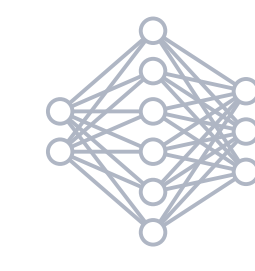
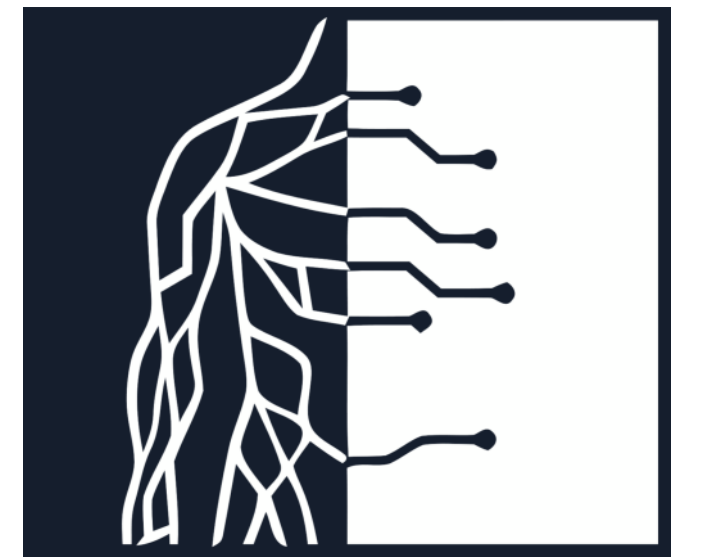


