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Hybrid Framework Combining Pre-Trained Supervised Image Priors with Neural Representation for Extremely Sparse-View CT Reconstruction (HYPER)

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ABSTRACT

Purpose: Extremely sparse-view CT benefits for reducing radiation dose while causing streak artifact when using the traditional filtered-back projection (FBP). We propose HYbrid framework combining pre-trained supervised image Priors with Neural Representation for Extremely sparse-view CT Reconstruction(HYPER).

Methods: HYPER framework has three features: (1) deep learning-based pre-trained networks, (2) streak artifact removal to the image generated, (3) self-supervised Implicit Neural Representation(INR) reconstruction for data fidelity with image priors. ResNet model trained on paired FBP-reconstructed and ground-truth images generated high-quality CT images. These images were forwardly projected to generate full- and sparse-projection views, therefore producing realistic, streak artifact-free images. Finally, the INR was iteratively updated with the image priors generated by pre-trained ResNet and artifact removal process. We validated on the AAPM 2016 Low-Dose CT dataset using 9 subjects for training/validation and 1 unseen subject for testing with CT images resized to 256 × 256. We simulated parallel-beam projections with 10 views sampled from a total of 720 views. The performance of the HYPER framework was evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Results: The baseline FBP reconstruction achieved PSNR(dB) / SSIM of 22.08 / 0.3536. FBPConvNet (Jin et al., IEEE TIP, 2017) achieved 30.29 / 0.8275, NeRP (Shen et al., IEEE TNNLS, 2022) achieved 29.92 / 0.7746, MCG (Chung et al., NeurIPS, 2022) achieved 33.98 / 0.8769, DiffusionMBIR (Chung et al., CVPR, 2023) achieved 34.71 / 0.9139. In contrast, the proposed HYPER framework further improved performance, achieving a PSNR of 39.22 dB and an SSIM of 0.9531. The proposed method showed superior performance under the 10-view condition.

Conclusion: The proposed HYPER framework for extremely sparse-view CT reconstruction combined pre-trained supervised image priors with neural representation. This was demonstrated to successfully yield highly qualified CT images reconstructed from 10 views, outperforming competitive reconstruction baselines.

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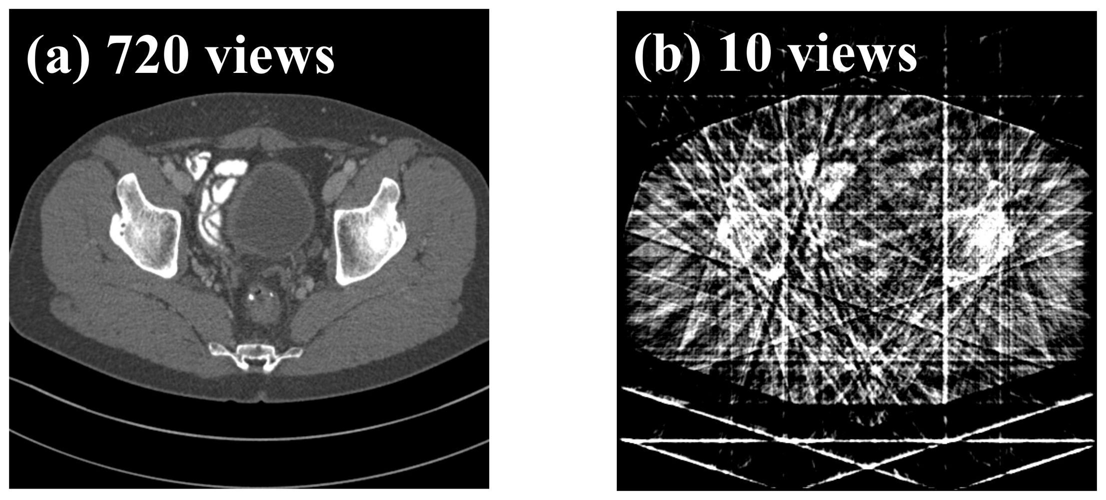
INTRODUCTION

Sparse-View CT (SVCT)

- Extremely sparse-view CT benefits for reducing radiation dose while causing streak artifact when using the traditional filtered-back projection (FBP).



