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JOINT AAPM | COMP MEETING

Efficient Dual-Domain Deep Learning Model for High-Pitch Helical CT Reconstruction

Ziyi Zeng[1], Hoyeon Lee [1,2]

[1]Department of Diagnostic Radiology, LKS Faculty of Medicine, The University of Hong Kong

[2]Centre of Cancer Medicine, LKS Faculty of Medicine, The University of Hong Kong

香港大學 THE UNIVERSITY OF HONG KONG

HKU Med School of Clinical Medicine Department of Diagnostic Radiology 香港大學放射診斷學系

HKU Med School of Clinical Medicine Centre of Cancer Medicine 香港大學癌症醫學中心

BACKGROUND

- High-pitch helical CT scans can reduce radiation exposure and scanning time.
- However, it introduces imaging artifacts due to incomplete sampling.
- Recent studies investigated deep learning (DL) approaches to suppress these artifacts in high-pitch CT.
- This study aims to develop an efficient dual-domain high-pitch reconstruction framework.

MATERIALS

- We collected whole-body diagnostic CT images from 93 patients using TCIA LDCT and projection data.
- The data were split into 50 (training) / 13 (internal validation) / 30 (testing).
- We used the forward-projection method was to obtain high-pitch data with pitches of 2.4, 3.2, and 4.8.
- High-pitch data were acquired using 2 scenarios:
  - Reduced detector coverage (RDC) (**Fig. 1 (b)**); and
  - Increased table feed (ITF) (**Fig. 1 (c)**).

METHODS

- We employed a dual-domain approach to synthesize the sinograms and refine the results further in the image domain.
- The sinogram- and image-domain models were both based on residual U-Net (**Fig. 3**)
- The models were pretrained individually, and they were fine-tuned in an end-to-end manner.
- For each pretraining and fine-tuning, the model was updated for 100 epochs using the AdamW optimizer.
- As shown in Eq. (1)-(3), we utilized L1 loss and gradient difference loss to improve the consistency.
- We calculated the mean-absolute error (MAE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) within the patient volume to quantitatively compare the results.

Sinogram U-Net pretraining

$$\mathcal{L}_{\text{sino-pre}} = \mathcal{L}_1(\hat{s}, s^*) + 0.3\,\mathcal{L}_\nabla(\hat{s}, s^*) \quad (1)$$

Image U-Net pretraining

$$\mathcal{L}_{\text{img-pre}} = \mathcal{L}_1(\hat{x}, x^*) \quad (2)$$

End-to-end fine-tuning

$$\mathcal{L}_{\text{joint}} = 1.0\mathcal{L}_1(\hat{x}, x^*) + 0.02\mathcal{L}_1(\hat{s}, s^*) + 0.01\mathcal{L}_\nabla(\hat{s}, s^*) \quad (3)$$

$\hat{s}, s^*$: predicted / ground-truth sinograms.

$\hat{x}, x^*$: reconstructed/ ground-truth CT images.

$\mathcal{L}_\nabla$: Gradient difference loss.

