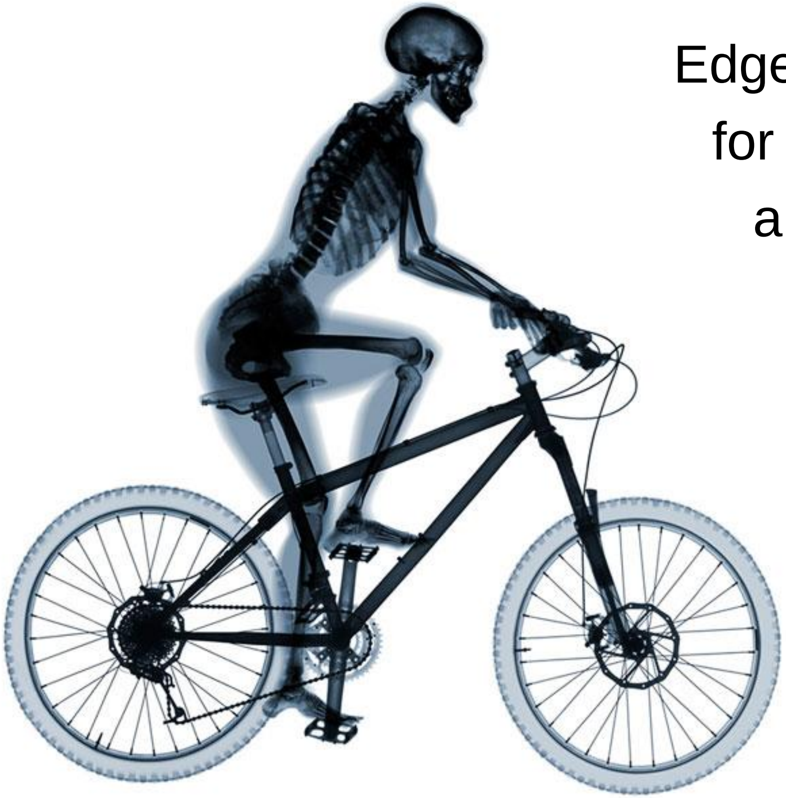


Edge-on illumination of a silicon detector for (spectral) Computed Tomography: a custom reconstruction algorithm

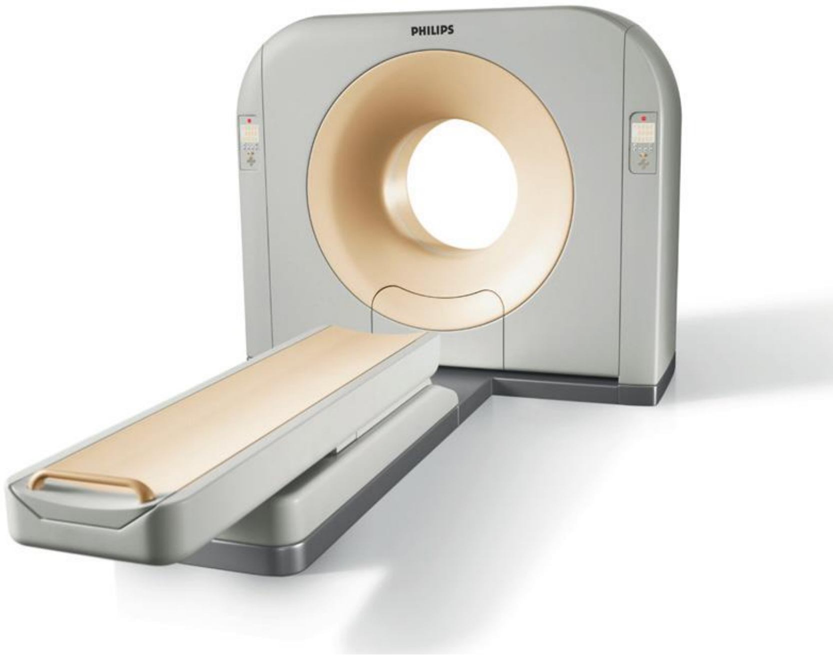
Michele Doni,
Nikhef
(Amsterdam)

* Supported by the EU FP7-PEOPLE-2012-ITN project nr 317446, INFIERI, "Intelligent Fast Interconnected and Efficient Devices for Frontier Exploitation in Research and Industry"

Silicon & edge-on illumination: why

State of the art CT detectors in hospitals:
ceramic scintillators coupled to Si photodiodes
working in Charge Integrating mode

Indirect detection process	Photons weighted by their energy
⇓	⇓
Loss in the efficiency	Degradation of the reconstructed image



SOLUTION:
use a semiconductor detector working in Photon Counting mode

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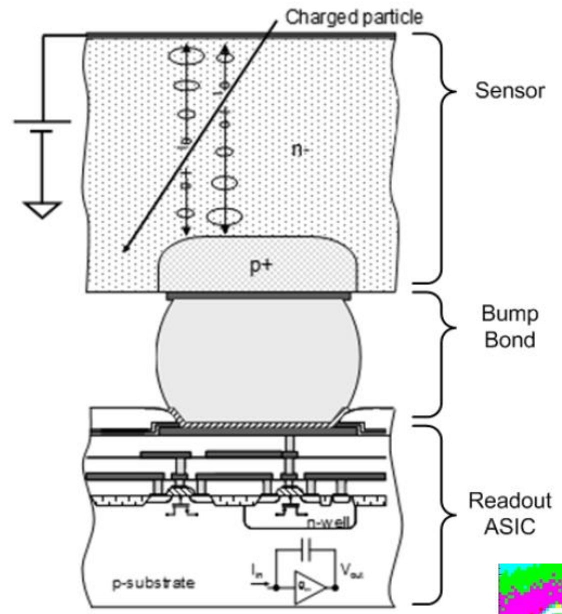
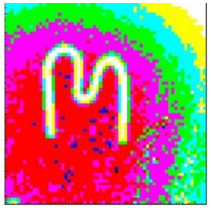


