Ultra-Sparse View Reconstruction of CBCT Using an Adversarial Implicit Neural Representation

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TAKE-HOME MESSAGE: High-quality CBCT from only ~25 projections using adversarial Implicit Neural Representation (INR)

BACKGROUND

- Standard pelvic CBCT requires ~600 projections, leading to high imaging dose and longer acquisition times.
- Reduced projections cause streak artifacts and degrade image quality
- Implicit Neural Representations (INRs) and adversarial learning enable accurate reconstructions from very few projections.

AIM & WHAT WE DID

- **Aim:** Develop a patient-specific deep learning framework to reconstruct high-quality CBCT from ultra-sparse 2D projections with minimal loss of anatomical details
- Implemented a SIREN-based INR + adversarial (GAN) learning.
- Validated the method on prostate cancer patients.
- Compared reconstruction quality with conventional Feldkamp–Davis–Kress (FDK) using full CBCT (~600 projections) as the reference.

IMPACT

- ✓ Enables major reduction in imaging dose.
- ✓ Supports faster CBCT acquisition.
- ✓ Improves efficiency of IGRT workflows.
- ✓ Potential for broader clinical applications

CONTACT

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METHODS: OVERVIEW

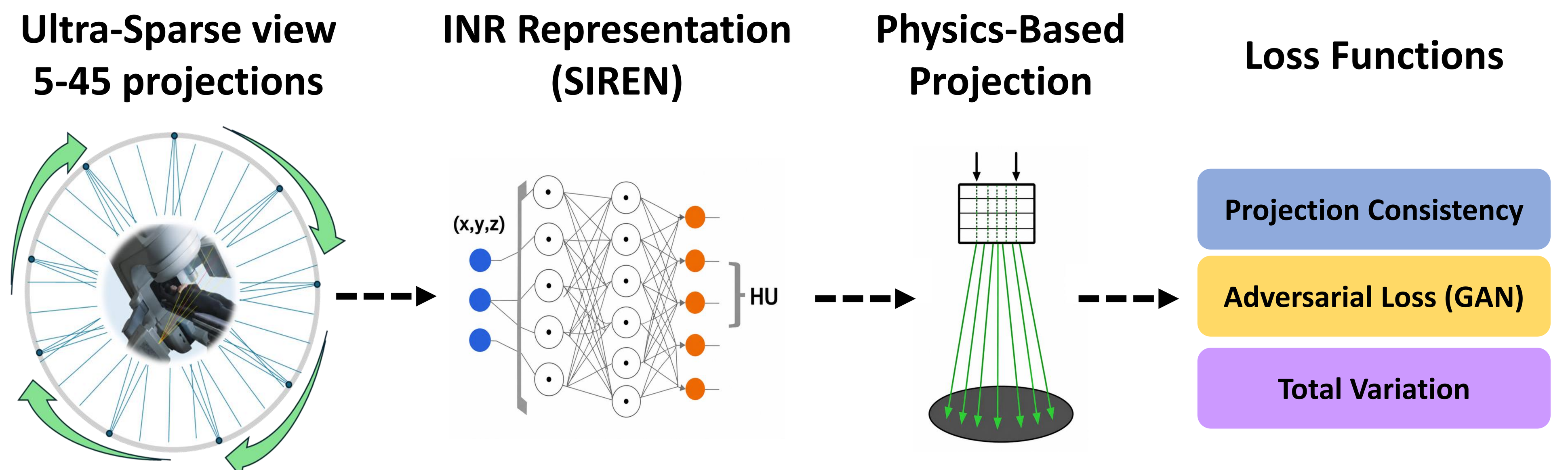

Figure 1: INR model training workflow

QUALITATIVE RESULTS

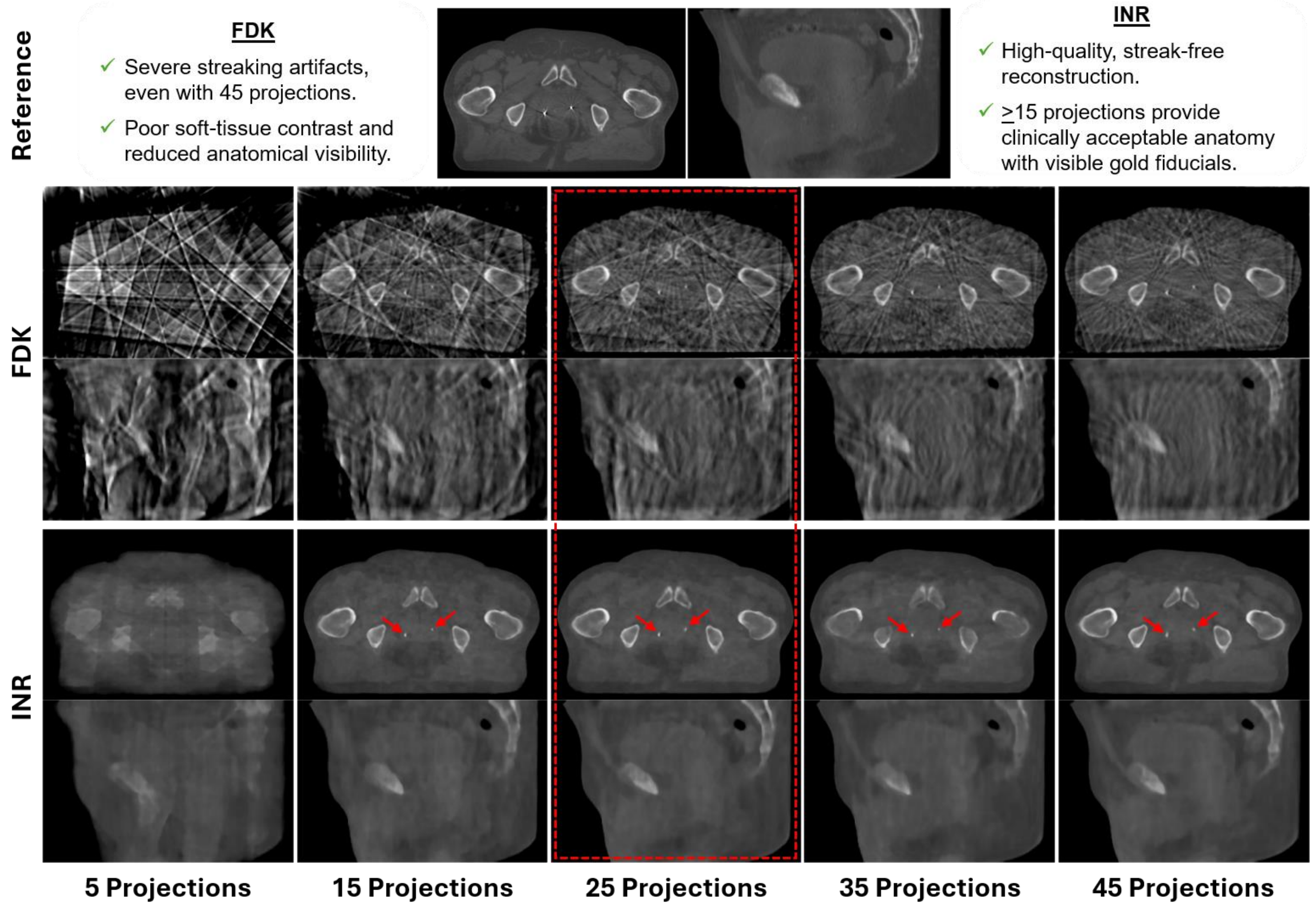

Figure 2: CBCT reconstructions comparing INR and FDK across different projection numbers.

QUANTITATIVE RESULTS

Table 1: Quantitative comparison of INR and FDK across different projection numbers.

Projections	FDK (Conventional)			INR (Adversarial)		
	SSIM ↑	PSNR(dB) ↑	MAE ↓	SSIM ↑	PSNR(dB) ↑	MAE ↓
5	0.22	12.8	231.4	0.70	25.4	70.5
15	0.36	17.7	129.7	0.89	32.4	31.4
25	0.47	18.4	90.9	**0.92**	**33.7**	**25.9**
35	0.54	22.0	70.6	**0.92**	**33.8**	**23.0**
45	0.59	22.8	59.9	**0.94**	**34.7**	**22.2**

Higher is better (SSIM, PSNR)

Lower is better (MAE)

Key results

- ✓ INR outperforms FDK across all sparsity levels.
- ✓ High-quality CBCT with >95% fewer projections.