# A Physics-guided Implicit Neural Representation for Streak Reduction in X-ray Dark-field CT



SAIMI 2026



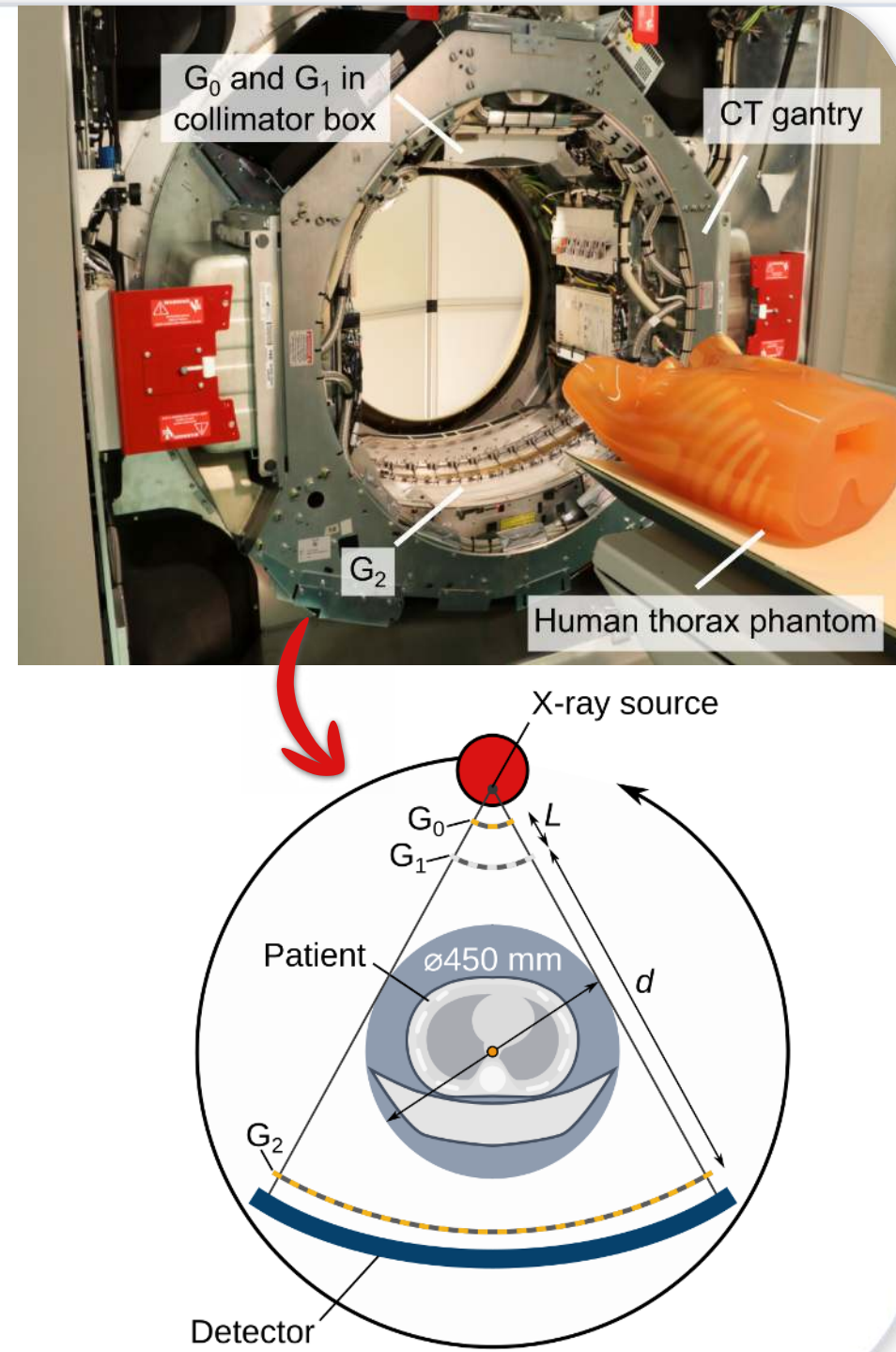
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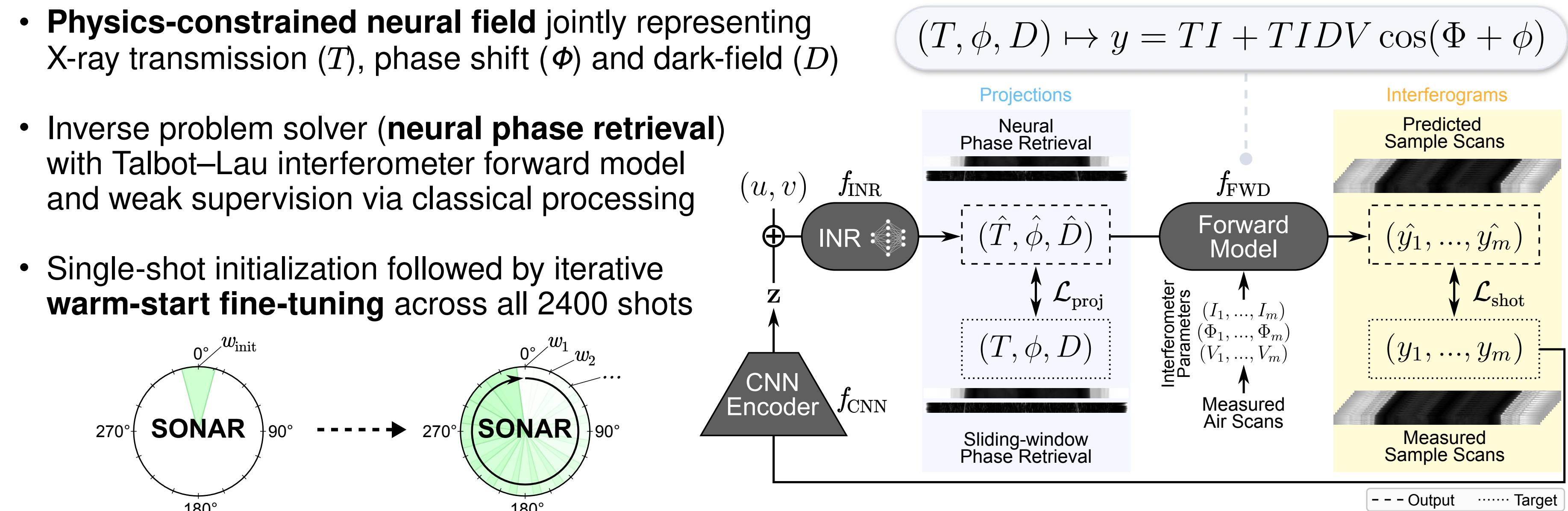
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## INTRODUCTION

