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Background

Spectral X-ray Computed Tomography (CT) is a promising technology for non-destructive testing, medical imaging and security inspection of luggage and cargo. Taking advantage of **energy-dependent material information** (attenuation coefficients) and **energy-resolved measurements** (photon counting detector), spectral CT can enable **material decomposition** and enhance imaging capabilities.

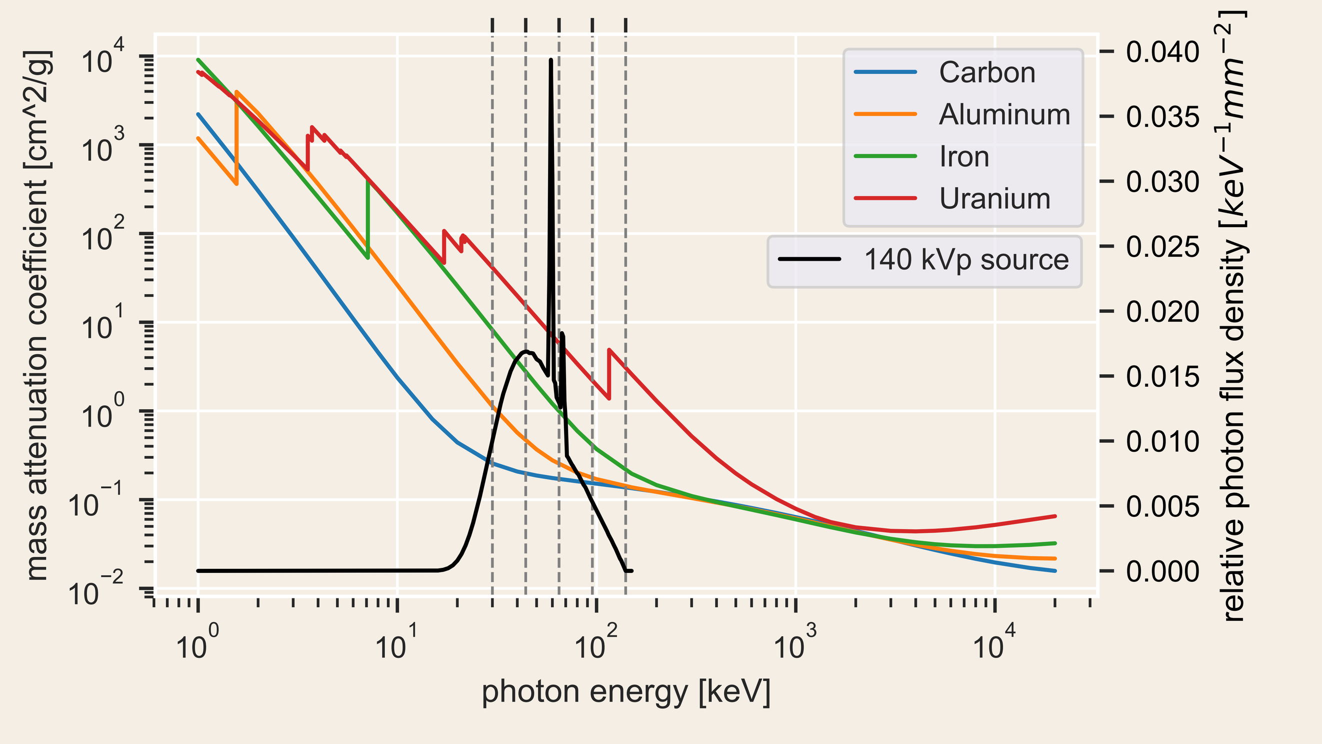

Figure 1: Mass attenuation coefficients $m(e)$ for different elements and a typical source spectrum. Vertical dashed lines represent 4 energy bins. Data from NIST [4].

Spectral X-ray CT measurement model

We decompose the linear attenuation coefficient $\mu(x, e)$ into an N-material basis

$$\mu(x, e) = \sum_{k=1}^{N} \rho_k m_k(e) \chi_k(x) \tag{1}$$

where ρ_k, $m_k(e)$ and $\chi_k(x)$ is the density, mass attenuation coefficient and spatial support of each material respectively. Setting $\beta_k = \int_L \chi_k(x)\,dx$, the attenuation model becomes

$$\bar{y}(\boldsymbol{\beta})_b = y_0 \int_0^\infty p_S(e) D_b(e) \exp\left\{-\sum_{k=1}^{N} \rho_k m_k(e) \beta_k\right\} de \tag{2}$$

where y_0 is the initial intensity, p_S is the normalised source spectrum and D_b the detector sensitivity for an energy bin b. The b^{th} energy bin measurements are modelled as a Poisson process $y_b \sim P\left(\bar{y}(\boldsymbol{\beta})_b\right)$ We implement the model in Python using the ASTRA [1] and ODL [3] libraries and validate with Monte-Carlo simulations using Geant4 [2].

