AI-accelerated SAXS tensor tomography by directional dark-field imaging

PhD Project

May 26, 2026

We announce the opening of a PhD Project starting in October 2026. The project is funded for three years by MIAI. This is a collaboration between three laboratories: STROBE/IAB (Grenoble, France), CREATIS (Lyon, France), and CEA (IRIG MEM, Grenoble, France).

Keywords X-ray Dark-field Imaging, Small Angle X-ray Scattering, Computational X-rays, Image Reconstruction, Deep Learning.

Overview This doctoral project aims to dramatically reduce the acquisition time and computational requirements of small-angle X-ray scattering (SAXS) tensor tomography (SAXS-TT) by using directional dark-field (DDF) tensor tomography enhanced with artificial intelligence at every stage of the measurement and reconstruction pipeline. Because DDF is a full-field technique, we will observe a drastic acquisition time reduction (partly compensated by the number of distances of propagation that be lower than the number of voxels in the image). By integrating AI-driven optimisation of encoding masks, intelligent modelling of forward problems and advanced tensor reconstruction algorithms, we can achieve high-quality nanoscale structural characterisation with significantly reduced experimental overheads.

Workplan The first phase of the project will focus on implementing forward models that are differentiable (e.g. in Pytorch) and that can be integrated in training loops. Our models should predict realistic measurements of directional dark-field tensor tomography given the nanostructure tensors of the sample. Validation experiments will be performed using our Industrial partner devices (Xenocs).

The second phase of the project will aim to develop artificial intelligence methods for jointly estimating convolution kernels and object absorption from directional dark-field (DDF) measurements in the projection domain. The challenge lies in the fact that different spatial locations in the sample exhibit distinct scattering characteristics, resulting in different convolution kernels. Therefore, our algorithms will draw inspiration from blind deconvolution and non-negative matrix factorisation techniques. In practice, we will consider physics-aware neural networks that encode physical constraints on deconvolution kernel structure, as derived from X-ray scattering theory. Specifically, we will consider unrolled iterative algorithms that alternate between kernel estimation and deconvolution steps [5]. Unlike most blind deconvolution methods, we will leverage prior knowledge of object densities common to all DDF measurements obtained at different distances.

Then, we will optimize the encoding masks. Masks optimized for phase contrast imaging [4, 2], are not necessarily optimal for DDF. Therefore, we will formulate mask optimization as a machine learning problem, maximising the quality of images reconstructed from DDF while minimising acquisition time. We will also develop deep learning architectures specifically designed for tensor field reconstruction [3, 1], where we implement learned priors that encode physical constraints (positive definiteness, smoothness) on scattering tensors.

The final phase of this PhD project will be dedicated to the practical implementation of the developed methods on the newly built MusitoX multimodal X-ray imaging platform. This validation stage will yield the first experimental results on real use cases, bridging the gap between theoretical frameworks and actual imaging performance. This work will be carried out in close collaboration with our consortium partners, ensuring cross-disciplinary synergy and rigorous benchmarking of the proposed approaches.

Skills interdisciplinary skill set throughout the PhD project. They will gain a deep understanding of X-ray physics, particularly the principles of Small Angle X-ray Scattering and Dark-field Imaging, along with expertise in both laboratory-based and synchrotron X-ray imaging techniques. A core focus will be on mastering computational imaging, specifically the theory and practice of structured illumination, including the underlying mathematics of compressive sensing and multiplexing. The candidate will become proficient in tomographic reconstruction methods, learning to develop and apply algorithms to create 3D volumetric images from projection data while specifically addressing complex physical artifacts.

In parallel, the candidate will acquire advanced data science and machine learning expertise. This includes developing and applying deep learning models, such as convolutional neural networks, for critical tasks like image reconstruction and denoising extremely low-signal data corrupted by Poisson-Gaussian noise. They will gain hands-on experience with self-supervised and unsupervised learning paradigms, which are essential for training models when ground-truth data is scarce. The project will also hone their skills in sophisticated signal and image processing, spectral analysis, and the fusion of multi-modal data. Computationally, the candidate will become highly proficient in scientific programming with Python, using key libraries like NumPy, SciPy, and scikit-learn, and will master machine learning frameworks such as PyTorch or TensorFlow for algorithm development.

How to apply? Please send a curriculum, a motivation letter, and your academic records before **June 19th** to emmanuel.brun@inserm.fr, nicolas.ducros@creatis.insa-lyon.fr, nicola.vigano@cea.fr.

References

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