- Human-scale X-ray dark-field computed tomography (DFCT) enables functional lung imaging [1]
- Reconstructions suffer from prominent streak artifacts due to limited phase sampling [2, 3]
- Implicit neural representations (INRs) recover regularized continuous fields from discretized data by mapping pixel coordinates  $u, v$  to image values  $I$  [4]:  
 $f_{\text{INR}} : (u, v) \mapsto I$

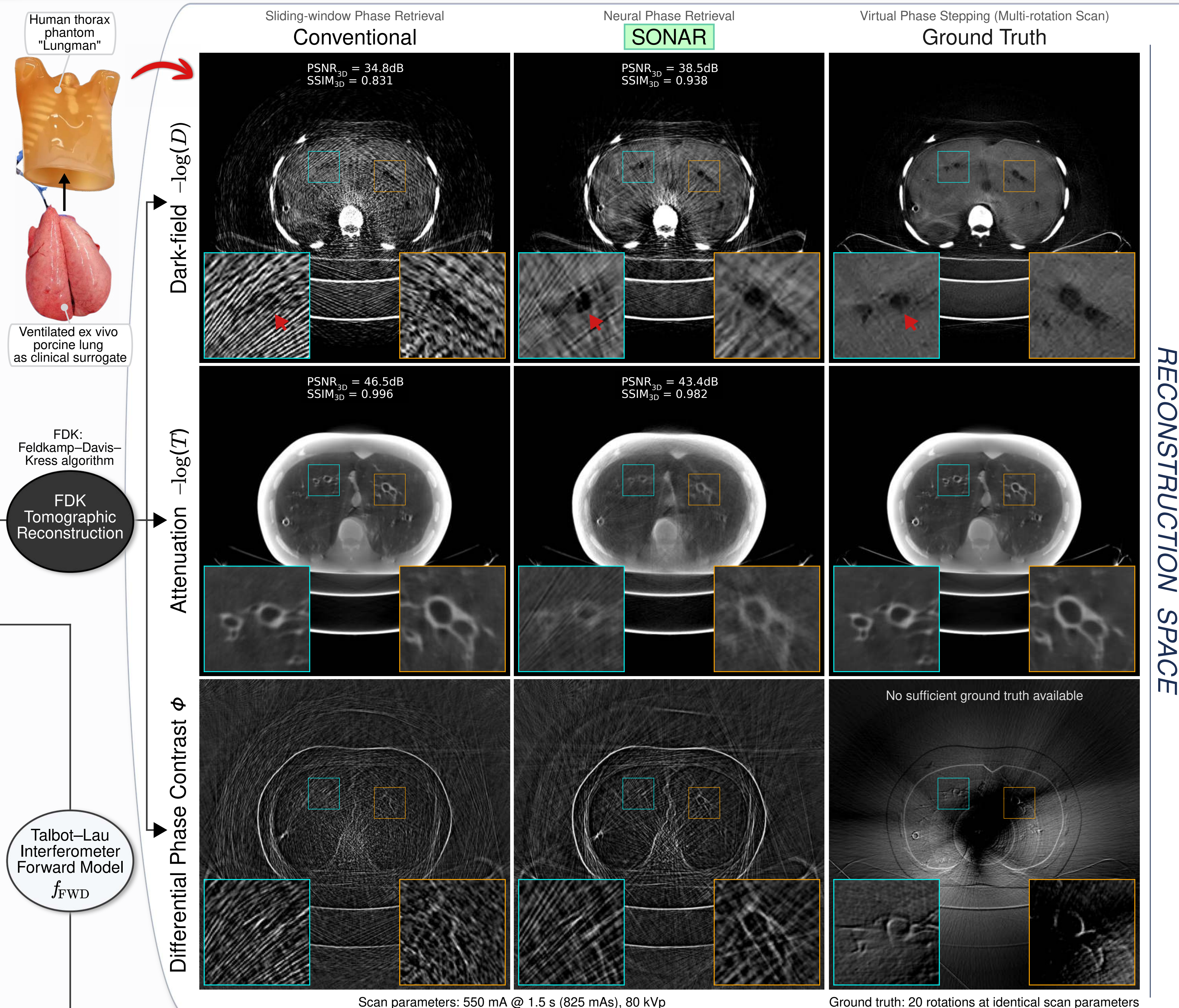
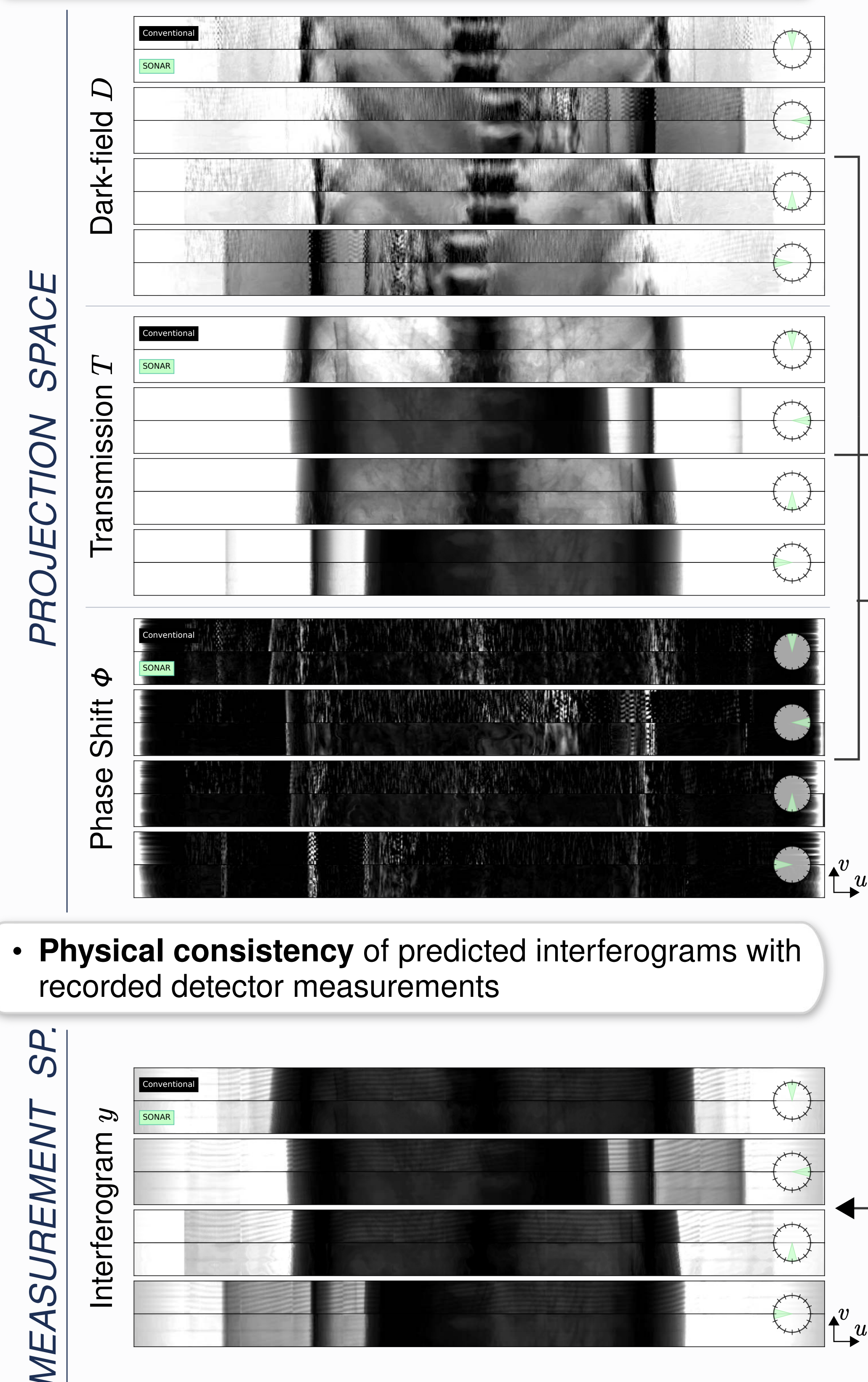