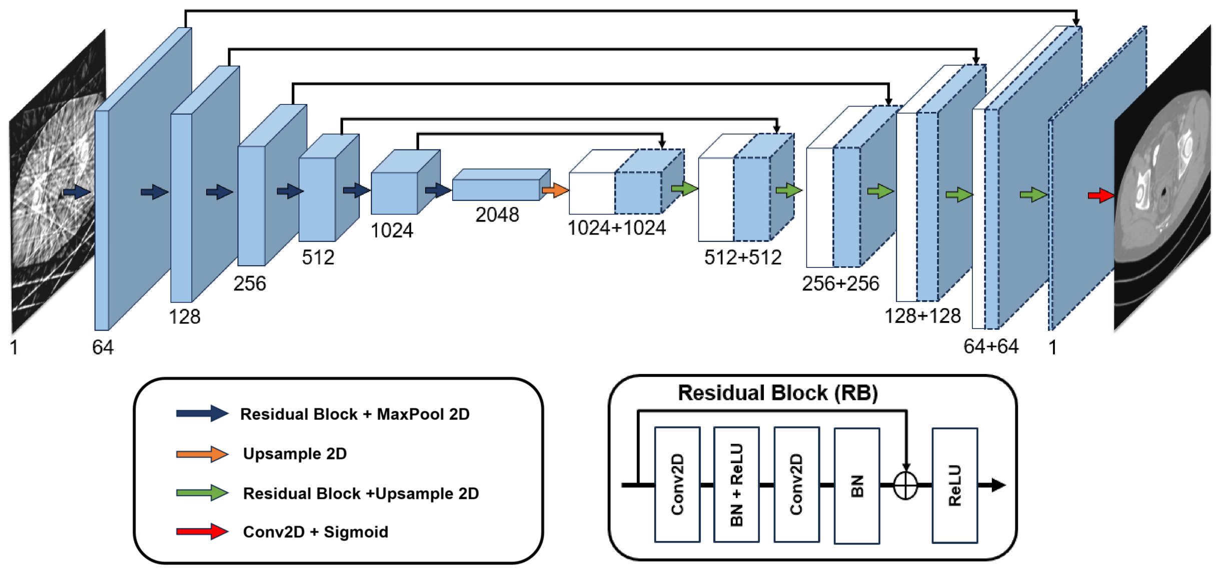
In This Work

- We propose a hybrid framework that combines self-supervised implicit neural representation with pre-trained supervised network prior images to reconstruct extremely sparse-view CT.

METHODS AND MATERIALS

Residual U-Net (ResNet)

- We used a DL-based pre-trained ResNet, trained on pairs of FBP-reconstructed and ground-truth images, to generate a high-quality prior image.

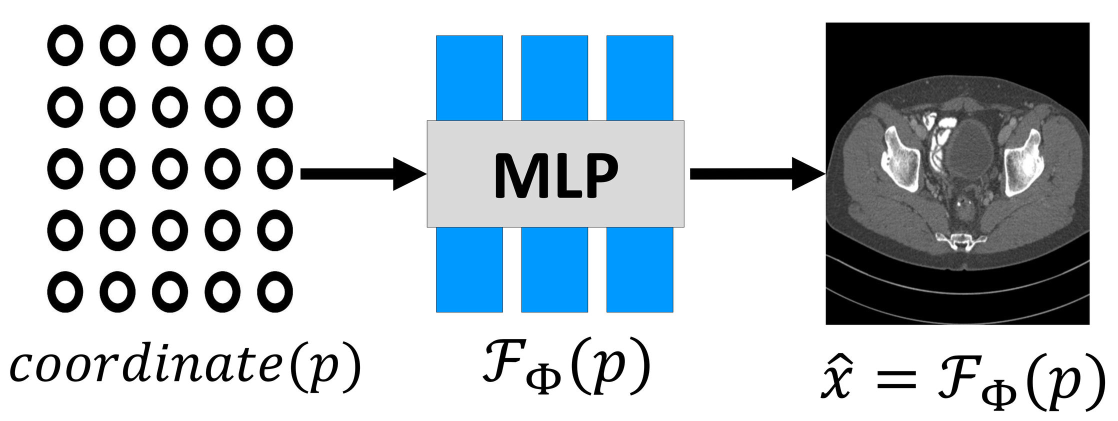


Artifact Removal Process

- The prior image was forwardly projected to generate full- and sparse-projection views, therefore producing realistic, streak artifact-free images.

Implicit Neural Representation (INR)

- INR was employed for data fidelity enforcement using the image priors generated by the pre-trained ResNet and streak artifact removal process.



