A Physics-guided Implicit Neural Representation for Streak Reduction in X-ray Dark-field CT

Objective – X-ray dark-field computed tomography (DFCT) enables functional lung imaging based on small-angle scattering, but image quality is typically limited due to streak artifacts. We propose an implicit neural representation (INR) that jointly encodes X-ray transmission, phase shift, and dark-field in the projection domain guided by a Talbot–Lau interferometer forward model, generating smoothed neural fields for enhanced DFCT reconstruction quality.

Motivation & Background – Human-scale dark-field computed tomography (DFCT) has recently been realized using a grating-based gantry prototype (Viermetz et al., 2022). This technique shows strong clinical potential; however, continuous rotation fundamentally complicates phase retrieval, often leading to pronounced streak artifacts (Viermetz et al., 2023; Schmid et al., 2023; Haeusele et al., 2023). Convolutional neural networks (CNNs) have shown promise for DFCT image enhancement, but training data scarcity and the prospective domain gap limits the applicability of supervised approaches (Kumschier et al., 2024). In contrast, implicit neural representations (INRs) are trained on a per-instance basis to learn a continuous mapping of spatial image coordinates to intensity values, sinusoidal representation networks (SIRENs) being particularly popular (Sitzmann et al., 2020). In this work, we introduce a physics-constrained neural field representing grating-based X-ray projections improving DFCT phase retrieval.

Methods – We modeled projection transmission T, phase shift ϕ, and dark-field D using a tri-head SIREN. For each projection, the corresponding stack of raw detector measurements (interferograms) was encoded via a lightweight CNN and resampled to match coordinate dimensions. This conditioned latent vector was concatenated with the image coordinates into a combined input for the INR. Given the air-scan mean intensity I, the phase of the fringe pattern Φ, and the fringe amplitude (visibility) V, interferometer physics were modeled via

$$y = TI + TIDV\cos(\Phi + \phi),$$

corresponding to a truncated Fourier series (Haeusele et al., 2024). We optimized the INR directly in measurement space using $m = 12$ stacked adjacent interferograms, equivalent to phase stepping across a full interferometer period (Viermetz et al., 2022). We trained the INR per projection using a hybrid loss, where L_{shot} enforces consistency with measured interferograms and L_{proj} weakly supervises (T, ϕ, D) using classical sliding-window phase retrieval (SPR) (Haeusele et al., 2023). Leveraging shared features and angular consistency, we adopted a sequential warm start, initializing each projection from the previous one with few refinement steps.

Results – Our model is evaluated on a human-scale grating-based DFCT scan comprising ventilated ex vivo porcine lungs within a thorax phantom as a clinical surrogate. The neural dark-field projections and corresponding Feldkamp–Davis–Kress (FDK) reconstruction are shown in **Fig. 1**, compared against a conventional SPR baseline. Across projections, our method substantially reduces noise and artifacts, particularly in low-contrast and edge regions where the baseline degrades due to cross-talk artifacts (Haeusele et al., 2024). This improvement is consistently reflected in the reconstructed DFCT volume, where our INR yields coherent structural features while strongly suppressing streaks. These results suggest that the low-rank structure of dark-field signals aligns well with the spectral bias of neural fields (Rahaman et al., 2019), enabling recovery of structurally consistent details from limited phase information.

Conclusion – Our work demonstrates a physics-guided neural representation for DFCT that improves reconstruction quality in a reliable, physically consistent, and self-supervised manner. Our model builds on and complements conventional phase retrieval for continuous-acquisition scans. Future work will focus on assessing hyperparameter robustness with varying samples and extending the framework to limited- or sparse-view angular representations ensuring rotational consistency and computational efficiency.

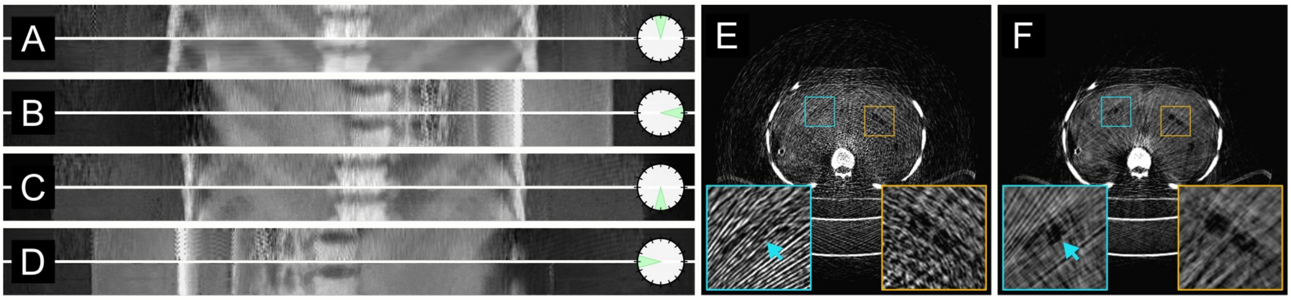

Figure 1: DFCT of porcine lungs inside of a thorax phantom. (A–D) Dark-field projections at 0°, 90°, 180°, and 270°, comparing classical SPR (top) and neural phase retrieval with our INR (bottom). (E) FDK reconstruction from SPR. (F) FDK reconstruction from the INR indicating recovered structural details at reduced noise and artifact levels.

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