DATA PREPARATION

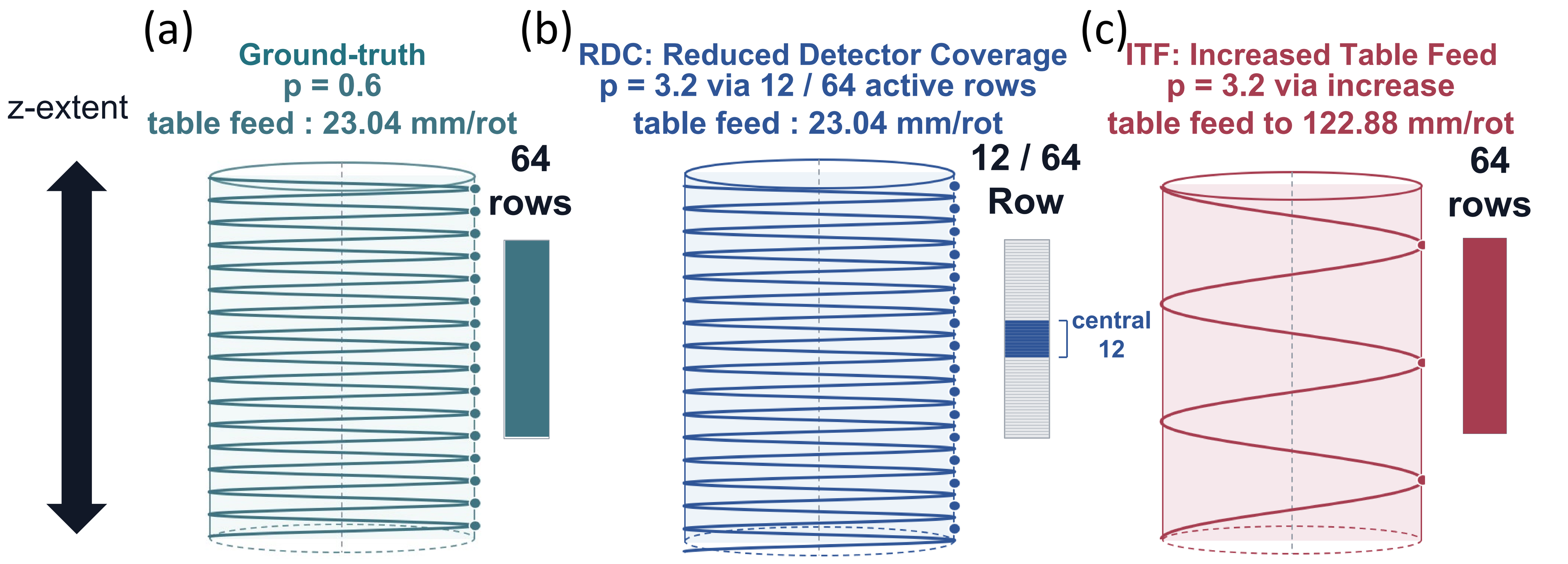

Fig. 1. High-pitch data acquisition scenarios. (a) low-pitch data acquisition for ground-truth (pitch: 0.6), (b) Reduced Detector Coverage (RDC), and (c) Increased Table Feed (ITF). RDC samples detector rows in the middle to implement high-pitch CT. ITF increases table travel length per rotation to implement high-pitch CT.

