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μPIU-Net

A Domain-Specific Sinogram Infilling U-Net for Micro-CBCT

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Abstract

Purpose: Sparse-view cone-beam computed tomography (CBCT) reduces radiation dose but produces streaking artefacts when reconstructed with conventional algorithms. Deep learning sinogram infilling can address this, but evaluation typically relies on conventional metrics that may not capture clinically relevant image characteristics. We present a metric analysis comparing domain-specific and domain-transferred models, examining how standard metrics can be misleading and why domain-specific training remains essential.

Methods: We developed μPIU-Net, a lightweight U-Net trained on micro-CBCT projection data. Given two adjacent X-ray projections, the network predicts the intermediate projection at the midpoint angle. We evaluated μPIU-Net alongside five general-purpose inpainting models (LaMa, MAT, DeepFill v2, RePaint, Stable Diffusion 2) pre-trained on natural images. All models were assessed on held-out mCTP 610 phantom data using conventional metrics (SSIM, PSNR) and physical image quality metrics (MTF, NPS, NEQ) in both sinogram and reconstruction domains.

Results: In the reconstruction domain, μPIU-Net achieved SSIM of 0.697, doubling the undersampled baseline (0.348). Domain-transferred models achieved SSIM of 0.081-0.107, performing worse than the baseline despite achieving reasonable sinogram-domain fidelity (SSIM 0.52-0.82), demonstrating that sinogram-domain metrics do not reliably predict reconstruction quality. Physical image quality assessment revealed that individual metrics can be misleading: RePaint's smoothing reduced NPS below ground truth, appearing beneficial, but degraded MTF resulted in worse NEQ than baseline.

Conclusion: Domain-specific training is essential for CT sinogram infilling—domain-transferred models achieve high sinogram fidelity yet produce poor reconstructions. Physical image quality metrics (MTF, NPS, NEQ) must be interpreted together to capture clinically relevant characteristics. The projection infilling approach enables 50% reduction in acquired projections, supporting dose reduction in preclinical micro-CT applications.

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Code & data

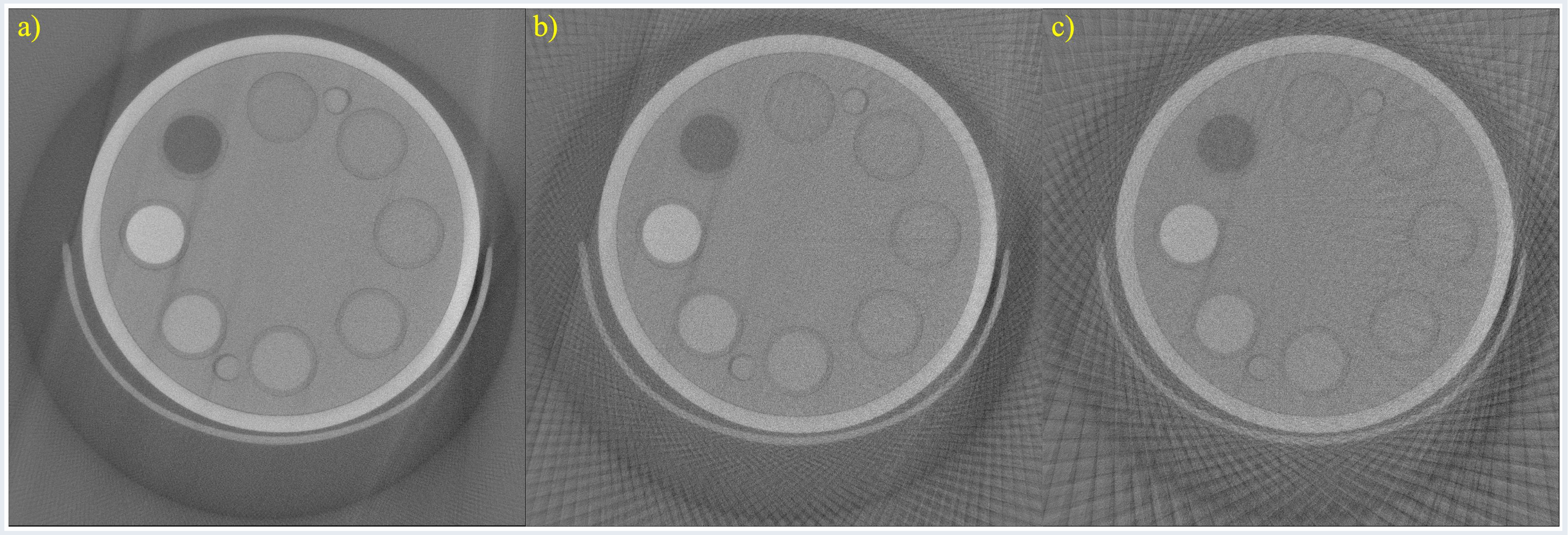
Code (GitHub)