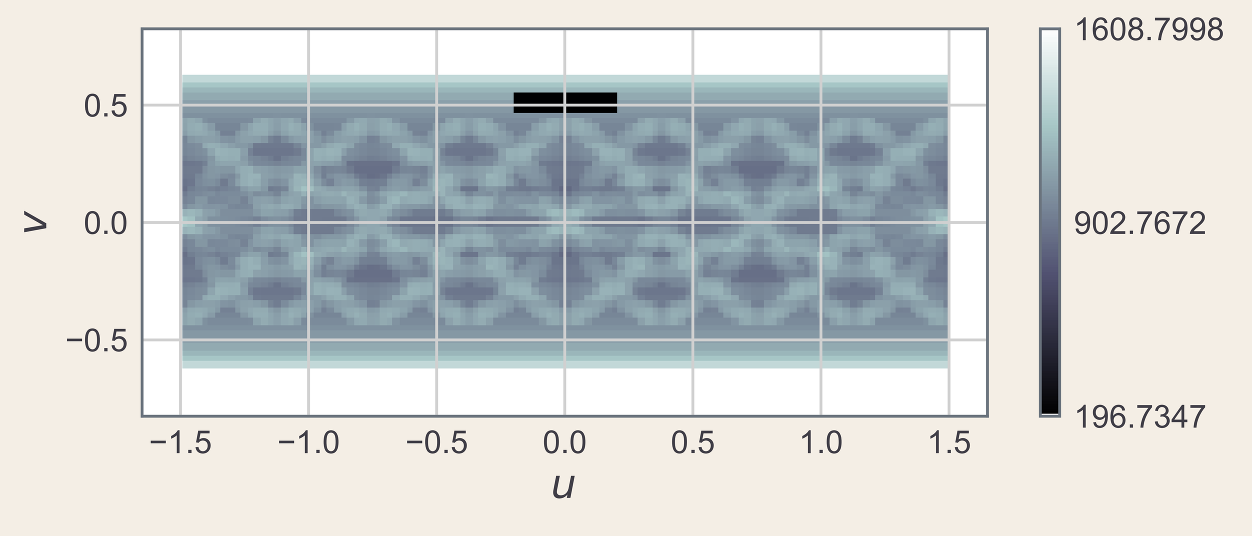

Figure 2: Simulated photon count at energy bin 60-70 keV for a SiO_2 target with a lead glass inhomogeneity using the attenuation model.

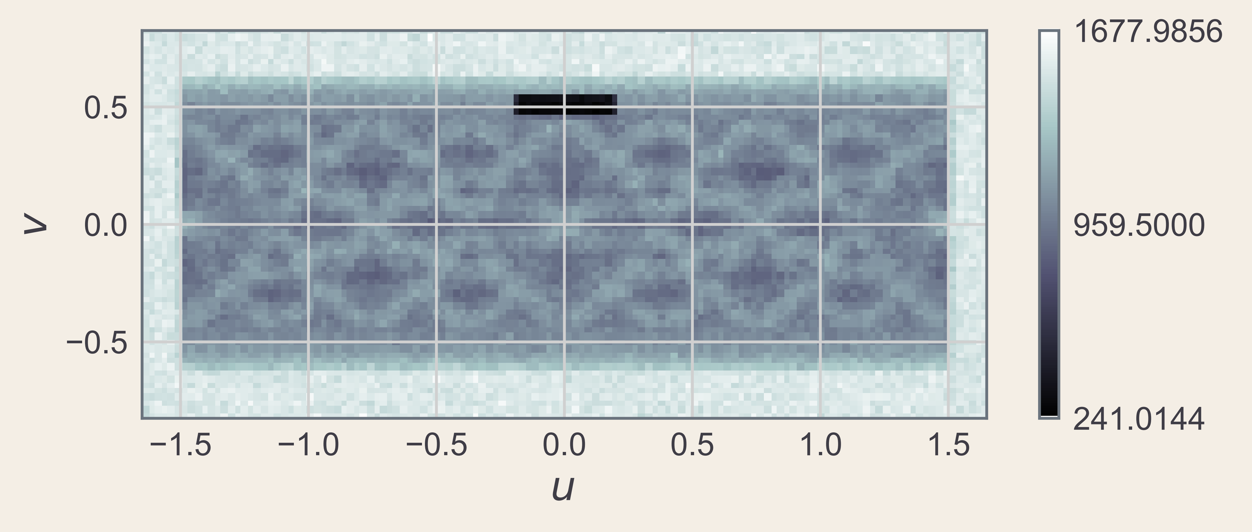

Figure 3: Corresponding Geant4 MC simulation of the full physics (includes scattering effects).