METHODS: COMPARISON

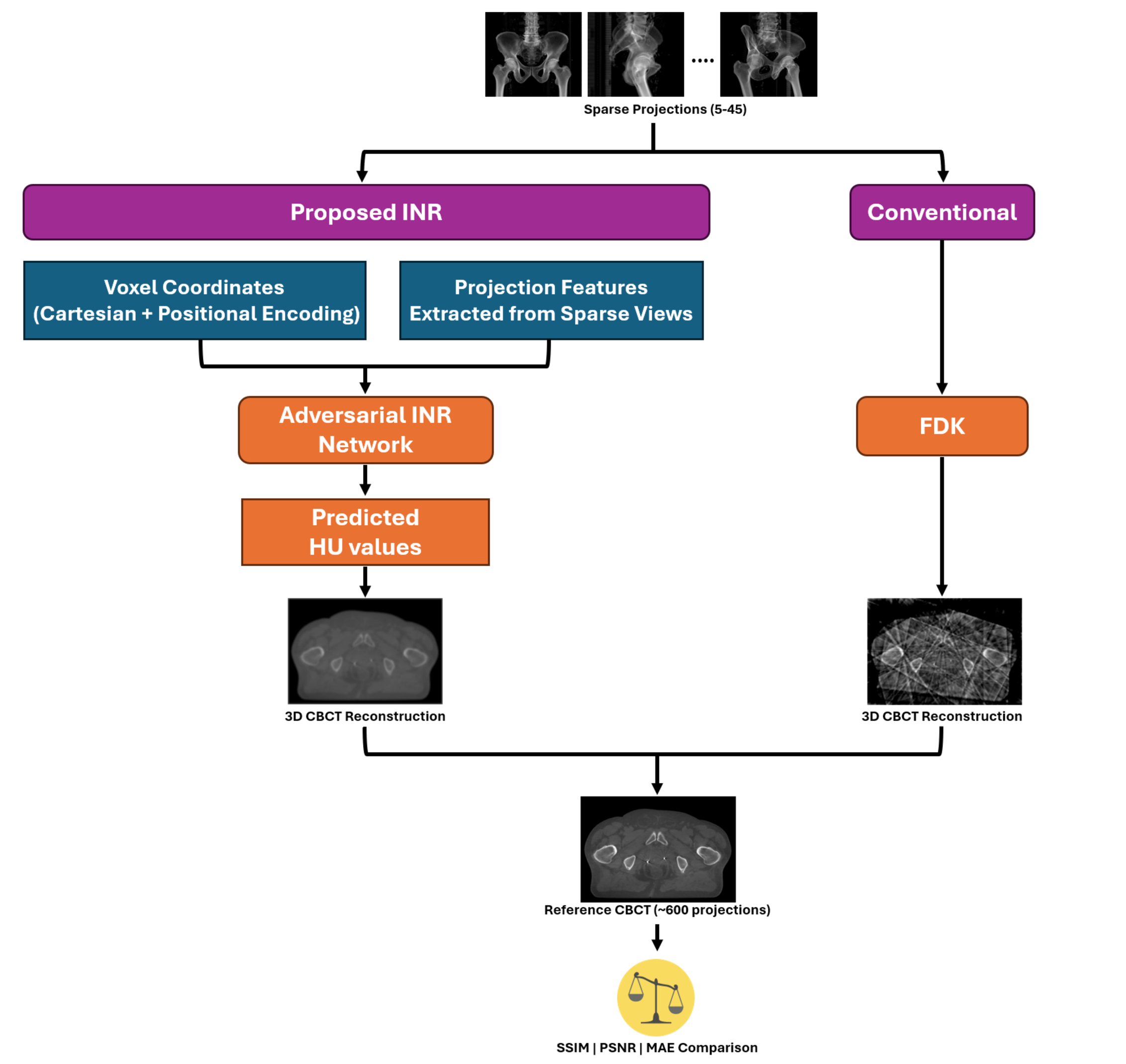

Figure 3: Workflow comparing the adversarial INR with conventional FDK reconstruction.

DISCUSSION & CONCLUSIONS

- ✓ Proposed adversarial-INR reconstructs high-quality CBCT images form ultra-sparse projection data.
- ✓ Only ~25 projections, reconstruction accuracy remains high (SSIM>0.92, PSNR>33 dB).
- ✓ Conventional FDK reconstruction shows substantial degradation even with 45 projections.
- ✓ This approach substantially reduces the number of projections required for preserving anatomical accuracy, enabling lower dose, faster imaging and improved IGRT workflows.

LIMITATIONS

- Evaluated using simulated projection data.
- Patient-specific training required (5-10 hours)

FUTURE WORK

- Validate using clinical kV projection data.
- Accelerate training and reconstruction for clinical deployment.

REFERENCES

1. Fang, Y., Mei, L., Li, C., Liu, Y., Wang, W., Cui, Z., & Shen, D. SNAF: Sparse-view CBCT Reconstruction with Neural Attenuation Fields. CoRR abs/2211.17048 (2022).
2. Zhang, Y., Mengke, T. Dynamic Cone-Beam CT Reconstruction using Spatial and Temporal Implicit Neural Representation Learning (STINR). arXiv:2209.11392 (2022).
3. Shen, L., Pauly, J., & Xing, L. NeRP: Implicit Neural Representation Learning With Prior Embedding for Sparsely Sampled Image Reconstruction. arXiv:2108.10991 (2021).
4. Lin, Y., Yang, J., Wang, H., Ding, X., Zhao, W., & Li, X. C^2RV: Cross-Regional and Cross-View Learning for Sparse-View CBCT Reconstruction. arXiv:2406.03902 (2024).