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Deep Learning-Based Projection Extrapolation for Limited-Angle CBCT Reconstruction

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ABSTRACT

Limited-angle cone-beam CT (CBCT) reconstruction is affected by incomplete angular sampling, which can lead to severe artifacts, intensity nonuniformity, and structural distortion. This study presents a projection-domain deep learning framework for recovering missing views before conventional reconstruction. CBCT projections were generated from three-dimensional CT volumes using the TIGRE[1] toolbox. The reference acquisition consisted of 400 projections over 240°, while the 120° limited-angle input contained 200 measured views and 200 missing views. A ResUNet first generated a coarse estimate of the missing projection region, and a conditional residual diffusion model[2] was then used to refine the remaining artifact and error. The completed projection sets were reconstructed using the Feldkamp–Davis–Kress algorithm and evaluated using MAE, RMSE, PSNR, and SSIM. In the missing projection region, PSNR increased from 17.91 dB for the limited-angle input to 28.38 dB after diffusion refinement. In reconstruction space, PSNR improved from 25.78 to 36.18 dB, while SSIM increased from 0.872 to 0.966. These results show that projection-domain extrapolation can substantially improve limited-angle CBCT reconstruction without modifying the reconstruction algorithm.

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INTRODUCTION

Cone-beam computed tomography (CBCT) is widely used in image-guided radiotherapy because it provides volumetric anatomical information for patient positioning and treatment guidance. In standard CBCT reconstruction, a sufficient angular range of projection data is required to generate accurate three-dimensional images. However, when the acquisition angle is limited and part of the projection information is missing, conventional reconstruction methods such as Feldkamp–Davis–Kress (FDK) cannot directly recover the missing views. This problem can lead to streak artifacts, intensity nonuniformity, and structural distortion in the reconstructed volume. To address this problem, this study focuses on projection-domain extrapolation before reconstruction. Instead of correcting artifacts after FDK reconstruction, missing projection views are estimated first using a deep learning framework. A ResUNet model provides an initial extrapolation of the missing-angle region, and residual diffusion is then used to refine the projection estimate before final FDK reconstruction.

METHODS AND MATERIALS

CBCT projection data were simulated from three-dimensional CT volumes using the TIGRE toolbox. The reference acquisition covered 240° with 400 projections. For the 120° limited-angle setting, the first 200 projections were used as measured views and the remaining 200 views were treated as missing.

Projection data were reformatted into 768×1024×400, where each detector row was treated as a 1024×400 projection-domain sample.

A ResUNet model was first trained to estimate the missing-angle region while preserving the measured views. The resulting projection estimate was then refined using a conditional residual diffusion model. Instead of predicting the full projection directly, the diffusion model learned the residual between the ResUNet estimate and the reference projection.

The refined projection was obtained by adding the predicted residual back to the ResUNet estimate:

$$x_{refined} = x_{ResUNet} + r_{pred}$$

During inference, measured projections were kept unchanged, while diffusion refinement was applied only to the missing-angle region.

The completed projections were reconstructed using TIGRE FDK. Performance was evaluated in both projection and reconstruction domains using MAE, RMSE, PSNR, and SSIM.

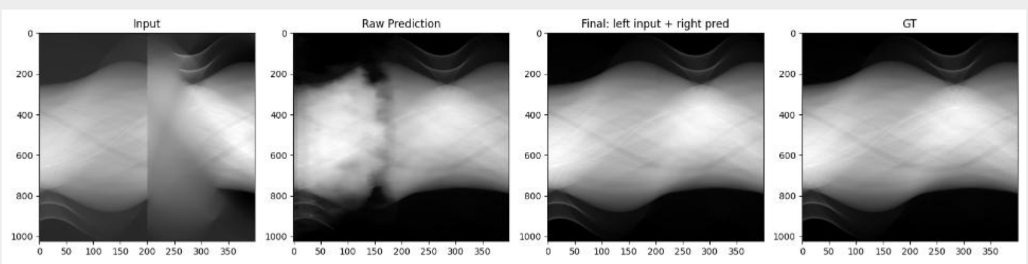

Fig 1. Projection-Domain Extrapolation Workflow

RESULTS

For the 120° limited-angle setting, the proposed projection-domain extrapolation framework substantially improved both projection-domain and reconstruction-domain image quality. In the projection domain, the limited-angle input showed a large discrepancy from the 240° reference in the missing-angle region. After projection completion, the missing-view structures became more consistent with the reference projection, and the discontinuity between measured and extrapolated regions was reduced. Quantitatively, the missing-region PSNR increased from 17.91 dB for the limited-angle input to 28.38 dB after extrapolation, while SSIM increased from 0.669 to 0.949. These results indicate that the proposed method successfully recovered a large portion of the missing projection information. The improvement was also reflected in the FDK reconstruction results. The reconstruction from the limited-angle input contained visible streak artifacts, intensity nonuniformity, and reduced structural fidelity. In contrast, the completed projection set produced a reconstructed volume with reduced artifacts and improved anatomical consistency compared with the 240° reference. In reconstruction-domain evaluation, PSNR improved from 25.78 dB to 36.18 dB, and SSIM increased from 0.872 to 0.966. These results demonstrate that projection-domain extrapolation can effectively reduce limited-angle artifacts while preserving the conventional FDK reconstruction pipeline.