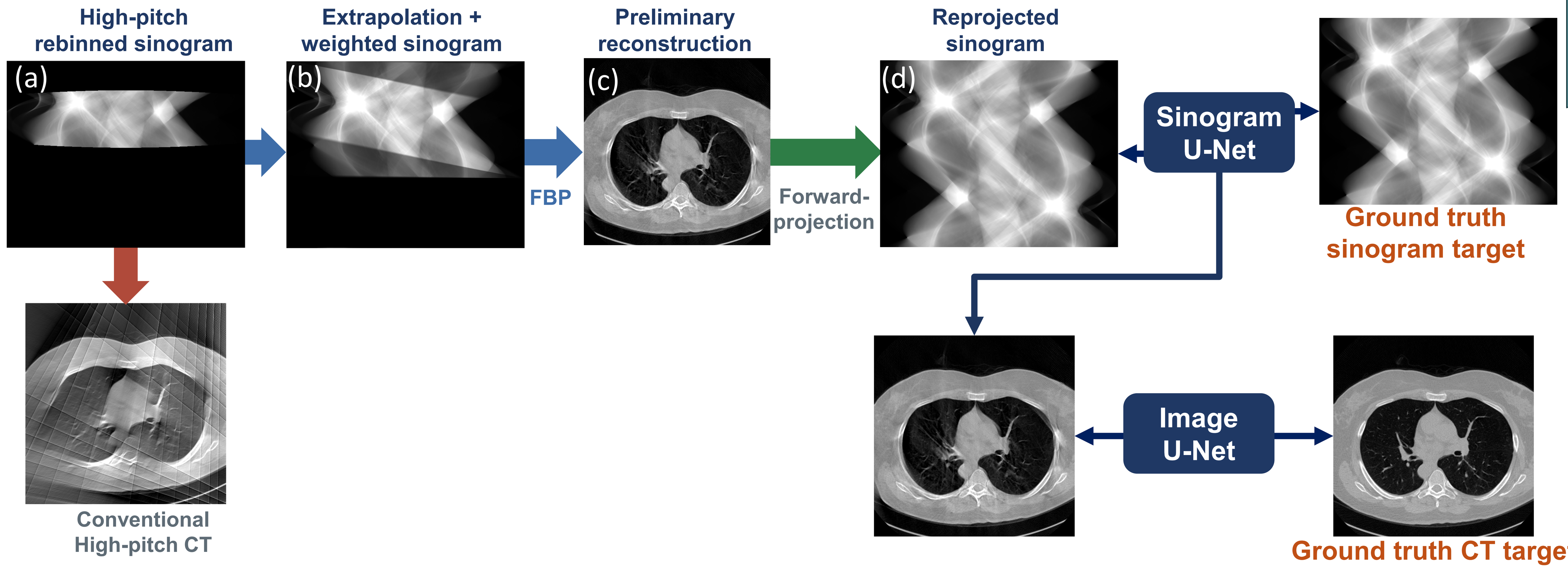

Fig. 2. The schematic diagram of the proposed dual-domain high-pitch reconstruction framework.

