



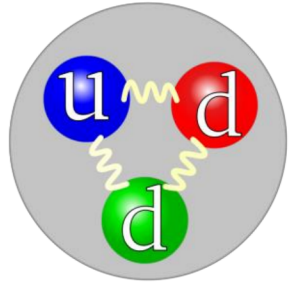
Neutron tomography and NeuTomPy toolbox: a Python package for neural network based tomographic reconstruction

IBFEM-4i 2019

Outlines

- The neutron
- Neutron interaction with matter
- Neutron Tomography (white-beam)
- Energy-resolved Neutron Tomography (4D)
- Data acquisition and processing
- Software for neutron CT
- NeuTomPy Toolbox
- NeuTomPy Toolbox: let's make a data analysis
- NeuTomPy Toolbox: image quality indexes
- NeuTomPy Toolbox: image quality assessment
- Accelerating Neutron Tomography experiments
- Conclusions

The neutron

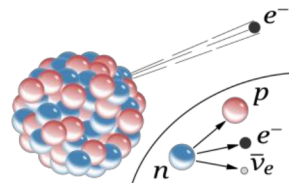


- **composite particle in the Standard Model with no net electric charge**
 $udd \rightarrow \text{Charge} = +2/3 - 1/3 - 1/3 = 0$

- **Free neutron is slightly heavier than a proton**

$$M_{\text{neutron}} = 939.5654133 \text{ MeV}/c^2 \quad M_{\text{proton}} = 938.2720813 \text{ MeV}/c^2$$

- **Free neutrons are unstable; they undergo b-decay, lifetime $\sim 885.7 \pm 0.8 \text{ s}$ (NIST source)**



$$Q_{\text{value}} = 1.29332 \text{ MeV}$$

$$\text{Kinetic energy of electrons: } 0 \leq T_e \leq 783 \text{ keV}$$

$$\text{Kinetic energy of protons: } 0 \leq T_p \leq 751 \text{ eV}$$

- **neutrons can interact with external magnetic fields and with the magnetic moments of unpaired electrons in matter**

Spin $s = 1/2$ and the associated magnetic moment $\mu_n = -0.9662 \times 10^{-26} \text{ J T}^{-1}$

- A neutron moving with linear momentum p can be described as a wave with the corresponding deBroglie-wavelength $\lambda = h/p$:

$$E = \frac{p^2}{2 m_n} = \frac{h^2}{2 m_n \lambda^2}$$

Neutron interacts primarily with nuclei via the **strong interaction**, which have effect only at short range (fm). **High penetration through bulk materials**: both strong and magnetic interaction probabilities are small for a large number of materials!!!

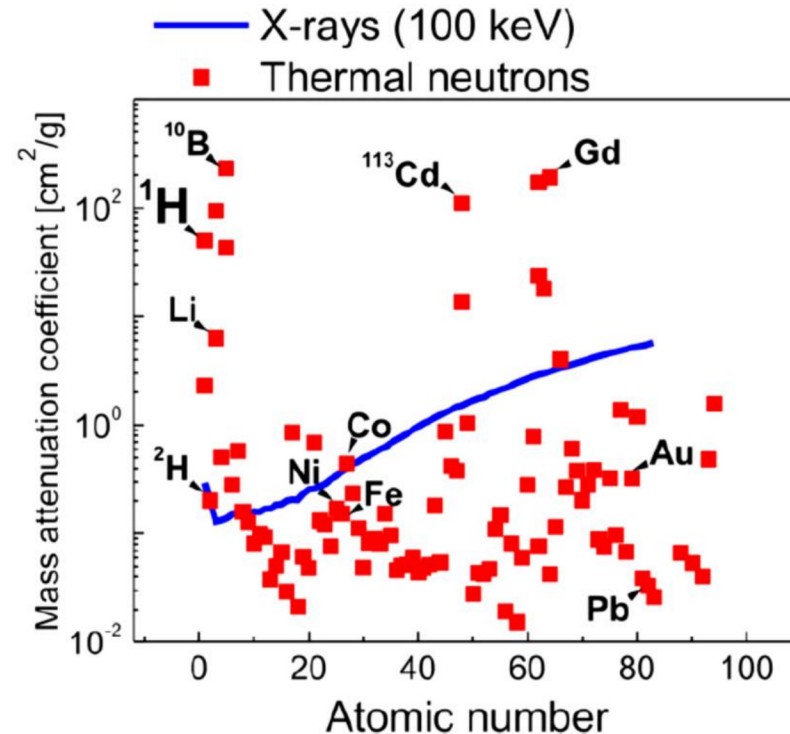
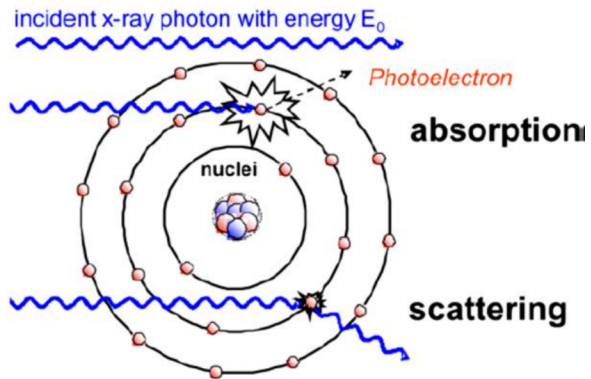
Neutron interaction with matter

In neutron imaging applications, the neutron-matter interactions of interest are those that are able to attenuate a neutron beam. Particles are removed from the incoming beam by **absorption** or by **scattering**.

