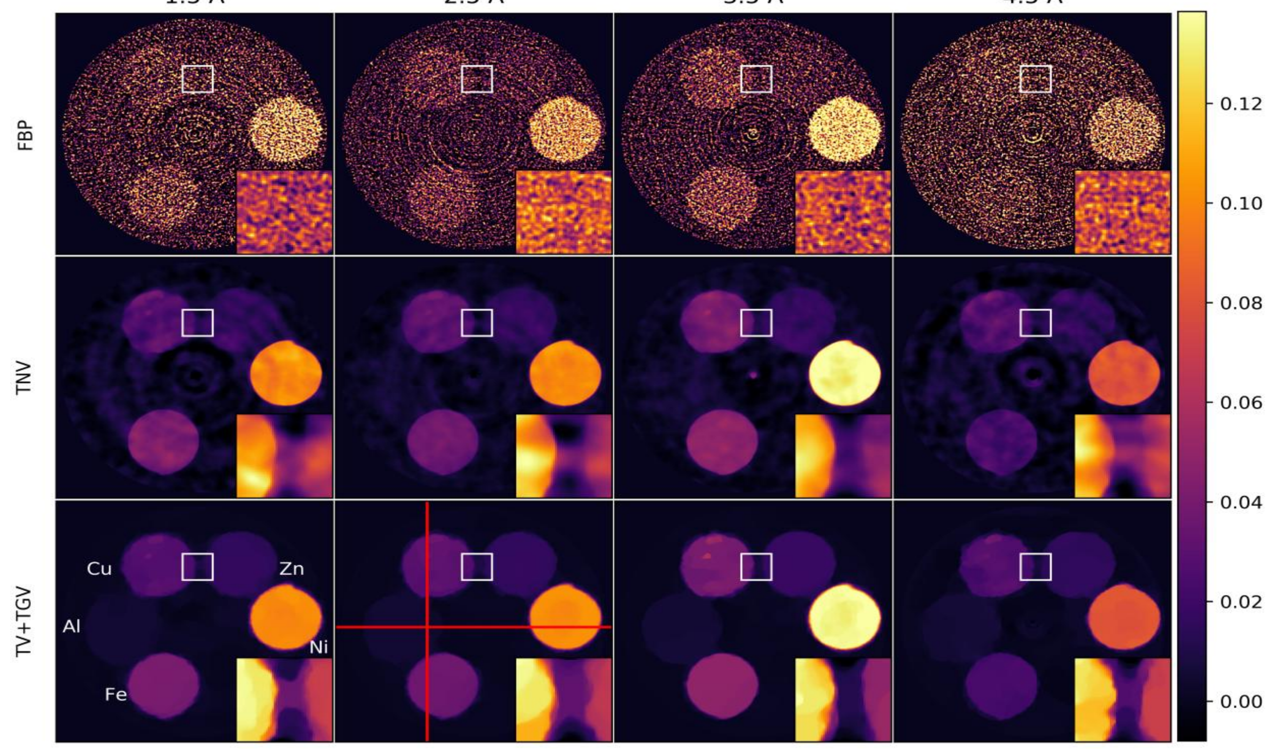
- 5 aluminum foil cylinders filled with metallic powder + 1 empty
- Neutron time-of-flight setup, IMAT@ISIS
- 2840 energy channels between 1 and 5
- TV in space and TGV across energy channels:

$$\arg\min_u \frac{1}{2}\|Au - b\|_2^2 + \alpha TV(u_{space}) + \beta TGV(u_{spectral})$$

- Solved using PDHG in CIL
- Improved reconstruction compared to Total Nuclear Variation







Ametova et al. 2021: *Crystalline phase discriminating neutron tomography using advanced reconstruction methods*, J. Physics D, doi.org/10.1088/1361-6463/ac02f9

Stochastic CIL – Accelerating reconstruction with stochastic optimisation in CIL

Plugging stochastic gradients into deterministic algorithms leads to stochastic algorithms e.g.