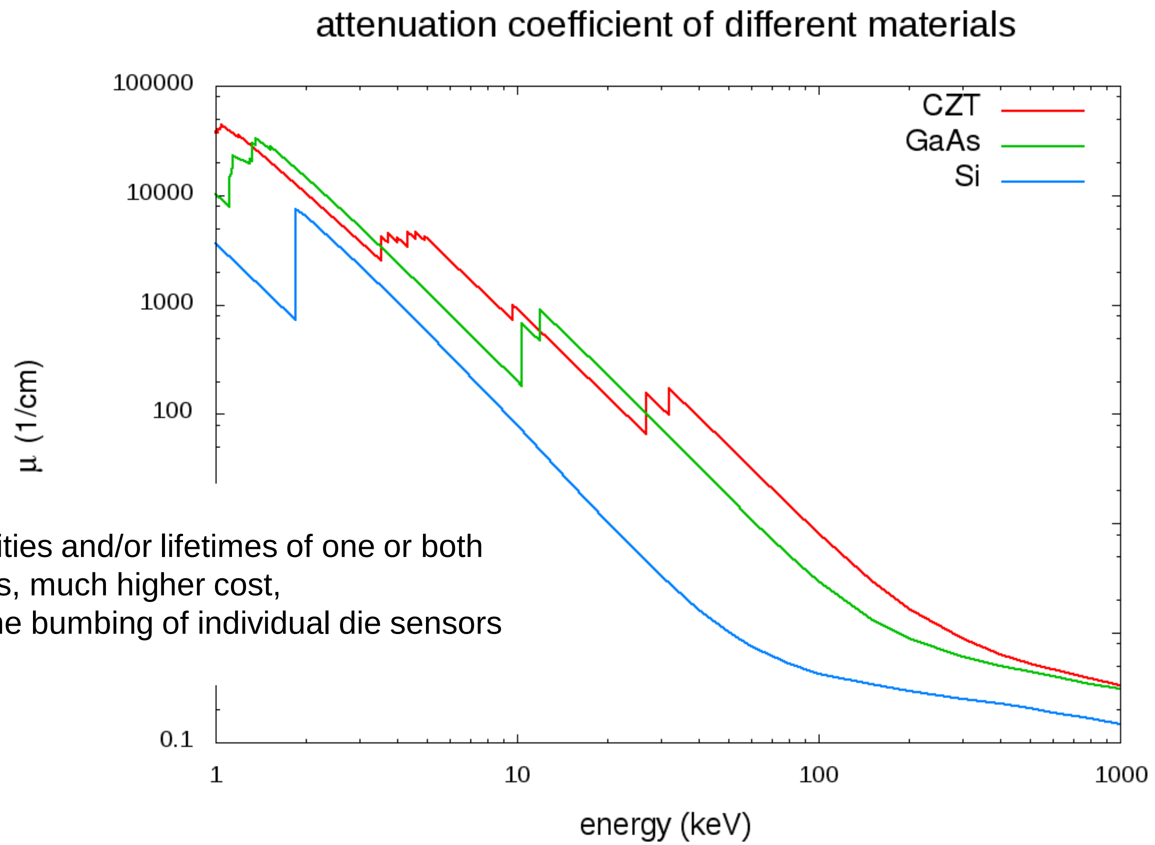
SOLUTION:
use a semiconductor detector working in Photon Counting mode

Medipix chip



Silicon & edge-on illumination: why

Hybrid pixelated
semiconductor detector:
the sensor material

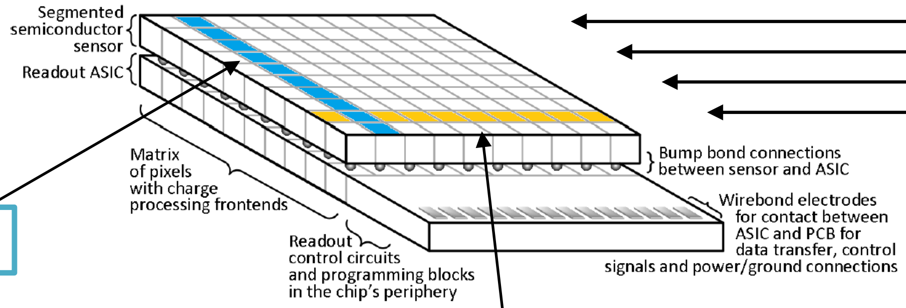


Problems: low mobilities and/or lifetimes of one or both
of the charge carriers, much higher cost,
technical issues in the bumbing of individual die sensors