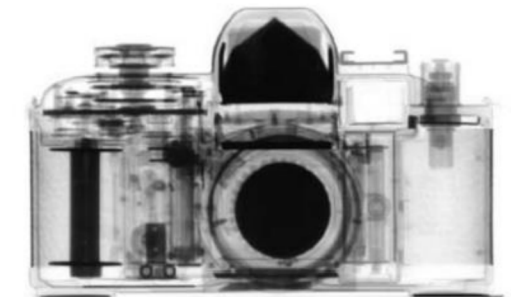
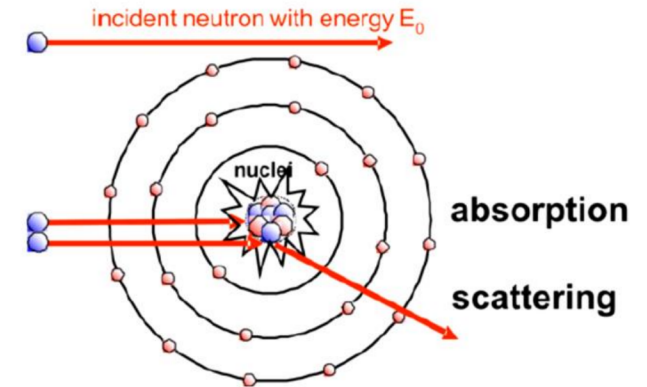
The probability of physical process is described by quantum mechanics and it is represented in terms of a quantity called **cross section** σ expressed in barns (1 barn = 10^{-24} cm²). The total cross section σ_T

$$\sigma_T = \sigma_a + \sigma_s$$

(a) x-rays



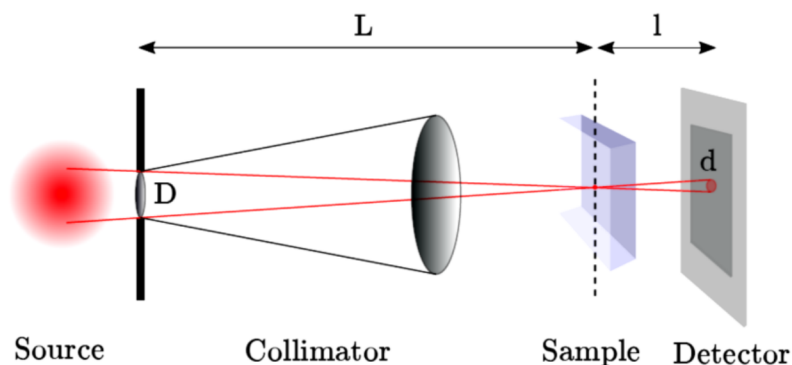
(b) neutrons



Neutron Tomography (white-beam)

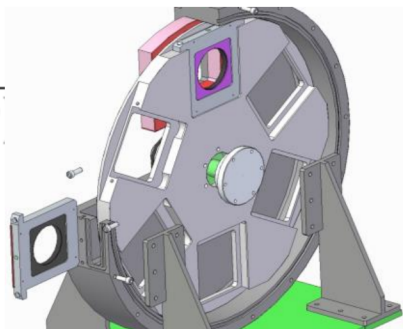
Similarly to other tomographic techniques, Neutron Tomography (NT) provides the threedimensional map of the neutron attenuation coefficient within a sample

Simplified geometry of a neutron tomography experiment (pinhole collimator).
Almost **PARALLEL BEAM**.

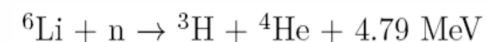
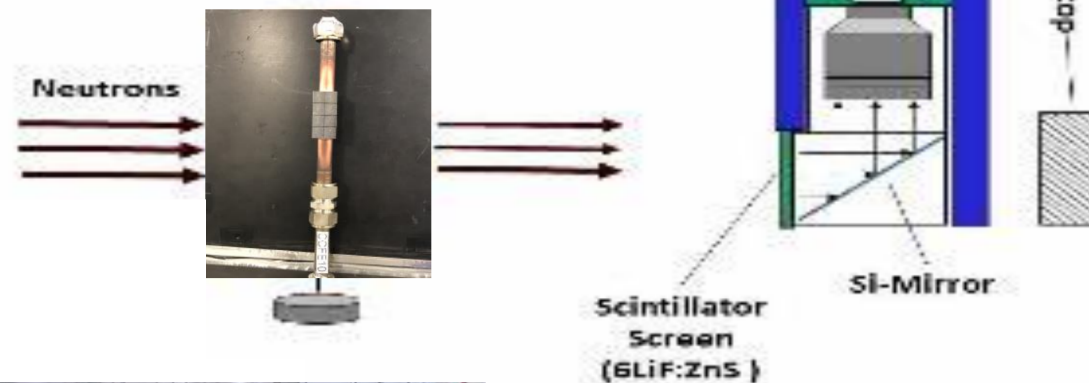