Optimization of the form

$$F(x) = \min_x \sum_{i=1}^{n} f_i(x)$$

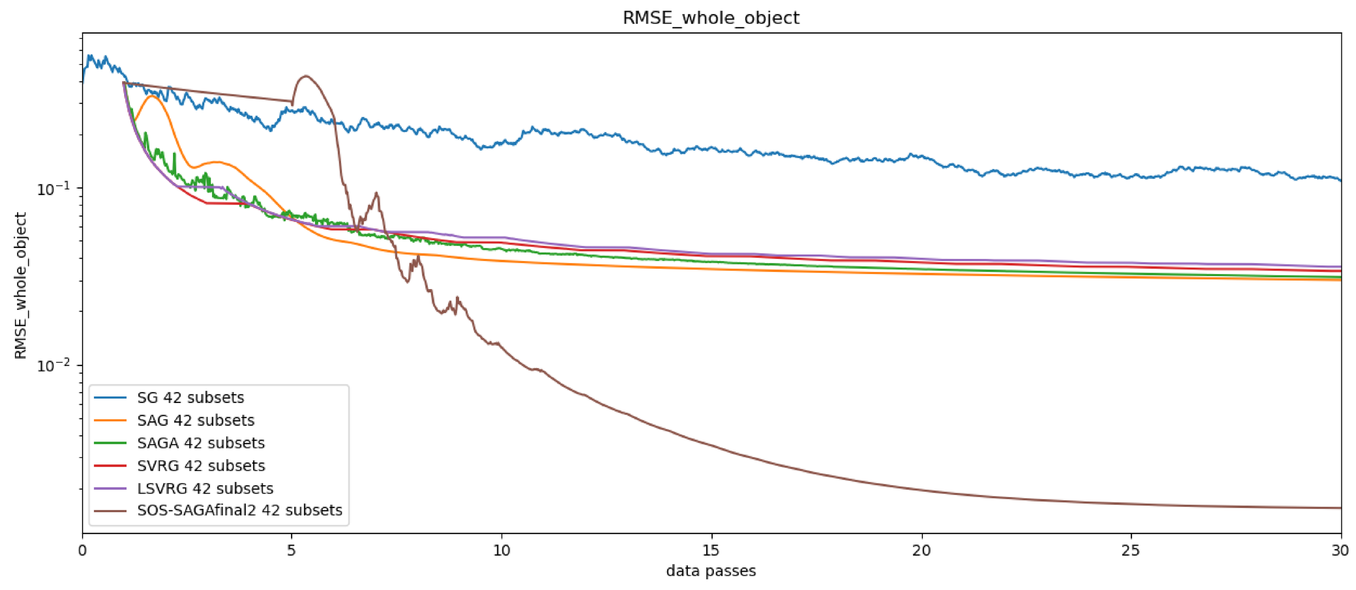
Can be solved by gradient descent

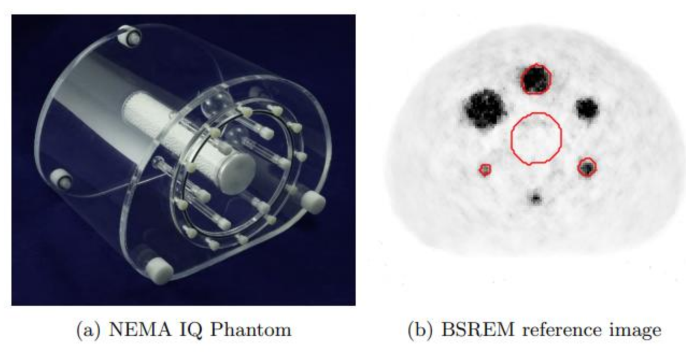
$$x_{k+1} = x_k - \gamma \nabla F(x_k)$$

Replacing the gradient ∇F by the gradient of just one sampled function f_i gives stochastic gradient descent

$$\tilde{\nabla} F(x_k) := \nabla f_{i_k}(x_k)$$

Similarly other approximations can give variance reduced algorithms e.g. SAG, SAGA, SVRG and LSVRG.





(a) NEMA IQ Phantom (b) BSREM reference image

E. Papoutsellis et. al., *Stochastic Optimisation Framework using the Core Imaging Library and Synergistic Image Reconstruction Framework for PET Reconstruction,* PSMR 2024, arXiv:2406.15159

TomographicImaging / CIL