Silicon & edge-on illumination: how

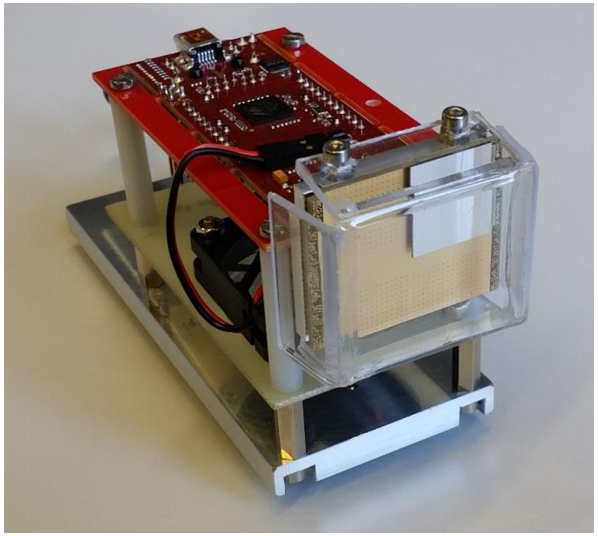
Solution: use a bigger thickness of Si

X-rays



EO row

EO column

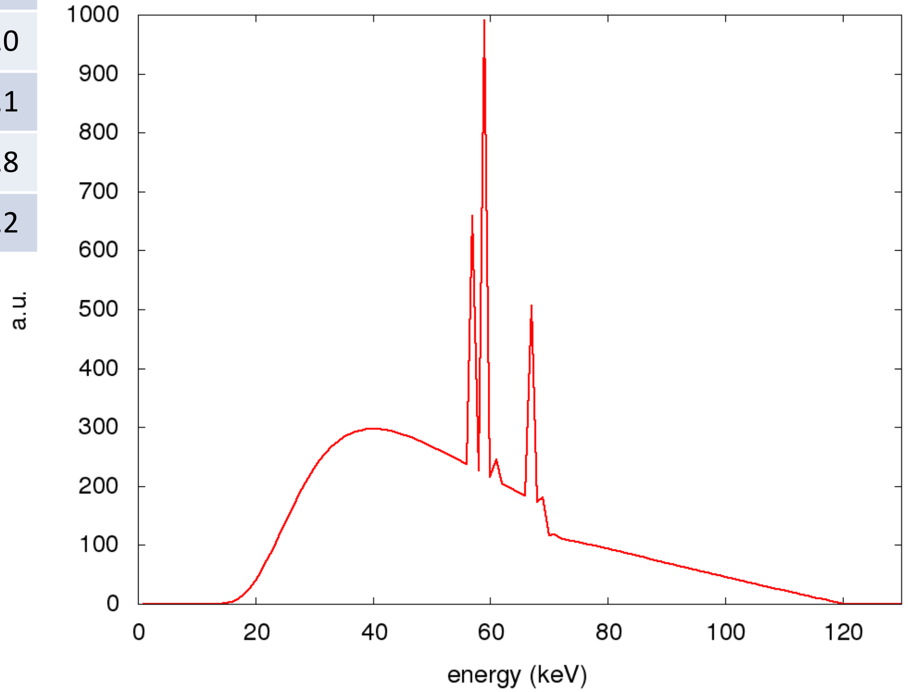


X-rays are impinging on the detector from the top (perpendicularly to the red board)

Silicon & edge-on illumination: advantages

1) Increased attenuation efficiency, thanks to the deeper active area:

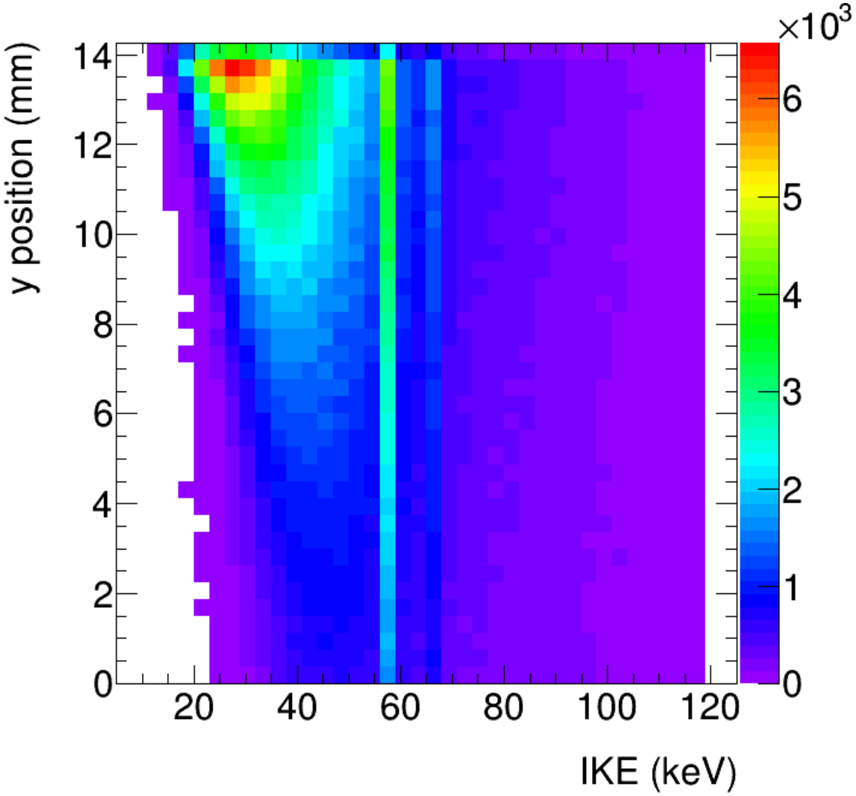
Energy (keV)	Face-on absorption	Edge-on absorption
20	40.5	100.0
40	7.8	90.0
60	3.7	66.1
80	2.6	51.8
100	2.1	45.2



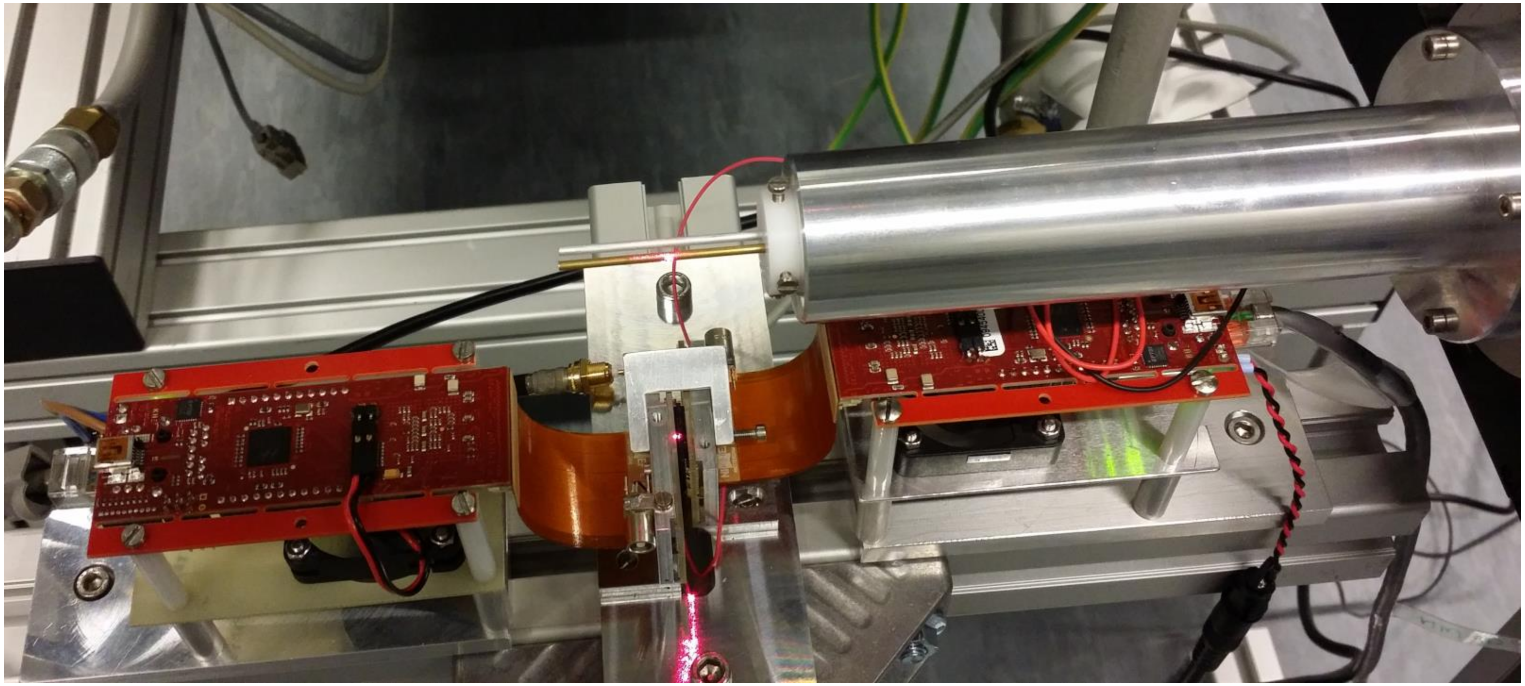
Silicon & edge-on illumination: advantages