Extended source – geometrical unsharpness

$$d = \frac{D}{L}l = \frac{l}{(L/D)}$$

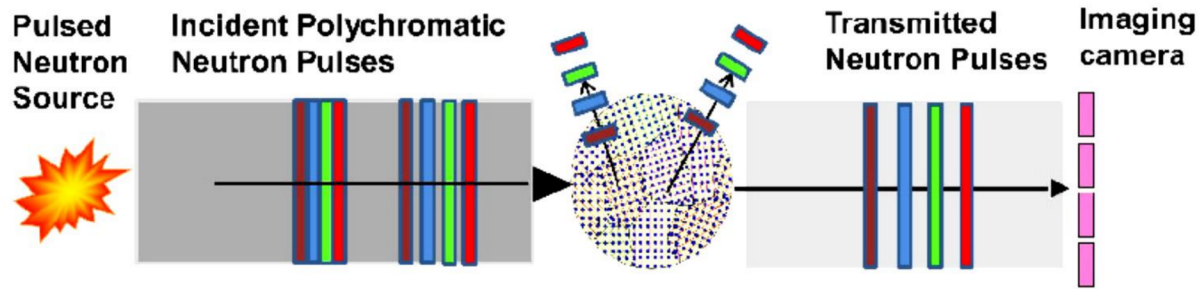


Example of neutron tomography setup



Example of the neutron imaging facility IMAT@ISIS, STFC, UK

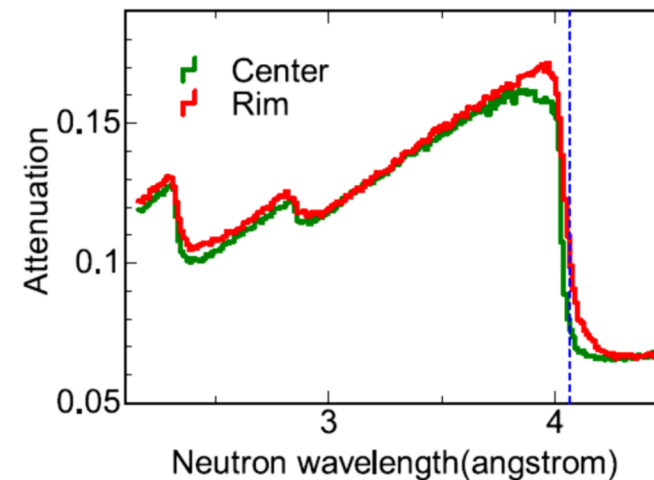
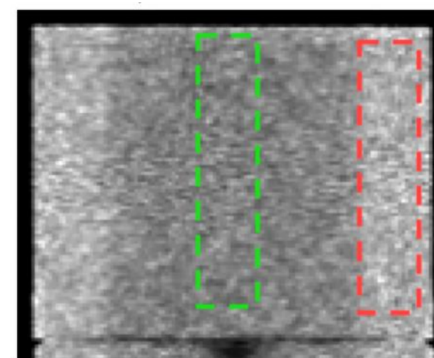
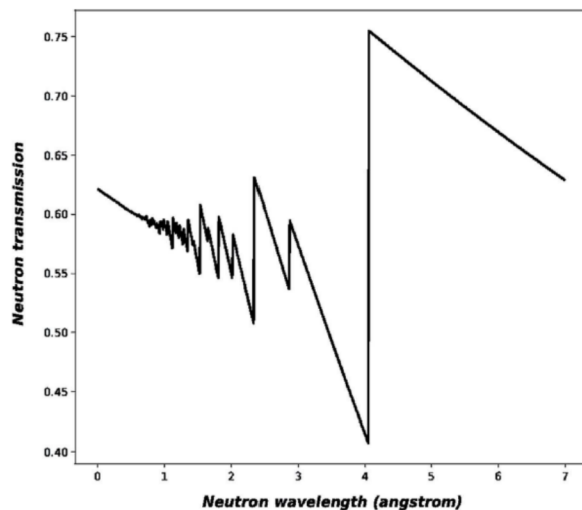
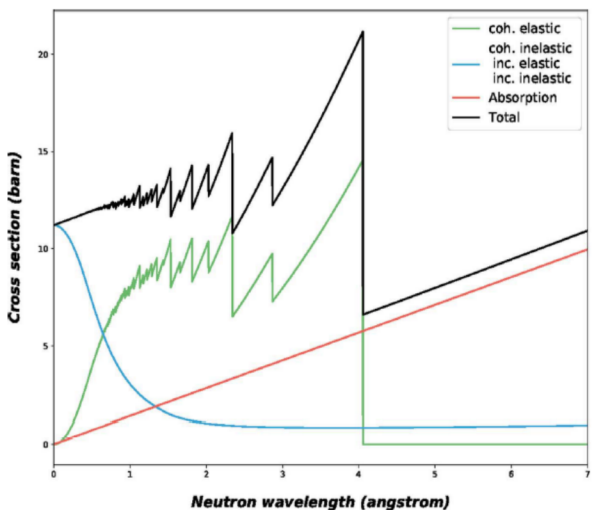
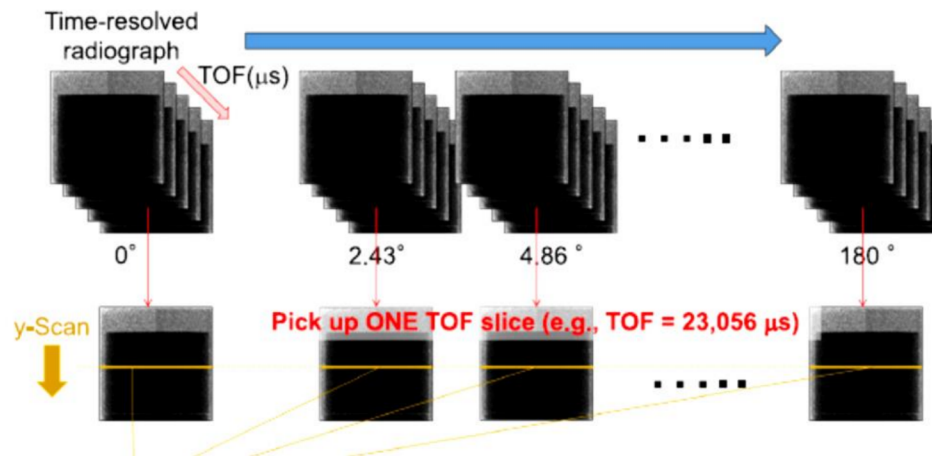
Energy-resolved Neutron Tomography (4D)