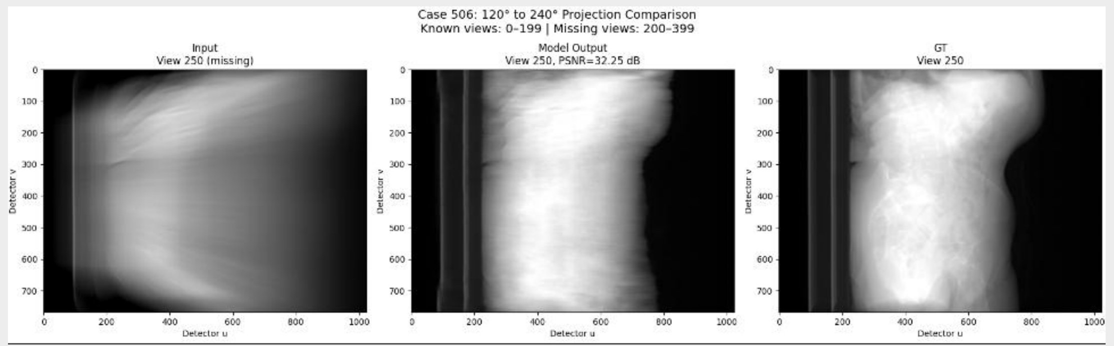

Fig 2. Projection-Domain Missing-View Extrapolation

Table 1. Projection-Domain Evaluation (120° → 240°)
Metrics compare the completed projection set with the 240° reference projection.

Metric	Limited 120°	Proposed Method	Improvement
MAE (full projection)	0.0815	**0.0105**	**−87.1%**
PSNR (missing, dB)	17.91	**28.38**	**+10.47**
SSIM (missing)	0.669	**0.949**	**+0.280**

Proposed Method = final ResUNet + residual diffusion projection-completion framework.

Table 1. Projection-Domain Evaluation (120° → 240°)

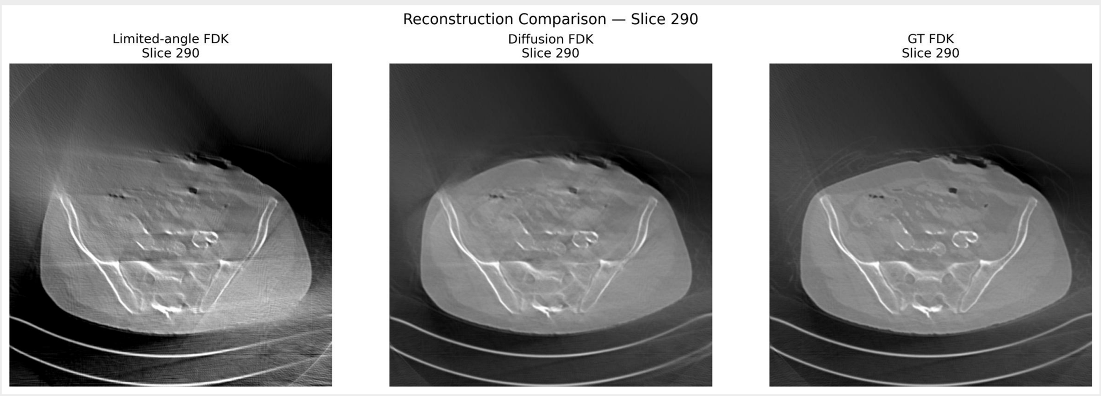

Fig 3. FDK Reconstruction Results After Projection Completion

Table 2. Reconstruction-Domain Evaluation (120° → 240°)
Metrics compare FDK reconstructions against the 240° reference FDK reconstruction.

Metric	Limited 120°	Proposed Method	Improvement
MAE (raw)	219.43	**52.29**	**−76.2%**
RMSE (normalized)	0.0514	**0.0155**	**−69.8%**
PSNR (normalized, dB)	25.78	**36.18**	**+10.40**
SSIM	0.872	**0.966**	**+0.094**

Proposed Method = FDK reconstruction from the completed projection set.

Table 2. Reconstruction-Domain Evaluation (120° → 240°)

DISCUSSION

Projection-domain completion substantially improved limited-angle CBCT reconstruction, but several challenges remain. Artifacts can appear near the boundary between measured and extrapolated views because the known region comes from measured projections, while the missing region is generated by the model. Although measured views are fixed during inference, boundary consistency remains important for reducing reconstruction artifacts.

In this study, each detector row was processed independently as a 1024×400 sample. This reduces memory cost but does not explicitly model correlations along the detector-height direction, which may lead to row-wise texture variation. The upper and lower detector regions may also show stronger variation due to less stable projection information near the edge of the detector.

The diffusion sampling timestep also influences results. A smaller t_{start} gives conservative refinement and preserves the ResUNet estimate, while a larger t_{start} allows stronger correction but may introduce noise or structural inconsistency. Therefore, residual diffusion is best interpreted as a refinement stage, and future work will focus on improving boundary consistency, cross-row continuity, and timestep selection.

CONCLUSIONS

This study demonstrates that projection-domain extrapolation can effectively improve limited-angle CBCT reconstruction. By completing missing projection views before FDK reconstruction, the proposed ResUNet–diffusion framework reduced limited-angle artifacts and improved both projection-domain and reconstruction-domain image quality.

Residual diffusion provided an additional refinement on top of the ResUNet estimate while preserving measured-view consistency. Future work will focus on improving boundary continuity, cross-row consistency, and diffusion sampling strategies for more robust CBCT reconstruction.

REFERENCES

[1] Biguri A, Dosanjh M, Hancock S, Soleimani M. TIGRE: a MATLAB-GPU toolbox for CBCT image reconstruction. Biomedical Physics & Engineering Express. 2016;2(5):055010.

[2] Ho J, Jain A, Abbeel P. Denoising diffusion probabilistic models. Advances in Neural Information Processing Systems. 2020;33:6840–6851.

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