2) Energy discrimination due to the beam hardening phenomenon:

Deep layers of the detector see an energy spectrum with a relative component at high energies bigger than the original one

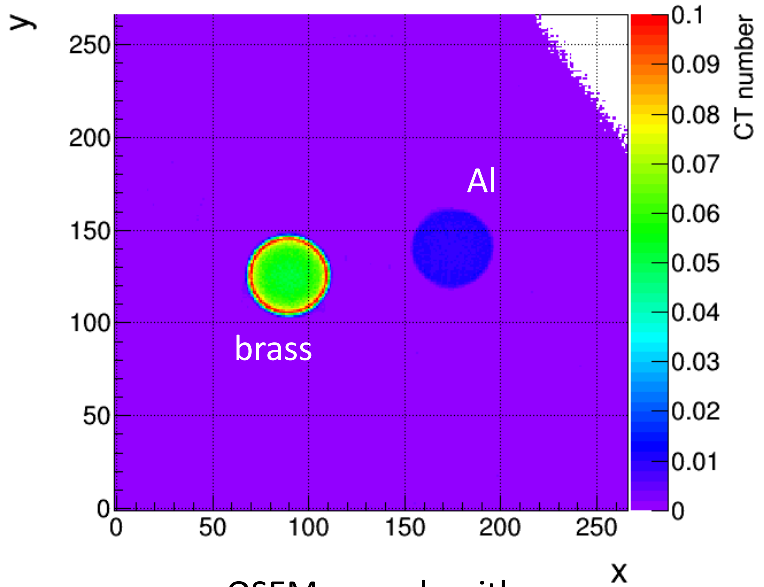


Experimental test: CT scan of 2 bars (Al and brass)

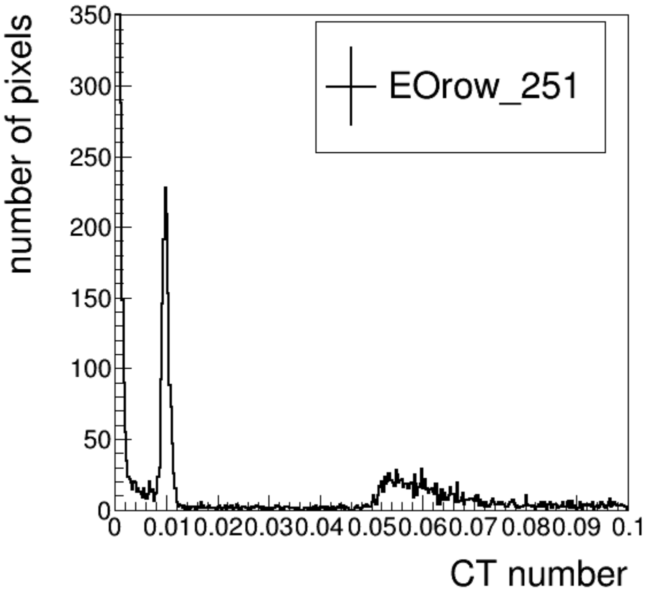


Tube voltage: 120 kV   Tube current: 0.8 mA   Expo time: 3 min/frame   Frame step: 2˚

CT scan results



OSEM reco algorithm



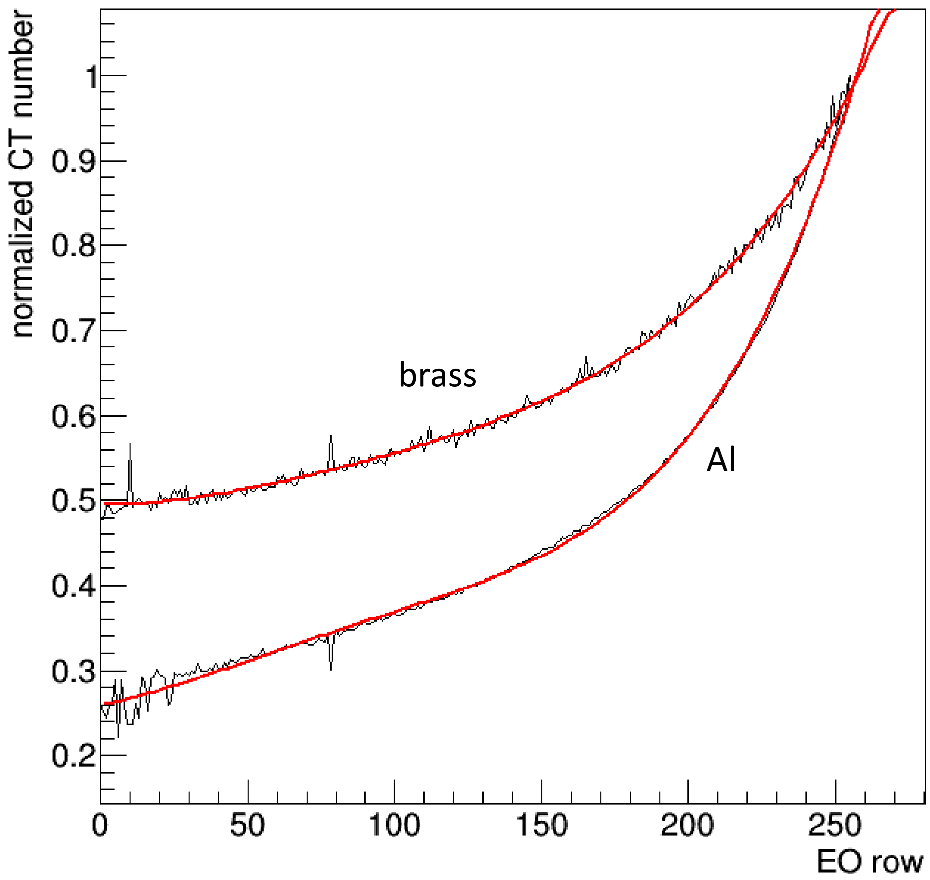
$$CT\ number = HU = \frac{\mu - \mu_{water}}{\mu_{water} - \mu_{air}}$$