## SONAR: Shot-Optimized Neural Adaptive Representation



## RESULTS

- Improved dark-field projection quality
- Rotationally encoded X-ray projection contrasts
- Flexible neural field sampling for reconstruction



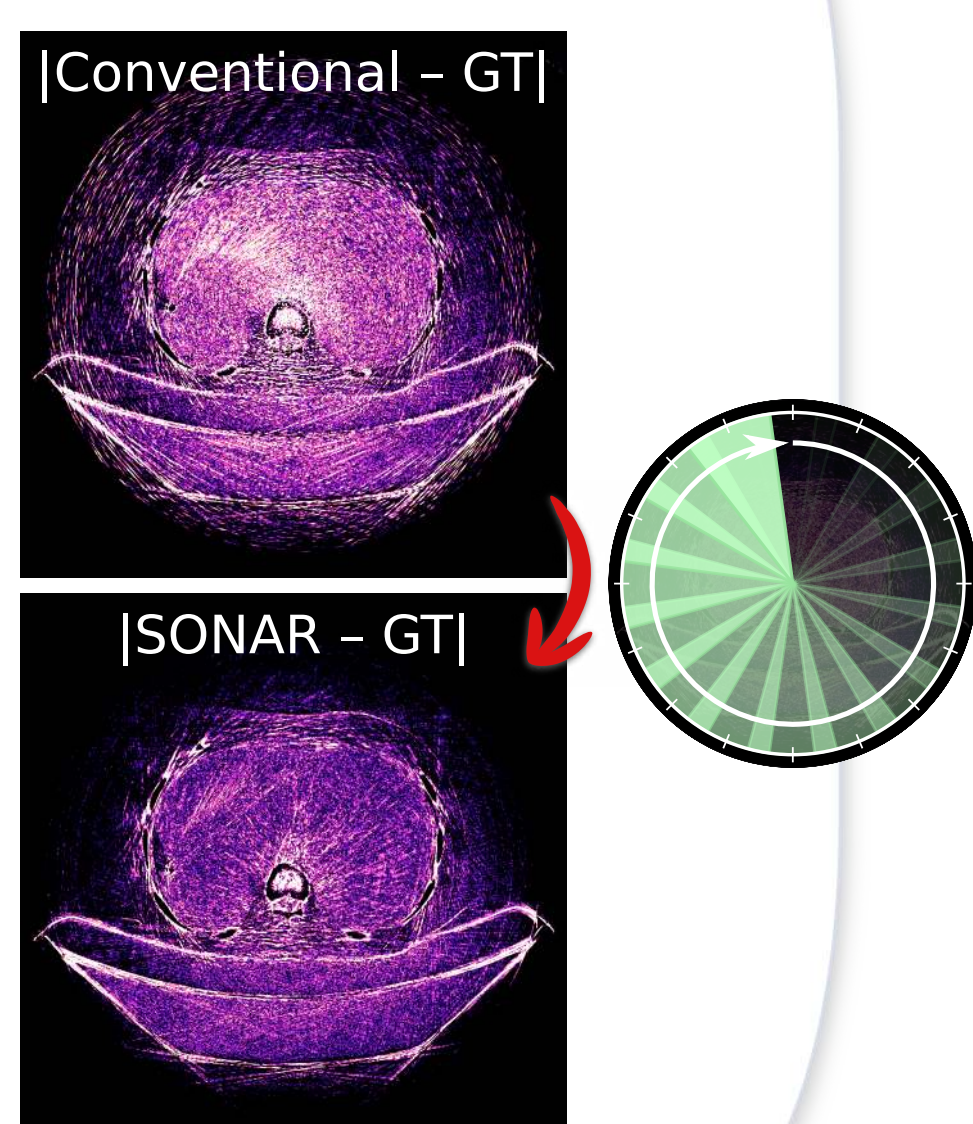
• Reduced DFCT artifacts and restored details  
• Physical plausibility across CT contrasts  
• Limited attenuation fidelity

**DFCT Metrics: Conventional → SONAR**  
PSNR<sub>3D</sub> (↑): 34.8 dB → 38.5 dB (+11%)  
SSIM<sub>3D</sub> (↑): 0.831 → 0.938 (+13%)

PSNR: Peak Signal-to-Noise Ratio. PSNR<sub>3D</sub> computed from axial volume. SSIM: Structural Similarity Index Measure. SSIM<sub>3D</sub> computed from axial volume.