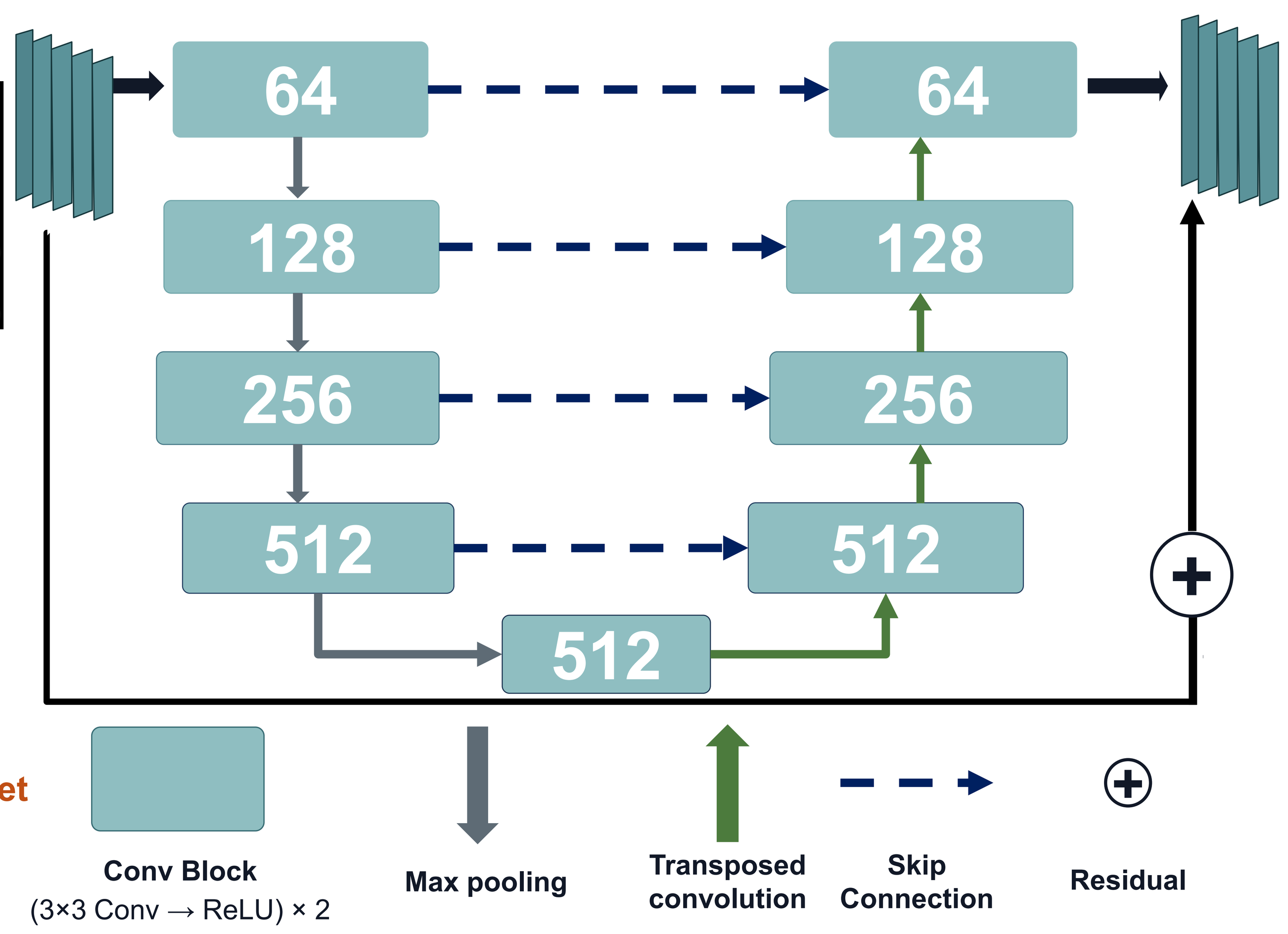

Fig. 3. Residual U-Net architecture

DATA PROCESSING

- We used the Single Slice Rebinning (SSRB) algorithm to rebin helical projection data into sinograms(**Fig. 2 (a)**).
- We employed extrapolation and short-scan weighting methods to reconstruct the high-pitch data (**Fig. 2 (b)**).
- The sinograms were reconstructed to obtain preliminary reconstruction images (**Fig. 2 (c)**).
- Subsequently, the preliminary reconstruction results were forward-projected to generate the input sinogram for training (**Fig. 2 (d)**).
- Additionally, we acquired low-pitch helical CT projection data (pitch: 0.6) to supervise the model training.