Weights + data (Zenodo)

The problem: Streaking at low angular sampling

Sparse-view cone-beam CT (CBCT) cuts radiation dose by acquiring fewer projections but conventional FDK reconstruction then produces severe streaking artefacts.

- Streaks are coherent distortions, not random noise.
- They arise at high/low-attenuation boundaries, not from undersampling alone.



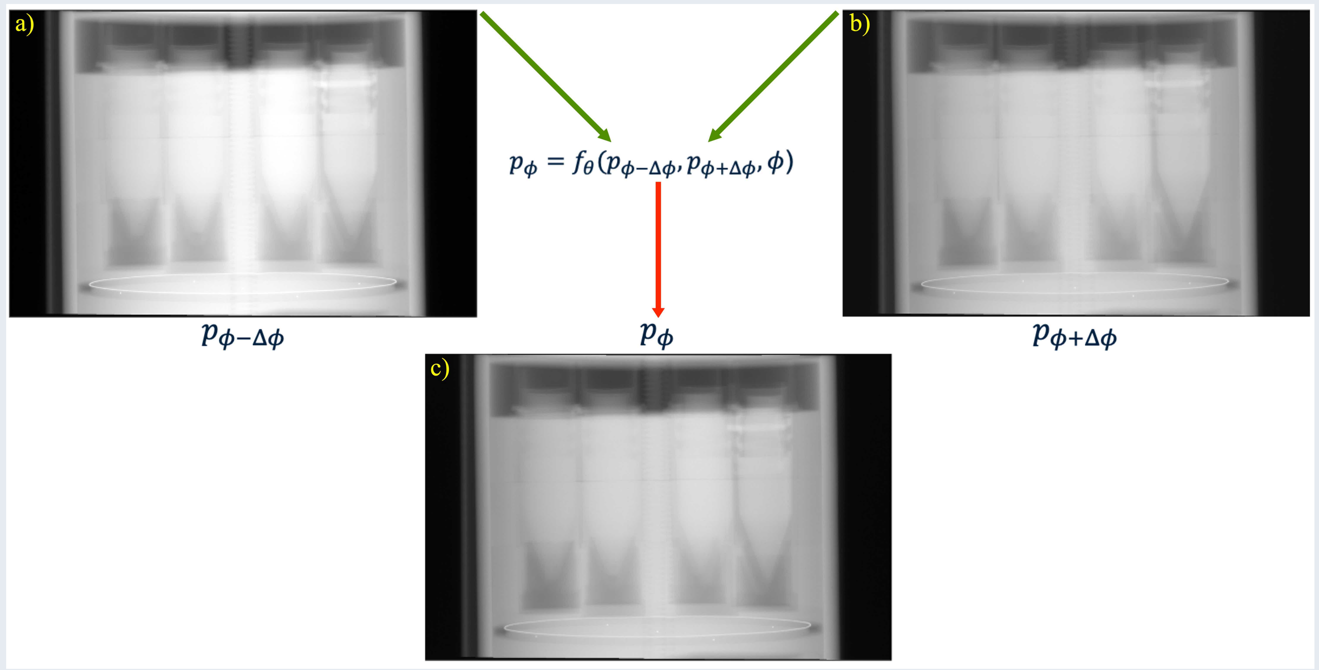
mCTP 610 phantom (eXplore CT 120, 80 kVp, 40 mA, 193°): 220 → 74 → 44 projections. Streaks worsen as projections drop.