Space = flight path of the beamline

$$v = \frac{L}{(T + T_0)}$$

Time + error



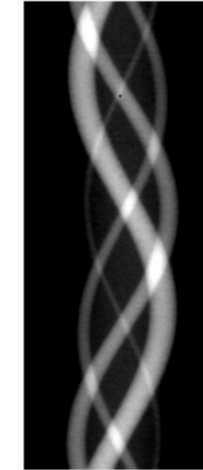
K. Watanabe, T. Minniti et al., NIM A 944 (2019) 162532

Data acquisition and processing

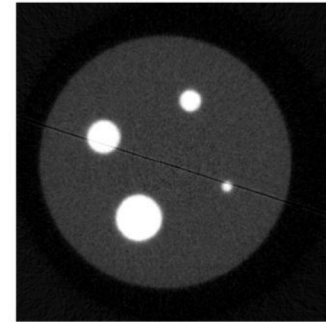
- Data acquisition and processing of a NT experiment can be summarized by the following steps:
- the sample is placed on the rotation stage as close as possible to the detector in order to reduce the geometrical blurring;
- several radiographs were acquired by rotating the sample generally with equal angular steps over 360°;
- some open-beam (beam on, sample removed) and dark-current (beam off) images are acquired;
- the projections are normalized with respect to dark-field images, open-beam images and radiation dose, using the following formula:

$$p = -\log \left(\frac{D_{\text{flat}}}{D} \cdot \frac{I - I_{\text{dark}}}{I_{\text{flat}} - I_{\text{dark}}} \right)$$

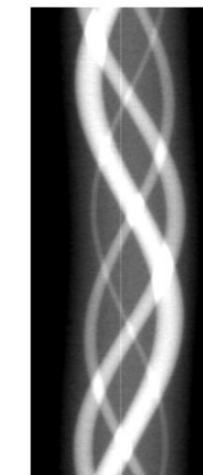
- image filters are used to suppress outlier pixels caused by damaged detector elements or by hits of γ -rays on the detector;
- outlier pixels not yet removed appearing in most of all projections are suppressed by de-striping filters; single outlier pixel appears as line artefact in the reconstructed image;
- a reconstruction algorithm, generally the FBP method, for parallel beam geometry is used to compute the 2D map of the attenuation coefficient for each slice of the volume



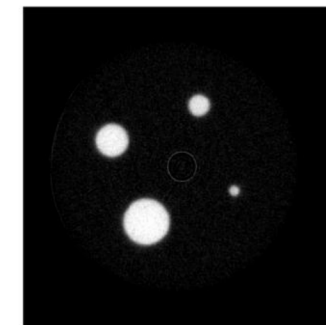
(a) Sinogram



(b) Reconstructed slice



(a) Sinogram



(b) Reconstructed image

Software for neutron CT

Common software tools for reconstruction of tomographic data at neutron imaging beamlines:



Commercial software



Octopus by Inside Matters:
<https://octopusimaging.eu/>

PROS: easy to use,
optimized for neutron data,
CPU/GPU support
CONS: only FBP and
SART, Windows only

Open source software



MuhRec:
<https://github.com/neutronimaging/imagingsuite>

PROS: optimized
for neutron data
CONS: only FBP
and CPU support,
Windows/Mac



TomoPy:
<https://tomopy.readthedocs.io/en/latest/#>

PROS: state-of-the-art
reconstruction
methods, CPU/GPU
support
CONS: not optimized
for neutron data, no
UI



Astra toolbox:
<https://www.astra-toolbox.com/>

PROS: state-of-the-art
reconstruction
methods, CPU/GPU
support
CONS: not optimized
for neutron data, no UI



NeuTomPy toolbox:
<https://pypi.org/project/neutompy/>

PROS: state-of-the-art
reconstruction methods,
CPU/GPU support,
optimized for neutron
data
CONS: no UI