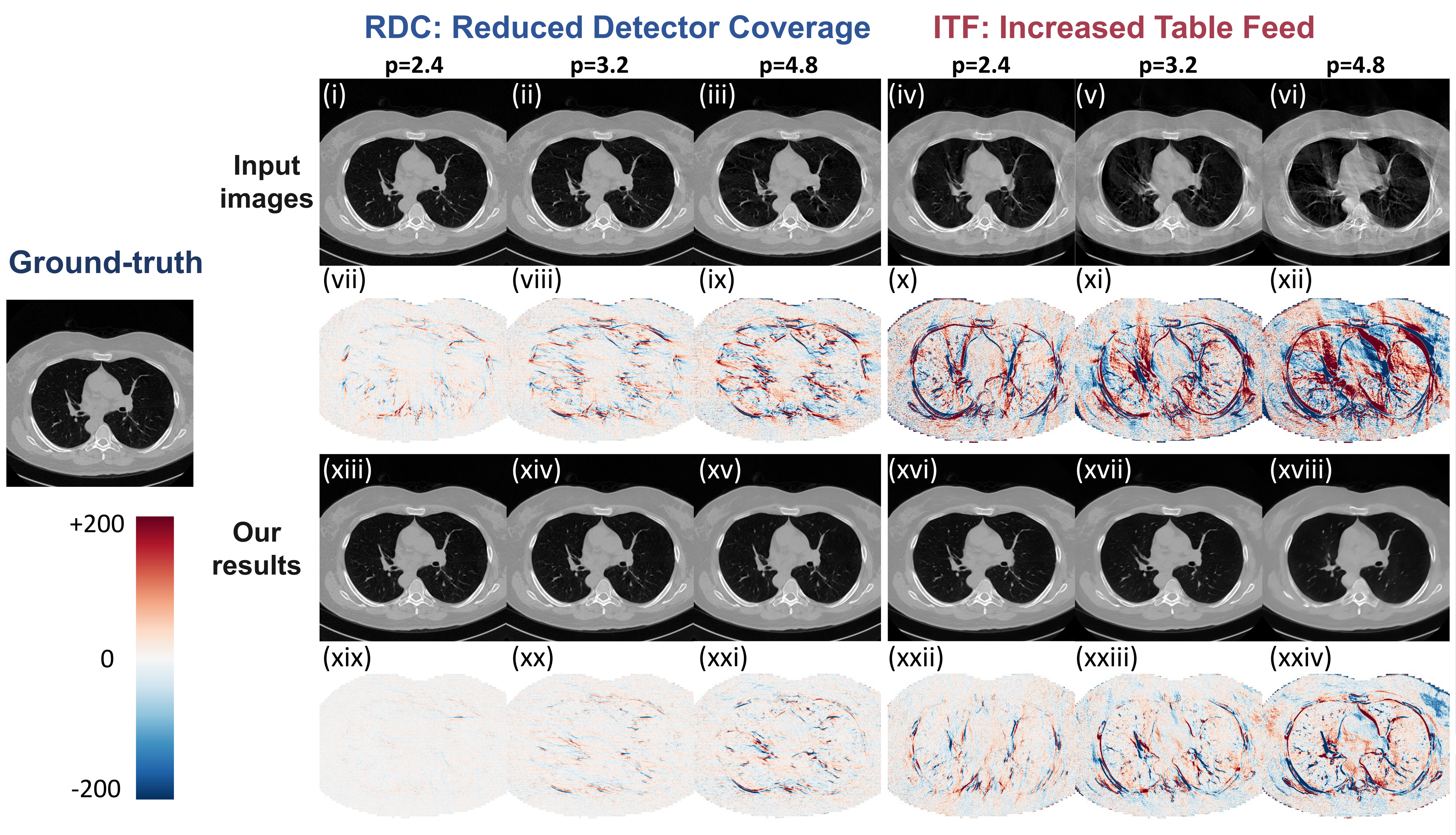

Fig. 4. Representative slices of a test case. (i)-(vi) input high-pitch images, (vii)-(xii) error maps between input high-pitch images and the ground-truth, (xiii)-(xviii) results of the proposed framework, and (xix)-(xxiv) error maps between the results and the ground-truth.

Table 1. Quantitative comparison results

Helical pitches	Input high-pitch images			Proposed dual-domain results			Gain in %		
	MAE (HU)	PSNR (dB)	SSIM	MAE (HU)	PSNR (dB)	SSIM	ΔMAE	ΔPSNR	ΔSSIM
RDC 2.4	13.83±5.25	41.73±4.08	0.999±0.001	**7.34±2.44**	**47.86±3.72**	**1.000±0.000**	46.9	14.7	0.09
RDC 3.2	21.15±8.99	37.78±4.40	0.997±0.003	**11.23±4.58**	**43.80±4.16**	**0.999±0.001**	46.9	15.9	0.24
RDC 4.8	31.08±13.35	34.20±4.43	0.993±0.006	**16.89±6.05**	**39.60±3.85**	**0.998±0.001**	45.7	15.9	0.52
ITF 2.4	65.01±14.89	26.71±3.59	0.957±0.010	**29.04±7.86**	**34.31±3.86**	**0.990±0.003**	55.3	28.5	3.41
ITF 3.2	88.19±17.48	24.42±3.37	0.932±0.015	**42.98±8.27**	**29.91±3.35**	**0.980±0.006**	51.3	22.4	5.18
ITF 4.8	135.71±24.73	21.23±3.23	0.866±0.034	**62.68±9.05**	**26.14±2.99**	**0.957±0.009**	53.8	23.1	10.51

RESULTS

- Representative slices of a test case are shown in **Fig. 4.**
- As shown in the figure, the proposed approach successfully suppressed the high-pitch imaging artifacts.
- **Table 1** summarizes the quantitative comparison of the high-pitch reconstruction results.
- These results demonstrate that the proposed framework improved image quality compared to the input high-pitch images.
- The proposed dual-domain framework takes **13.8 sec** per patient for reconstruction.

CONCLUSION

- The proposed dual-domain model effectively suppressed image artifacts of high-pitch CT reconstruction.
- Compared to existing studies, which require 332.4 seconds, the proposed methods efficiently reconstructed the high-pitch CT images.

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CONTACT

Ziyi Zeng (andrewzeng@connect.hku.hk)

Hoyeon Lee (hlee01@hku.hk)