Our idea: projection/sinogram infilling

Rather than removing streaks after reconstruction, we prevent them by densifying angular sampling before reconstruction.

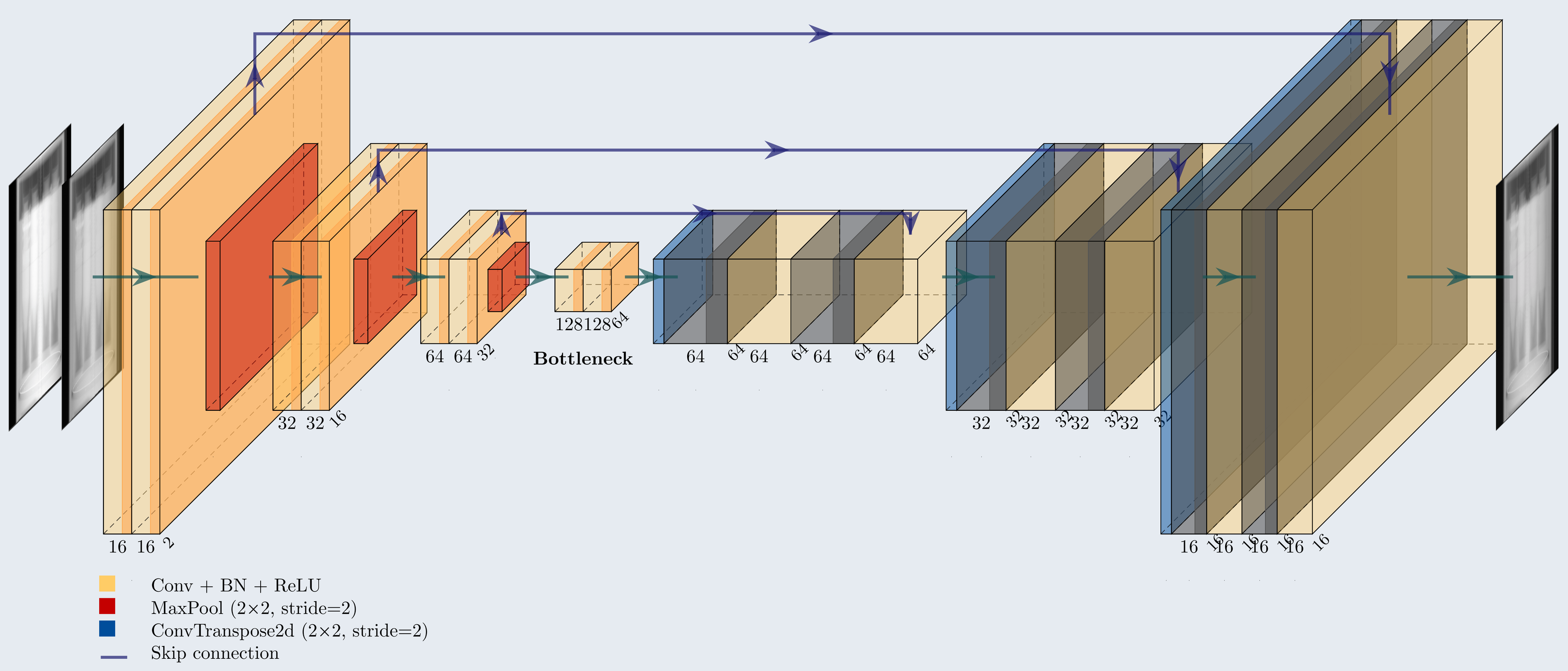
Given two adjacent projections at θ_{i-1} and θ_{i+1} (1.756° apart), predict the intermediate view at $\theta_i = (\theta_{i-1} + \theta_{i+1})/2$:

$$\text{input } (H, W, 2) \longrightarrow \text{output } (H, W, 1)$$



Adjacent projections (a),(b) ⇒ synthesised intermediate (c). Acquire half the projections leads to **50% dose reduction**.