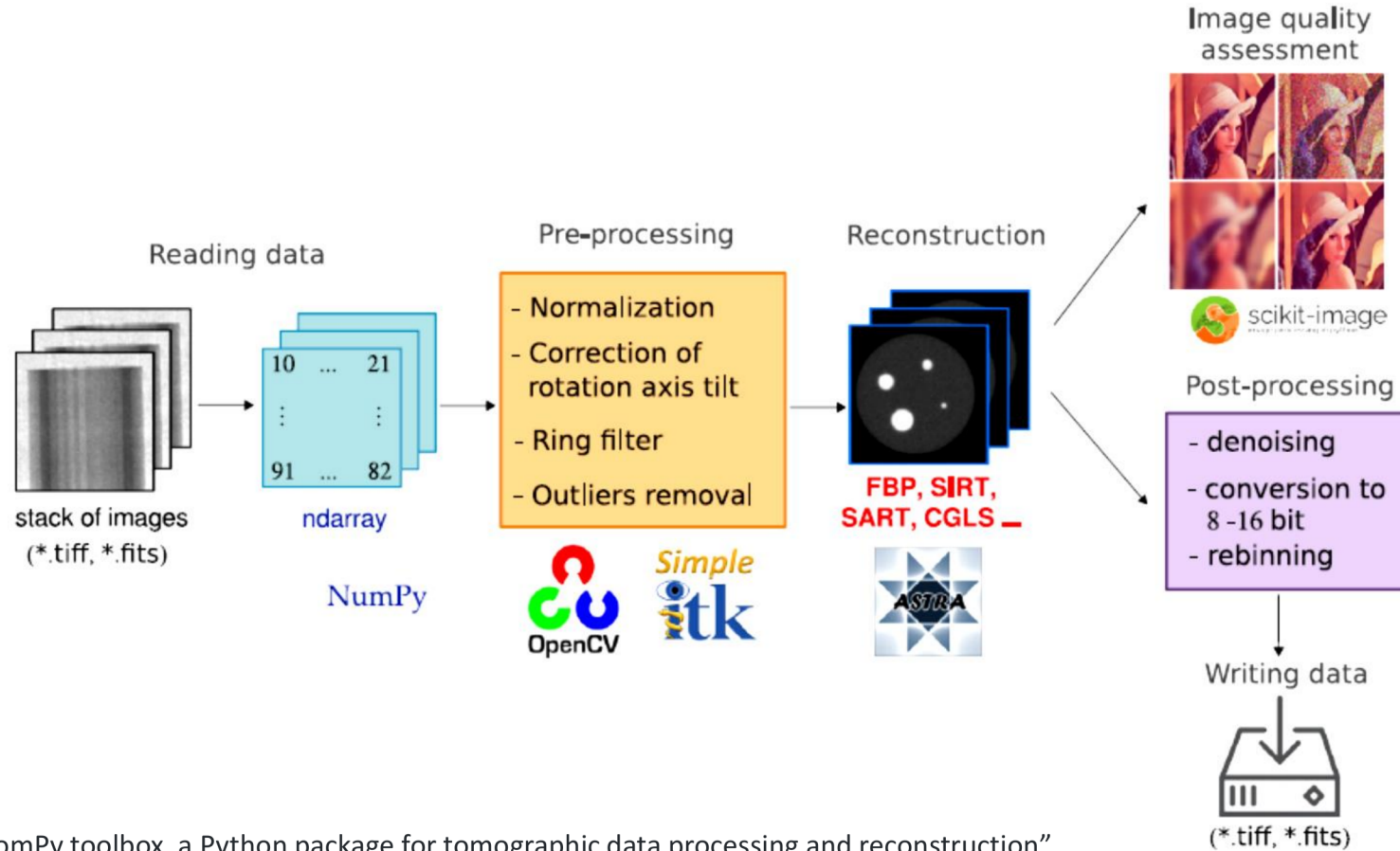
Primarily conceived for **NT** and developed to support the need of users and researchers to **compare state-of-the-art reconstruction methods** and choose the optimal data processing workflow for their data

Python

open source

modular design

Cross-platform:
Windows/Linux/Mac



multi-threading capabilities

image quality indexes

D. Micieli, T. Minniti, G. Gorini, "NeuTomPy toolbox, a Python package for tomographic data processing and reconstruction", SoftwareX, Volume 9 (2019), pp. 260-264, <https://doi.org/10.1016/j.softx.2019.01.005>

Steps of a typical CT reconstruction workflow:

1) I/O of the raw datasets

```
import neutompy as ntp  
proj, dark, flat, proj_180 = ntp.read_dataset()
```

2) Compute the transmission images with dose correction

```
norm, norm_180 = ntp.normalize_proj(proj, dark, flat, proj_180=proj_180, dose_draw=True, crop_draw=True)
```

3) Remove outliers (dark and bright spots, a median of the neighborhood pixels)

```
norm = ntp.remove_outliers_stack(norm, radius=1, threshold=0.018, outliers='dark', out=norm)  
norm = ntp.remove_outliers_stack(norm, radius=3, threshold=0.018, outliers='bright', out=norm)
```

4) Centre of Rotation (COR) correction

```
norm = ntp.correction_COR(norm, norm[0], norm_180)
```

5) Remove stripes in sinograms

```
norm = ntp.remove_stripe_stack(norm, level=4, wname='db30', sigma=1.5, out=norm)
```

6) Reconstruction module (ex SIRT reconstruction with 100 iterations using GPU)

```
rec = ntp.reconstruct(norm, angles, 'SIRT_CUDA', parameters={"iterations":100}, pixel_size=pixel_size)
```


NeuTomPy Toolbox: image quality indexes

The quality of a CT image is determined by several factors such as spatial resolution, image contrast, noise and artefacts. In order to assess these factors and compare the reconstructed images quantitatively we used *full-reference* and *no-reference* image quality indexes.

Contrast-to-Noise Ratio (CNR):
$$\text{CNR} = \frac{\mu_{\text{sign}} - \mu_{\text{bg}}}{\sigma_{\text{bg}}}$$
 quantifies the reconstruction error with respect to a reference image

Normalized Root Mean Square Error (NRMSE):
$$\text{NRMSE} = \frac{\|I_{\text{test}} - I_{\text{ref}}\|_2}{\|I_{\text{ref}}\|_2}$$
 I_{test} and I_{ref} are the test and reference images. Smaller NRMSE values indicate better image quality

Structural Similarity Index (SSIM):
$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$
 $\mu_x, \mu_y, \sigma_x, \sigma_y,$ and σ_{xy} are the local means, standard deviations and cross-covariance for windows $x, y,$ while C_1 and C_2 are constants

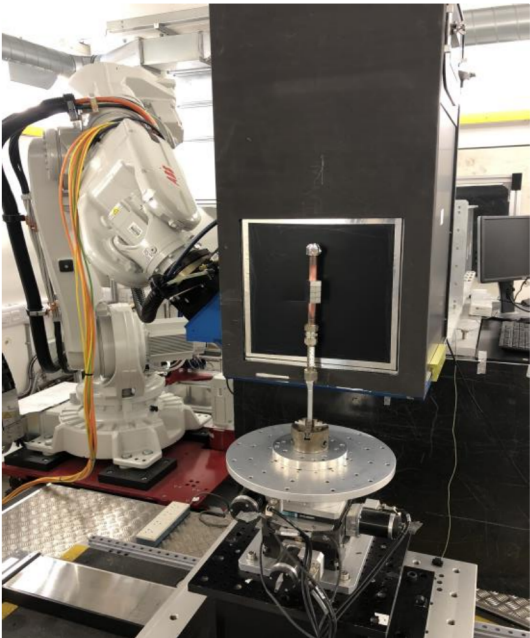
Edge quality - Full Width at Half Maximum (FWHM):
$$f(x) = \frac{p_0}{2} \{\text{Erf} [p_1(x - p_2)] + 1\} + p_3 \xrightarrow{f'(x) = \text{Gaussian function}} \text{FWHM} = \frac{2\sqrt{\ln 2}}{p_1}$$