Inversion and imaging

We formulate the inverse problem as a two-step process by splitting material decomposition (energy domain) and imaging (spatial domain).

1. From the **photon count histogram** data we recover each material β_k by minimization of the Kullback-Leibler divergence

$$D_{KL}(\mathrm{y}\|\bar{\mathrm{y}}) = \mathrm{y}^T \log\left(\frac{\mathrm{y}}{\bar{\mathrm{y}}}\right) + 1^T(\bar{\mathrm{y}} - \mathrm{y}) \tag{3}$$

   We optimize using a non-linear ADMM method and regularize via early termination or by the addition of a penalty term.
2. Having recovered β_k, we proceed to solving N **binary imaging problems** using the discrete tomography algorithm DART combined with unsupervised segmentation (Morphological Active Contours).

Example results

In this example we decompose and image 3 materials inside a 3D target volume consisting of a 20^3cm^3 box made of Carbon, with an Uranium ellipsoid placed inside and an Iron outer shell of thickness 0.3cm. We produce synthetic data for 20 **angles and** 8 **energy bins** in the interval [80, 190]keV, with a 190kVp source and $y_0 = 10^{12}$ initial intensity.

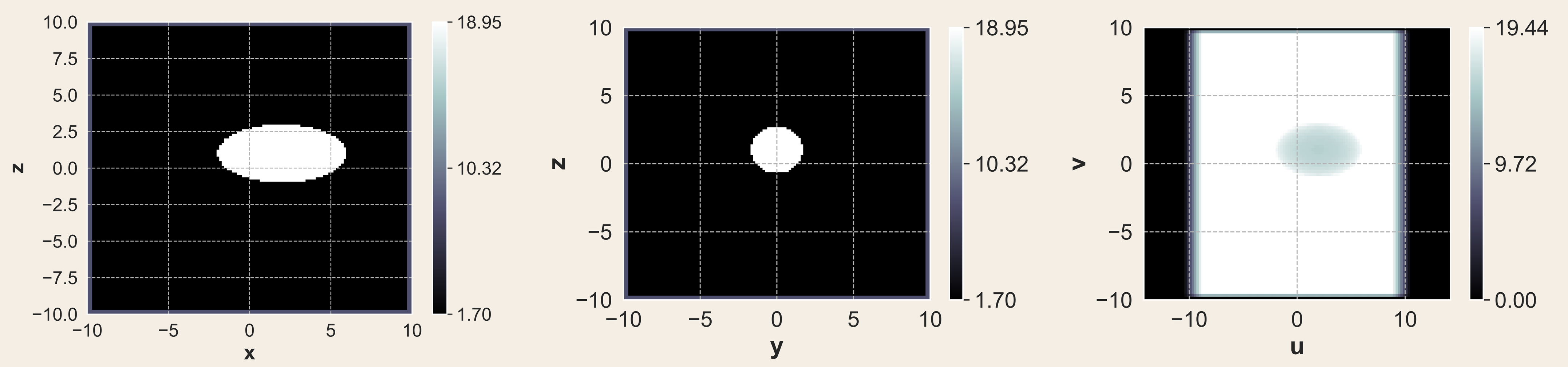

Figure 4: Left: y-slice of the phantom density consisting of 3 materials: Uranium, Carbon, Iron. Middle: x-slice of the phantom density. Right: Simulated β_k for Carbon and angle $\theta = 0$.