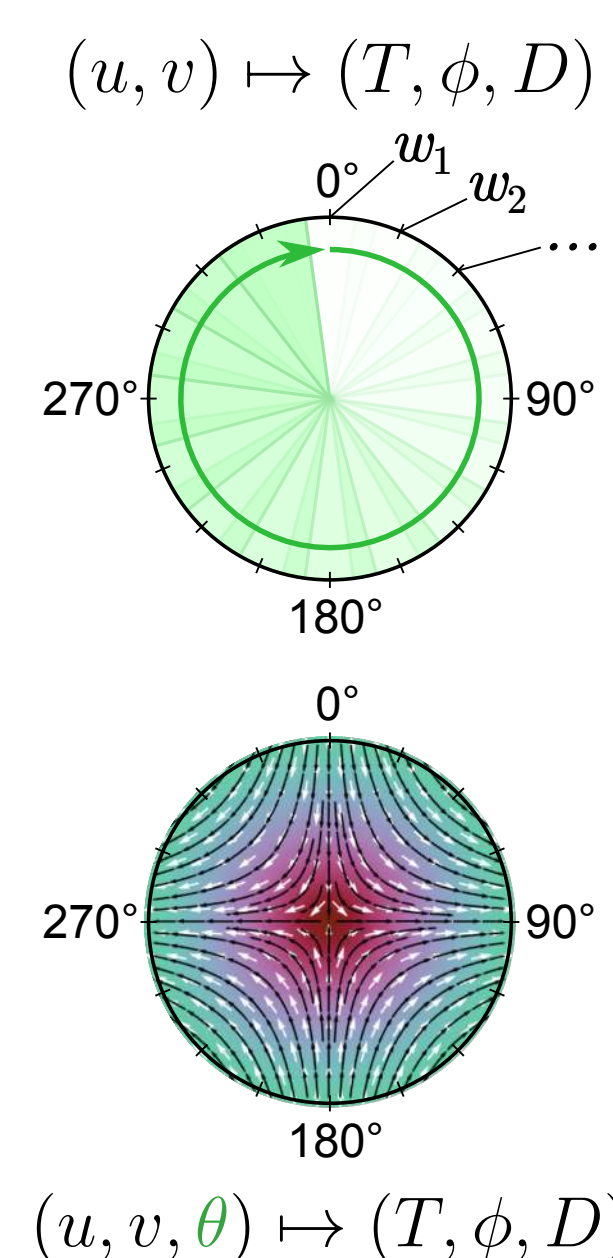
## CONCLUSION

- We present the first physics-guided neural phase retrieval model for feasible DFCT image quality
- Self-supervised and per-instance training mitigating the risk of hallucinations and omitting the need for ground truth
- Operation in the projection domain promotes flexible frameworks building explicitly on classical phase retrieval methods



## OUTLOOK

- Encoding angular dimension directly into the INR to facilitate training
- Generalization of hyperparameters across subjects and meta-learning
- Exploration of spectral bias modulation for regularization
- Application to other phase-sensitive X-ray imaging setups



## REFERENCES

- Viermetz et al. (2022). Development of the first Human-scale Dark-field Computed Tomography System. *PNAS*
- Schmid et al. (2023). Modeling Vibrations of a Tiled Talbot-Lau Interferometer on a Clinical CT. *IEEE TMI*
- Haeusele et al. (2024). Robust Sample Information Retrieval in Dark-Field Computed Tomography with a Vibrating Talbot-Lau Interferometer. *IEEE TMI*
- Sitzmann et al. (2020). Implicit Neural Representations with Periodic Activation Functions. *NeurIPS*

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