RESULTS

Qualitative Results

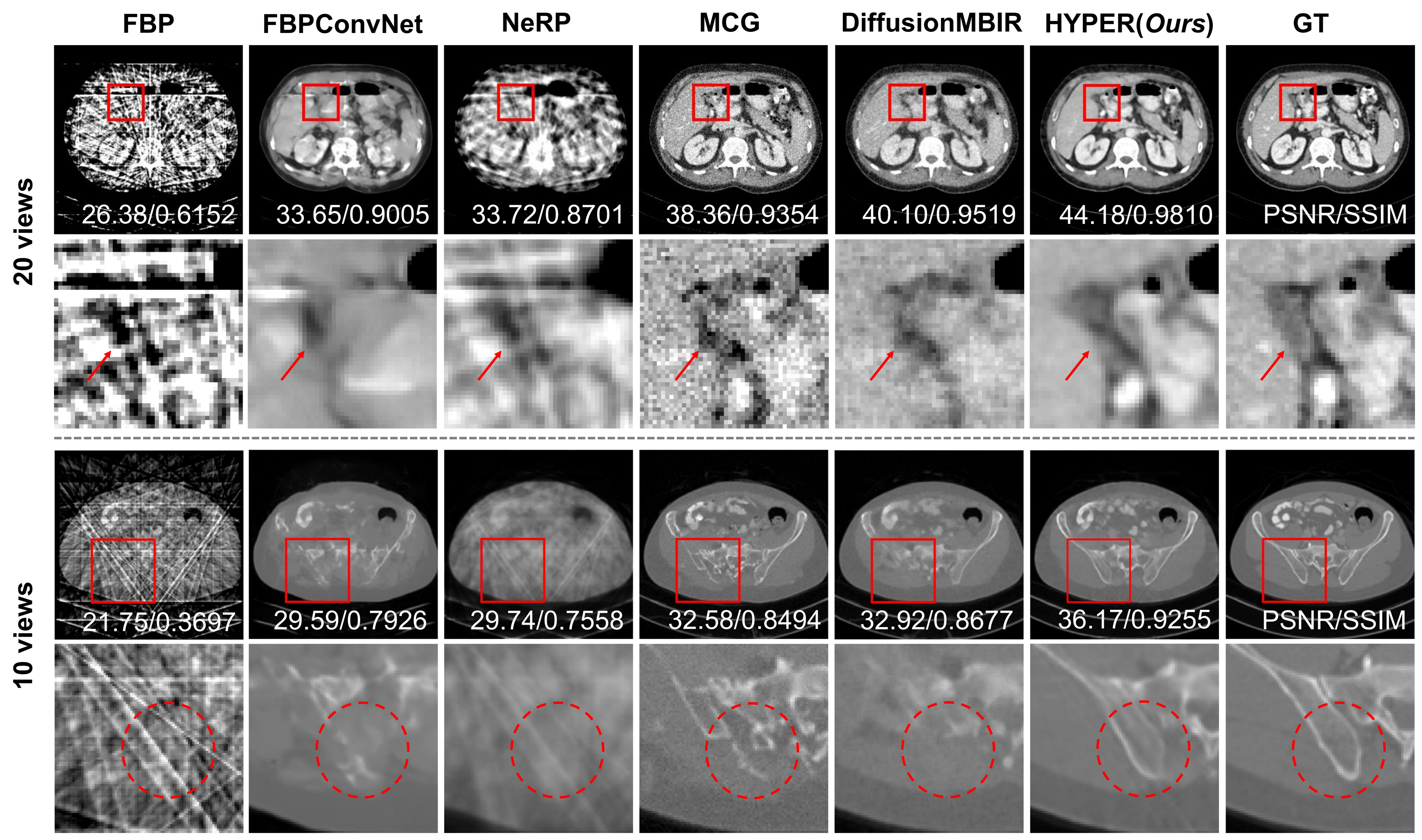


Figure 1. Qualitative comparison with existing methods under 20-view and 10-view conditions.

Quantitative Results

Dataset	Method	10 views		20 views	
		PSNR↑	SSIM↑	PSNR↑	SSIM↑
AAPM	**FBP**	22.08±0.56	0.3536±0.0223	26.26±0.49	0.4957±0.0237
	FBPConvNet	30.29±0.48	0.8275±0.0184	33.78±0.36	0.9064±0.0112
	NeRP	29.92±0.69	0.7746±0.0206	33.73±0.86	0.8748±0.0169
	MCG	33.98±1.91	0.8769±0.0323	38.52±0.31	0.9328±0.0664
	DiffusionMBIR	<u>34.71±1.04</u>	<u>0.9139±0.0193</u>	<u>40.41±0.87</u>	<u>0.9584±0.0056</u>
	HYPER(Ours)	**39.22±1.58**	**0.9531±0.0128**	**44.50±1.32**	**0.9801±0.0036**

Table 1. Quantitative comparison with existing methods under 10-view and 20-view conditions. The best and second-best results are highlighted in **bold** and <u>underlined</u>, respectively.

CONCLUSIONS

- In this study, we proposed HYPER, a framework that combines pre-trained supervised image-domain networks with self-supervised implicit neural representation.
- We successfully reconstructed high-quality CT images, outperforming state-of-the-art reconstruction methods under extremely sparse-view conditions.

REFERENCES

1. Kim, B., et al. "A Streak Artifact Reduction Algorithm in Sparse-View CT Using a Self-Supervised Neural Representation." Medical Physics, vol. 49, no. 9, Sept. 2022.
2. Jin, K., et al. "Deep Convolutional Neural Network for Inverse Problems in Imaging." IEEE Transactions on Image Processing, vol. 26, no. 9, Sept. 2017.