μPIU-Net: a lightweight U-Net

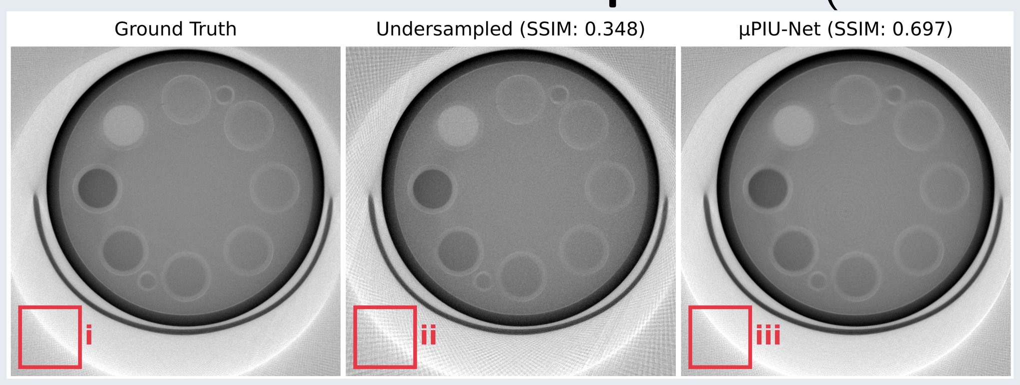


- Encoder 16/32/64, bottleneck 128, mirrored decoder.
- ~**279k parameters** (very lightweight).
- Addition (not concat) skips; stride-2 conv downsampling; transposed-conv upsampling; per-sample max-normalisation.
- Trained on **52 mouse micro-CT scans** (90/10 split), mean-squared-error (MSE) loss, the Adam optimiser, 75 epochs, full-resolution 3500 × 2300 projections.

Micro-CT data size forces a shallow architecture. Full-resolution 3500 × 2300 projections (~30× typical DL inputs), processed without tiling, make activations dominate VRAM (≈3.8 GB per sample).

Reconstruction quality versus literature

Tested on held-out **mCTP 610 phantom** ($n = 2296$).



Comparison with domain-transferred models

Model (recon domain)	SSIM	PSNR
μPIU-Net (ours)	**0.697**	**22.74**
Undersampled baseline	0.348	18.31
SD2	0.107	15.19
DeepFill v2	0.090	9.59
LaMa	0.089	9.58
MAT	0.088	9.56
RePaint	0.081	9.50