NeuTomPy Toolbox: image quality assessment

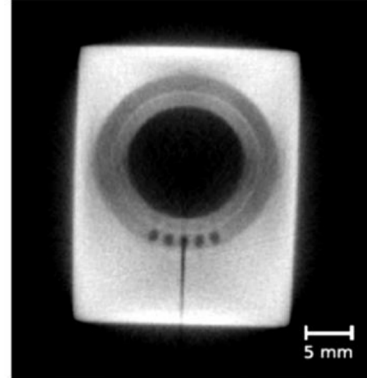
Phase 2 thermal break DEMO divertor mock-ups



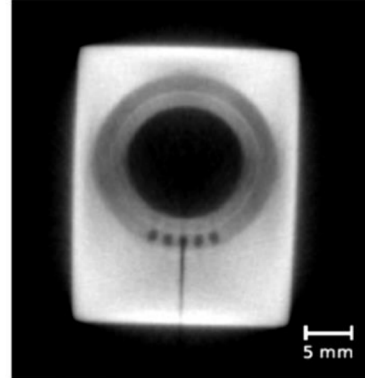
Setup at IMAT@ISIS, STFC, UK



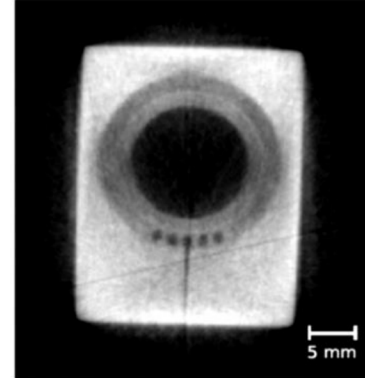
FBP
SSIM = 0.92, CNR = 38.9,
NRMSE = 0.12



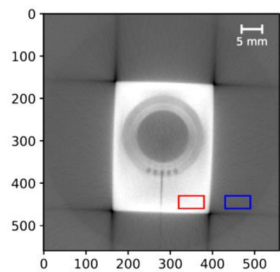
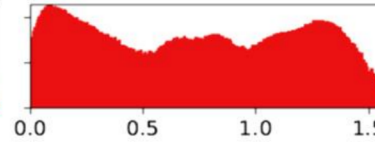
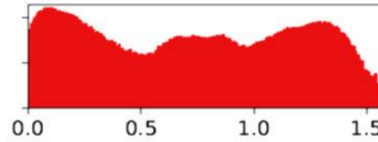
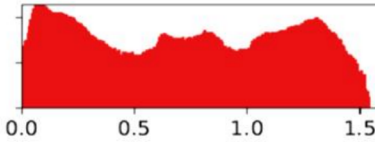
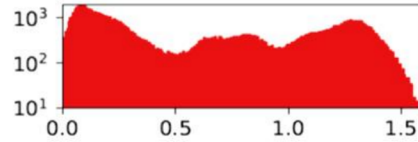
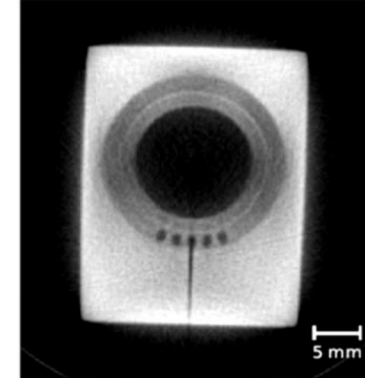
SIRT
SSIM = 0.99, CNR = 60.5,
NRMSE = 0.03



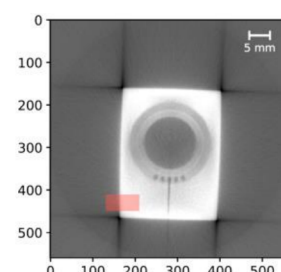
SART
SSIM = 0.78, CNR = 33.8,
NRMSE = 0.11



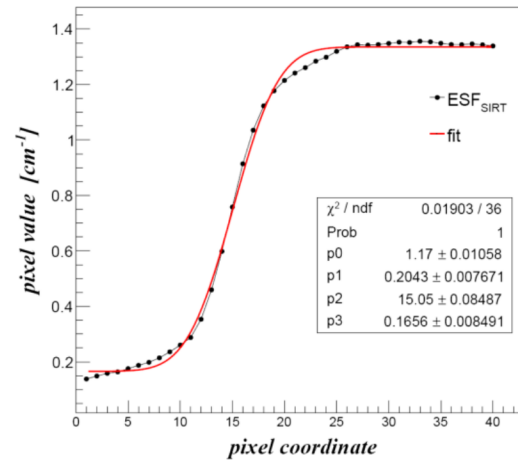
CGLS
SSIM = 0.96, CNR = 37.8,
NRMSE = 0.06



CNR ratio ROI
blue = background
red = signal



Edge Spread Function (ESF) ROI



Edge quality measurement

	σ	$\Delta\sigma$	FWHM	Δ_{FWHM}
FBP	0.23918	0.01362	6.96169	0.39641
SIRT	0.20430	0.00767	8.15035	0.30604
SART	0.18016	0.02026	9.24216	1.03911
CGLS	0.30896	0.02428	5.38943	0.42357

Accelerating Neutron Tomography experiments*

*D. Micieli, T. Minniti, Ll. M. Evans, G. Gorini, Scientific Report 9, 2450 (2019).