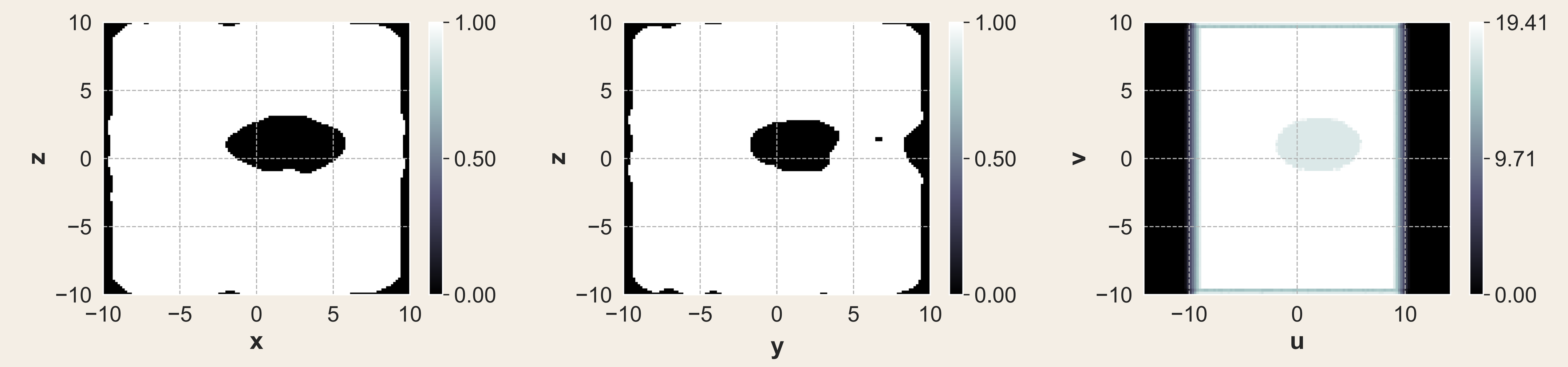

Figure 5: Reconstructions. Left: y-slice of Carbon spatial support. Middle: x-slice of Carbon spatial support. Right: Reconstructed β_k for Carbon and angle $\theta = 0$.

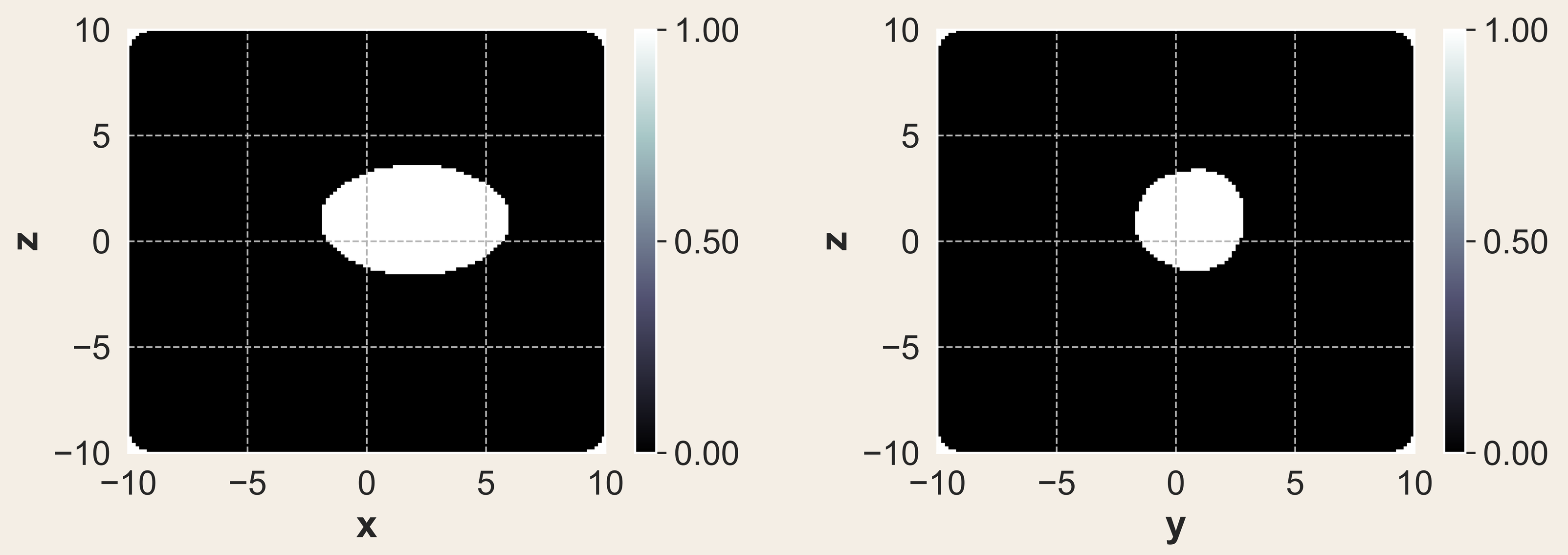

Figure 6: Reconstructions of spatial support of Uranium. Left: y-slice. Right: x-slice.

Outlook and challenges

Our results show that spectral CT can be a valuable tool for nuclear element detection. We are currently further investigating

- **Optimizing the measurement acquisition process** for nuclear element detection.
- Using **Deep Learning** tools to improve reconstruction quality and automate the detection task.
- Testing more realistic cases (e.g. cargo screening requires MeV energies).

Challenges include the application of our method when many materials are present and the inclusion of scattering effects.

Acknowledgements and references

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