CT scan results

The trend of the CT number shift depends on the shape of the energy spectrum in input to the detector

⇓

Theoretically, it is possible to discriminate between different atomic numbers and material densities



Reconstruction with the Astra toolbox

Home / Browse / ASTRA Tomography Toolbox

ASTRA Tomography Toolbox

A high-performance GPU MATLAB toolbox for 2D and 3D tomography

Brought to you by: eureka3, wjpalenstijn

Astra Tomography Toolbox:
platform developed by iMinds-Vision Lab of the University of Antwerp with the contribution of CWI (Amsterdam).

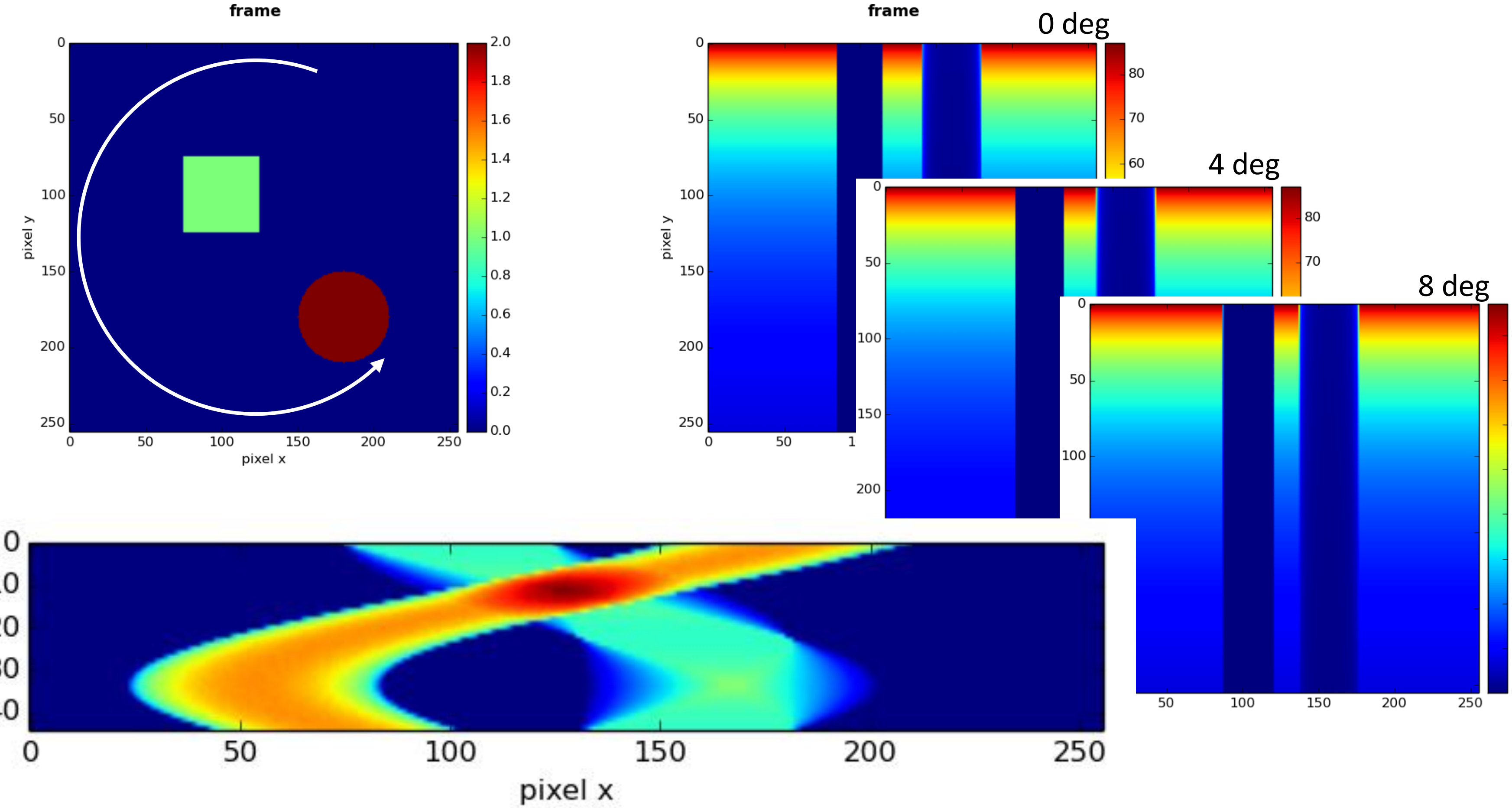
Centrum Wiskunde & Informatica

<u>AIM</u>:
To build a reco algo that takes into account the attenuation by the previous layers and that exploits the energy dependence of the attenuation coefficient

References:

- W. Van Aarle, W J. Palenstijn, J. De Beenhouwer, T. Altantzis, S. Bals, K. J. Batenburg, and J. Sijbers, "The ASTRA Toolbox: a platform for advanced algorithm development in electron tomography", Ultramicroscopy, vol. 157, pp. 35–47, (2015)
- W. J. Palenstijn, K J. Batenburg, and J. Sijbers, "Performance improvements for iterative electron tomography reconstruction using graphics processing units (GPUs)", Journal of Structural Biology, vol. 176, issue 2, pp. 250-253, (2011)

Intermezzo: the sinogram



A custom iterative algorithm

Iterative algorithm:

guess matrix: x^k

↓

For all the angles used in the CT scan:

- **forward-projection:** $\mathrm{F}(x^k)$

  ↓

- **difference with real data*:** $\mathrm{p} - \mathrm{F}(x^k) = r^k$

↓

residuals sinogram: $s^k = \sum r^k$

↓

back-projection: $B(s^k) = u^k$

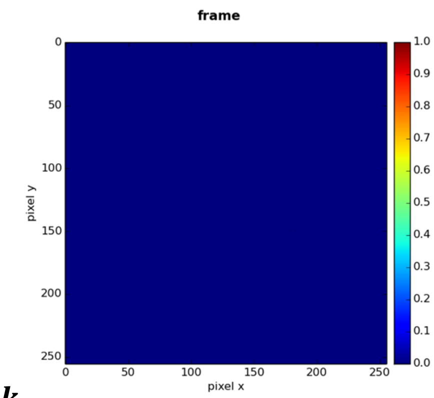
↓

new guess matrix: $x^k + \lambda u^k = x^{k+1}$ (→ back to guess matrix)

* After normalization for the DB

A custom iterative algorithm

Iterative algorithm:



guess matrix: x^k

↓

For all the angles used in the CT scan:

forward-projection: $\mathrm{F}(x^k)$

↓

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A custom iterative algorithm

Iterative algorithm:

guess matrix: $\boldsymbol{x}^{k}$

For all the angles used in the CT scan

forward-projection: $\mathbf{F}(\boldsymbol{x}^{k})$

Forward projector:

$$I_{j,n}(\bar{x}) = \int I_{0,j}(E)\, e^{-\left(W \sum_l \mu_l(E) \bar{x}_l\right)_j} L_n(E)\, A(E)\, dE$$

Attenuation by the sample

where the loss $L_n(E)$ due to the previous layers and the attenuation $A(E)$ by the considered layer are

$$L_n(E) = e^{-\mu_{SiTot}(E) d_p n} \quad A(E) = 1 - e^{-\mu_{SiPE}(E) d_p}$$

new guess matrix: $\boldsymbol{x}^{k} + \lambda \boldsymbol{u}^{k} = \boldsymbol{x}^{k+1}$

* After normalization for the DB

A custom iterative algorithm

Iterative algorithm:

guess matrix: x^k

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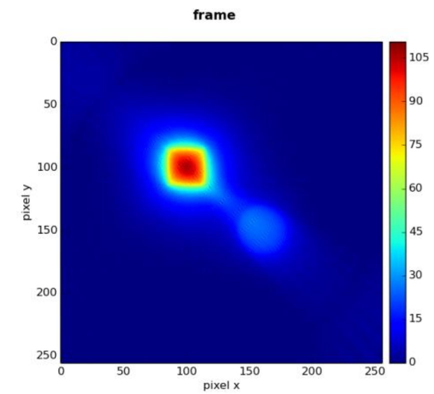
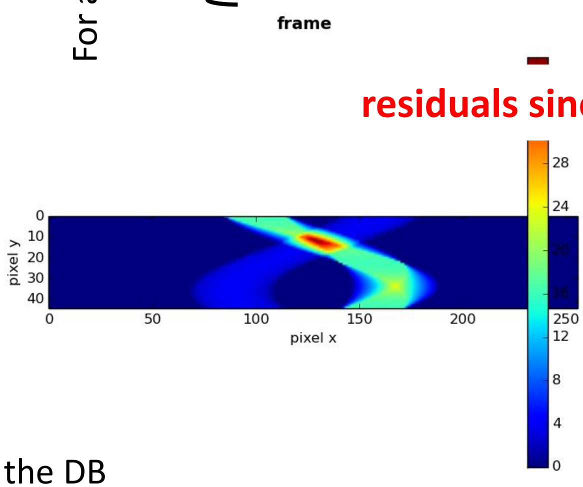
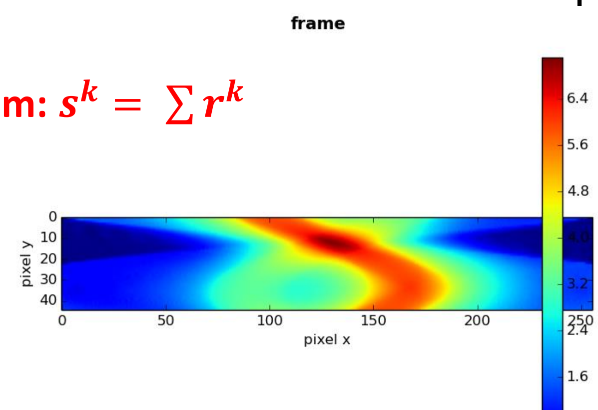
For all the angles used in the CT scan







Iteration 10

* After normalization for the DB

A custom iterative algorithm

Iterative algorithm:

angles used

CT scan

Backprojector:

$$\Delta x_{elem,i} = \frac{\sum_{j,n} \omega_{i,j}\ \tilde{\mu}_{elem,n}\ \tilde{r}_{j,n}}{\left(\sum_j \omega_{i,j}\right)\left(\sum_n \tilde{\mu}_{elem,n}\right)}$$

where

$$\tilde{\mu}_{elem,n} = \frac{\int I_0(E)\ \mu_{elem}(E)\ A(E)\ L_n(E)\ dE}{\int I_0(E)\ A(E)\ L_n(E)\ dE}$$

taken from the SIRT (Simultaneous Iterative Reconstruction Technique):

$$\Delta x_{elem,i} = \frac{\sum_{j,n} \omega_{i,j}\ r_{j,n}}{\sum_j \omega_{i,j}}$$

back-projection: $B\left(s^k\right) = u^k$

new guess matrix: $x^k + \lambda u^k = x^{k+1}$

* After normalization for the DB

A custom iterative algorithm

Iterative algorithm:

guess matrix: x^k

↓

For all the angles used in the CT scan:

- **forward-projection:** $F(x^k)$
- ↓
- **difference with real data*:** $p - F(x^k) = r^k$

↓

residuals sinogram: $s^k = \sum r^k$

↓

back-projection: $B(s^k) = u^k$

↓

new guess matrix: $x^k + \lambda u^k = x^{k+1}$ (→ back to guess matrix)

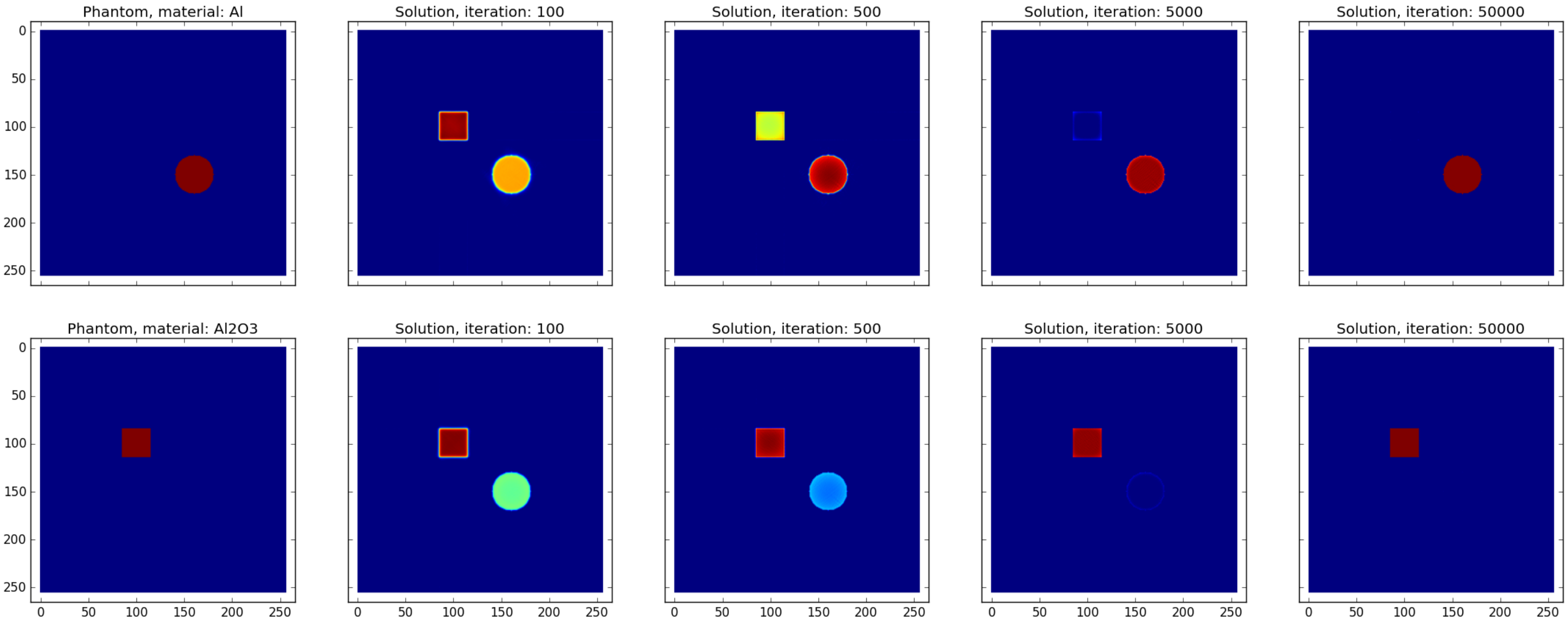
* After normalization for the DB

Nikhef

INFIERI

A custom iterative algorithm

Example: aluminium (Al) and aluminium oxide (Al2O3)



Conclusions

- Additional (small) energy information provided with the new geometry

- Custom reconstruction algorithm needed: work in progress
- Feasibility proved - still some work to be done
- As it is now, the algo is not practical:
  - slow convergence for too similar materials and
  - not possible to apply this method to too different materials

- Interesting algo for polychromatic problems where the detector has limited energy-resolving capabilities

Aknowledgments

All my gratitude to **Nicola Viganó** and **Willem Jan Palenstijn** (and **Joost Batenburg**), for sharing their knowledge on the topic and supporting me in the reconstruction algorithm development.

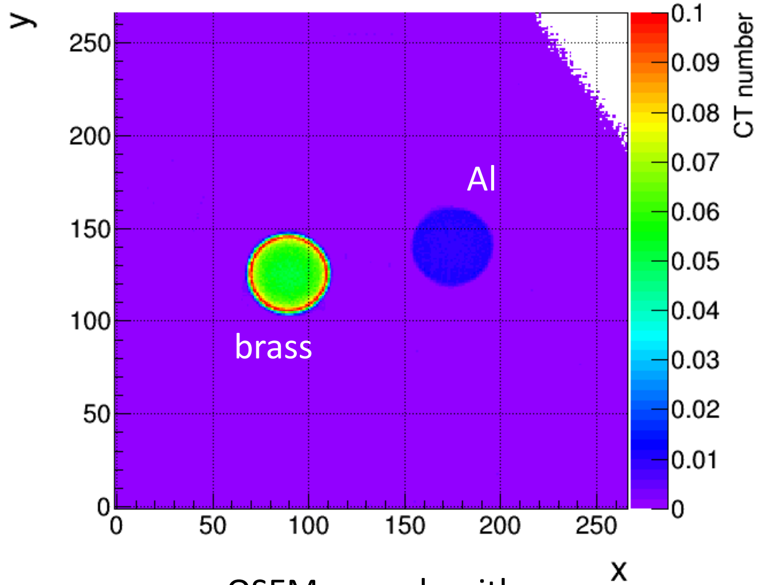
Thanks for your kind attention

Questions?