Problem: NT require long scan times - generally several hours, depending on the sample and the desired spatial resolution. Can we use NT to scan large quantities of similar samples, such as in quality check?

Answer: Maybe 😊

But how: One way to reduce the CT scan time is to **limit the number of projections. What about the CT reconstruction?**



Analytical method like FBP is not suitable if the number of projections not satisfy the Nyquist-Shannon condition



Algebraic methods like SIRT, SART, CGLS better handle sparse-view neutron datasets, but with high computational cost



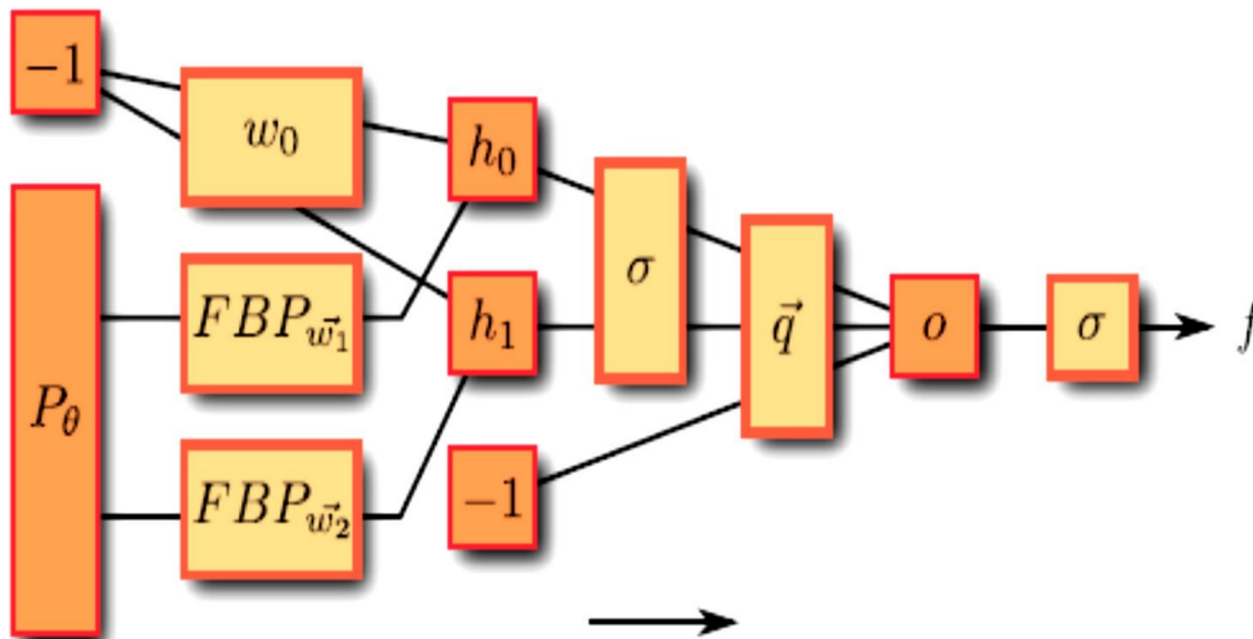
Machine Learning (ML) based methods were introduced to improve low-dose and Sparse-View X-ray tomography. We have introduced Neural Network Filtered Back-Projection (NN-FBP) method to reduce the acquisition time in NT experiments

Accelerating Neutron Tomography experiments*

*D. Micieli, T. Minniti, Ll. M. Evans, G. Gorini, Scientific Report 9, 2450 (2019).

NN-FBP method is based on a nonlinear weighted sum of different FBP reconstructions, each of these with a specific filter. An Artificial Neural Network (ANN) model is exploited to train these custom filters.

Type of network used for the NN-FBP is the multilayer perceptron



We take the projections P_θ and apply several FBP algorithms: to obtain the hidden node h_i , we apply the FBP algorithm with custom filter w_i and a bias. A linear combination of all hidden node images and a bias, with a sigmoid function applied to all pixels of each image, leads to a single image o . After we apply a final sigmoid function, we get an approximation of f .

TRAINING: During the training (supervised learning) we provide a ground true image usually reconstructed with other method (SIRT).

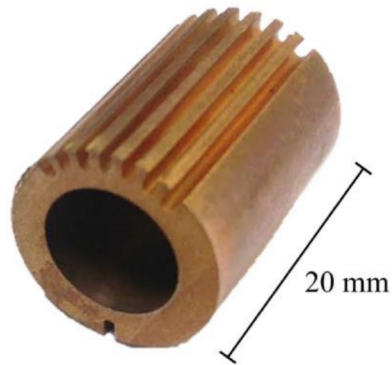
Network weights are found minimizing the cost function:

$$e(Q, W, b, b_0) = \sum_{i=1}^T (O(z_i) - f_i)^2$$

Accelerating Neutron Tomography experiments*

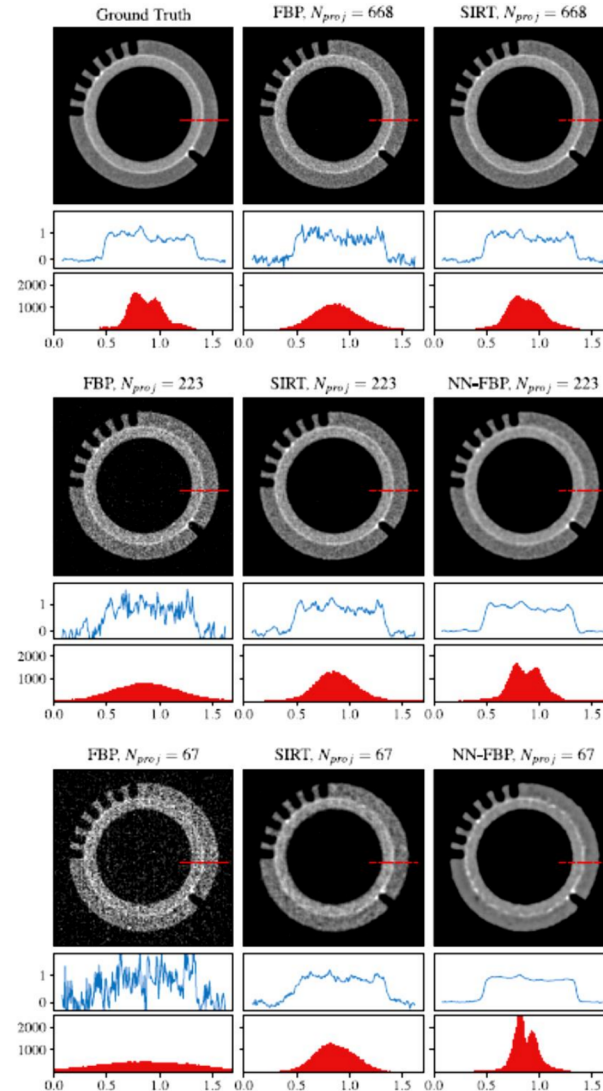
*D. Micieli, T. Minniti, Ll. M. Evans, G. Gorini, Scientific Report 9, 2450 (2019).

Cu-CuCrZr pipe for thermal break concept monoblock



Neutron tomography: scan parameters

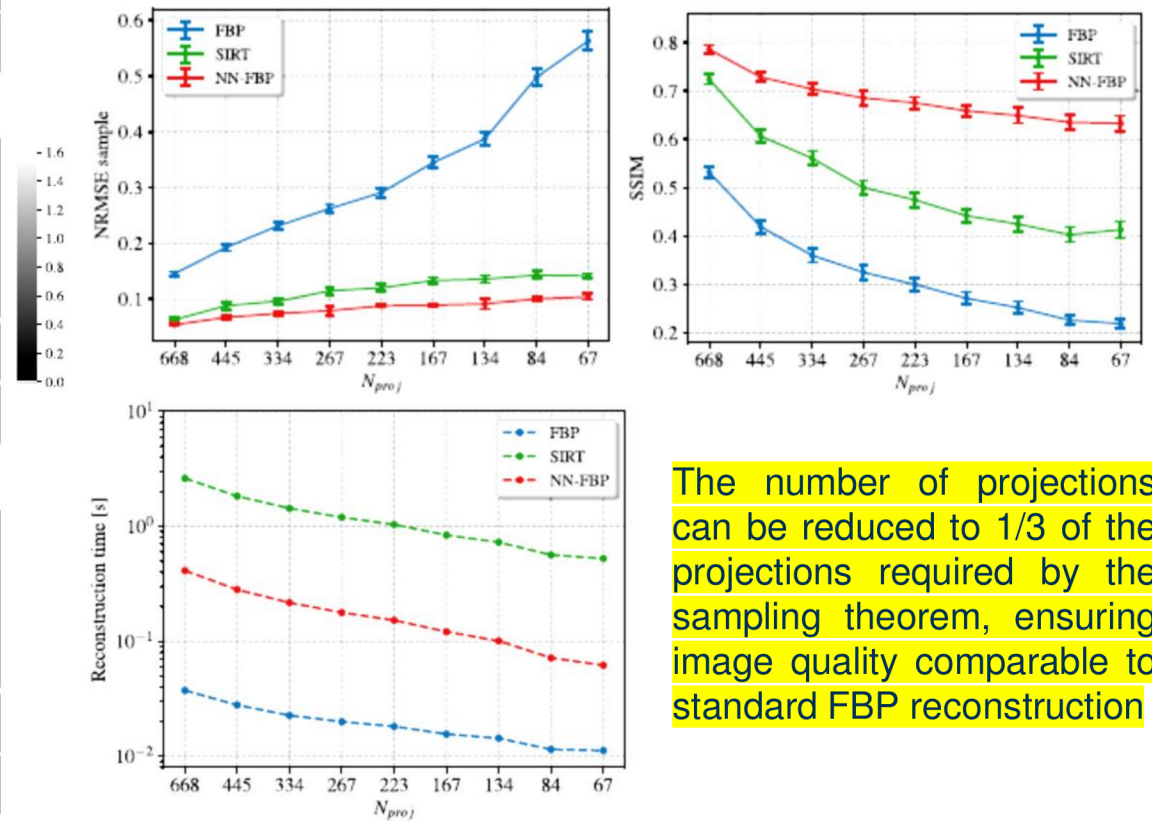
Neutron flux: $5.9 \cdot 10^6$ n/cm²/s
 L/D = 245
 FOV = 60 x 60 mm²
 Pixel size = 29 μm
 Exposure time = 30 s
 # projections = 1335 (over-sampled)
 angular range = [0°, 360°]



TRAINING:

ground truth image = SIRT (400 iterations with $N_{proj} = 1335$)

10^5 pixels/slice from 10 training images and 10^5 pixels/slice from 10 validation images (SIRT) were used to train the ANNs



The number of projections can be reduced to 1/3 of the projections required by the sampling theorem, ensuring image quality comparable to standard FBP reconstruction