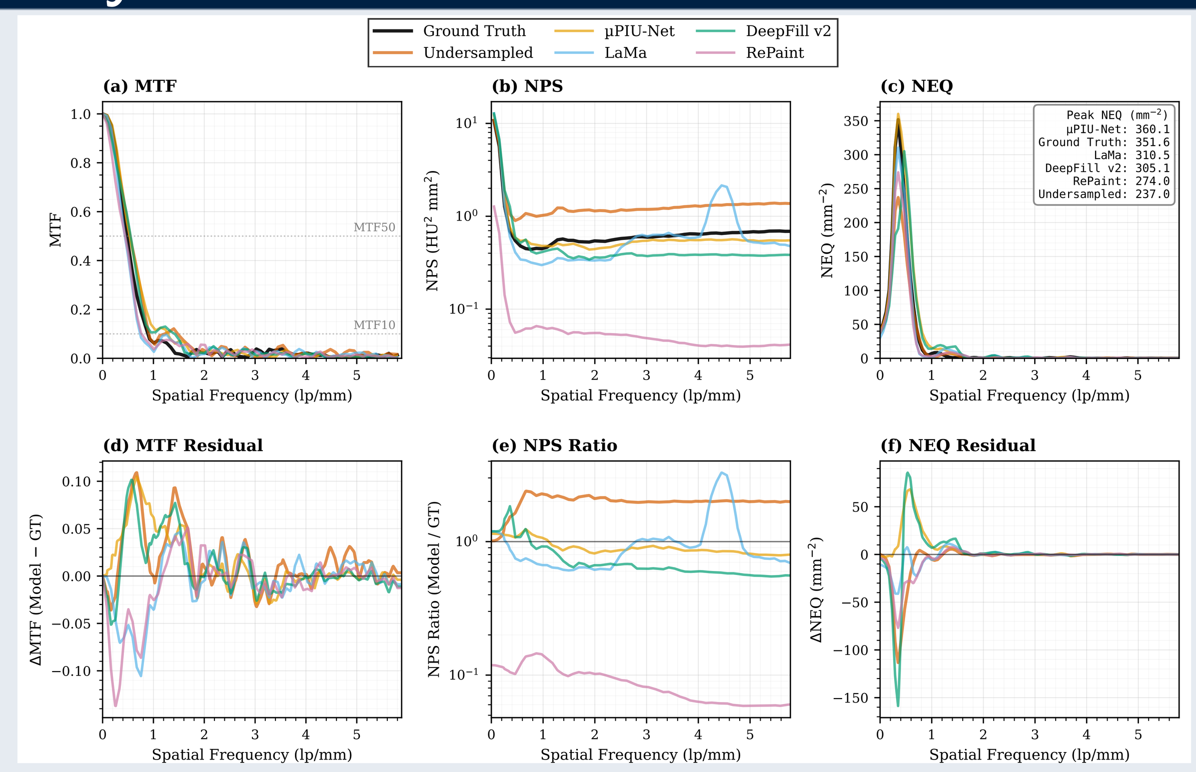
Comparison with domain-specific models

Method	Sinogram		Reconstruction		Dataset	Under-sampling
	SSIM	PSNR	SSIM	PSNR		
μPIU-Net (ours)	**0.952**	**25.7**	**0.697**	**22.7**	Micro-CBCT	50%
DRHT[1]	0.955	54.9	0.948	33.3	Walnut μCT	50%
FCDM[2]	0.964	31.5	0.921	28.9	Real-world	60%
SinoTx[3]	0.743	26.9	0.696	25.2	Real-world	60%
JDINet[4]	—	—	0.905	33.1	Clinical CBCT	12.5%
RFI-Net[5]	—	—	0.799	30.2	Walnut CBCT	25%
Wagner *et al.*[6]	—	—	0.729	29.0	Mouse tibia	50%

State-of-the-art inpainting models pre-trained on natural images (domain-transferred) do not suffice, whereas μPIU-Net is competitive with purpose-built domain-specific models. Cross-study comparison carries caveats:

- The evaluation domain (projection vs. image) must be stated.
- Noise realisation differs across datasets, so inter-comparison is only a rough estimate.
- No standard, literature-accepted micro-CT benchmark exists, to the authors' knowledge.

Image quality metrics



Top row: MTF (resolution), NPS (noise texture), NEQ (detectability). Bottom row vs. ground truth: NPS ratio $= \dfrac{\text{model NPS}}{\text{GT NPS}}$; residuals = model − GT.

- μPIU-Net matches the ground-truth NPS while slightly improving MTF, so its NEQ even exceeds the ground truth.
- No single metric is sufficient: some domain-transferred models look acceptable on a physical metric yet have poor SSIM/PSNR reconstructions.

References

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[5]Wang *et al.*, Computer Vision – ACCV 2022 (LNCS), Springer, 86–100 (2023). RFI-Net.
[6]Wagner *et al.*, arXiv:2302.06436 (2023).