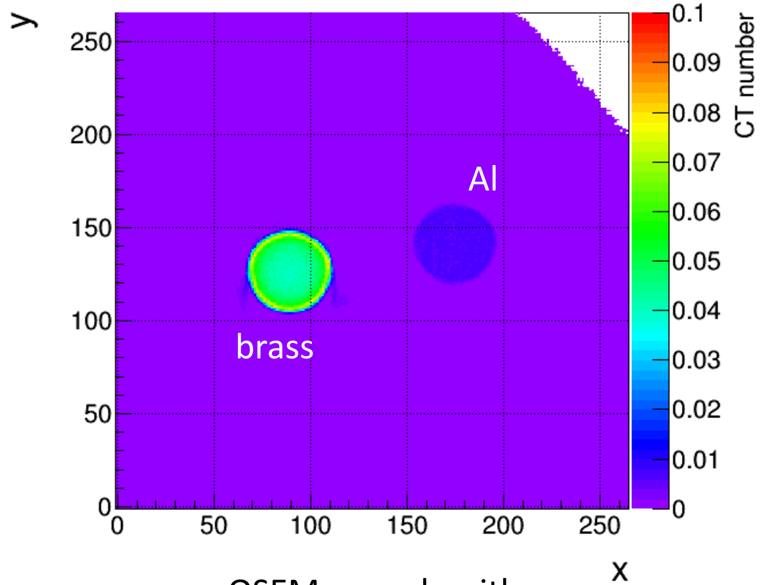
The research leading to these results has received funding from the People Programme (Marie Curie Actions) of the European Union’s Seventh Framework Programme FP7/2007-2013/ under REA grant agreement n° [317446] INFIERI "INtelligent Fast Interconnected and Efficient Devices for Frontier Exploitation in Research and Industry"

BACKUP SLIDES

Results



OSEM reco algorithm
EOrow 251
(layer 4)



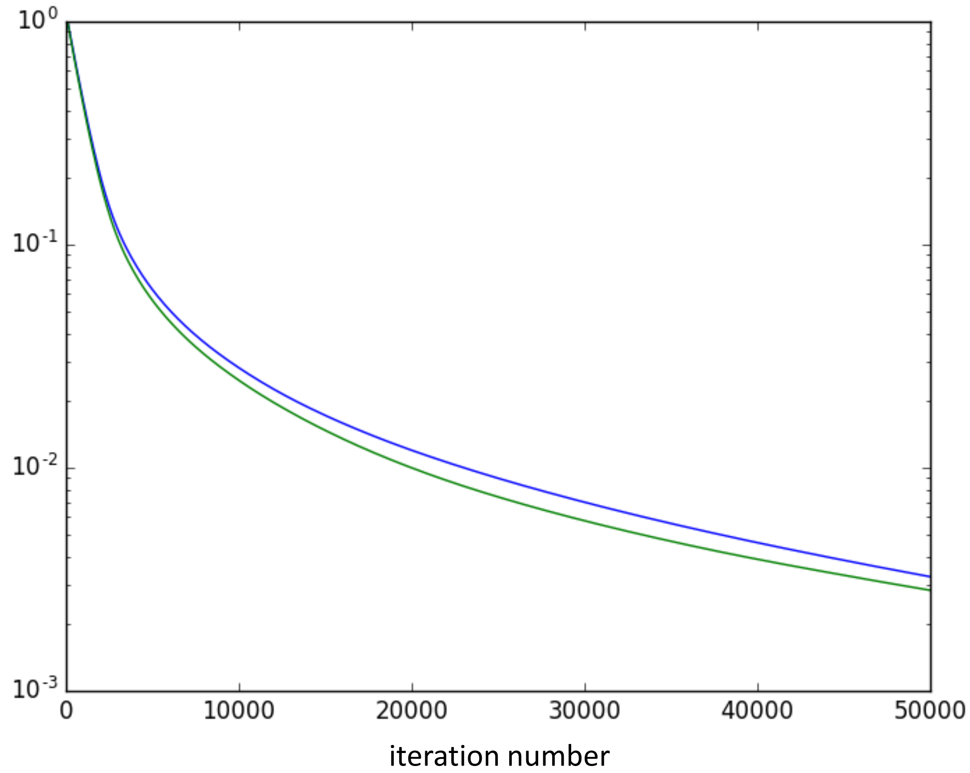
OSEM reco algorithm
EOrow 205
(layer 50)

OSEM = Iterative algorithm which performs better than FBP (Filtered Back Projection)

A custom iterative algorithm

Example: aluminium (Al) and aluminium oxide (Al2O3)

Norm of the error with respect to the real solution (i.e. my definition of the sample) for the two materials



Fluorescence in compound semiconductors

Table 1. K- and L- edges above 0.1keV for different detector materials used for photon detection. α_1 and α_2 are the energies of the generated fluorescence photons. The mean free path for the generated fluorescence photons ($d_{\alpha1}$ and $d_{\alpha2}$) is also indicated. ω_K is the fluorescence yield [8].

	Z	*K-edge [keV]*	*L1-edge [keV]*	*L2-edge [keV]*	*L3-edge [keV]*	α_1 [keV]	α_2 [keV]	$d_{\alpha1}$ [μm]	$d_{\alpha2}$ [μm]	ω_K
Si	14	1.839	0.150	0.100	0.100	1.74	1.739	11.86	11.86	0.041
Ga	31	10.367	1.298	1.142	1.115	9.25	9.225	40.62	40.28	0.505
Ge	32	11.110	1.426	1.259	1.228	9.89	9.856	50.85	50.40	0.548
As	33	11.867	1.527	1.359	1.323	10.54	10.508	15.62	15.47	0.566
Cd	48	26.711	4.018	3.727	3.538	23.17	22.984	113.2	110.7	0.836
Te	52	31.814	4.939	4.612	4.341	27.44	27.202	59.32	57.85	0.873

Review of hybrid pixel detector readout ASICs for spectroscopic X-ray imaging

R. Ballabriga, J. Alozy, M. Campbell, E. Frojdh, E. H. M. Heijne, T. Koenig, X. Llopart, J. Marchal, D. Pennicard, T. Poikela, L. Tlustos, P. Valerio, W. Wong, M. Zuber