Multi-stage Deep Learning Denoising for Computed Tomography

Jiayang Shi

Universiteit Leiden
The Netherlands

xCTing
Innovative training network

About Me

Jiayang Shi

Leiden Institute of Advanced Computer Science (LIACS), Leiden University

PhD student under supervision from Daan Pelt and Prof. Joost Batenburg

Research focus:

- Denoising and artifacts reduction for computed tomography with deep-learning
- Part of H2020 project “xCting”

Background

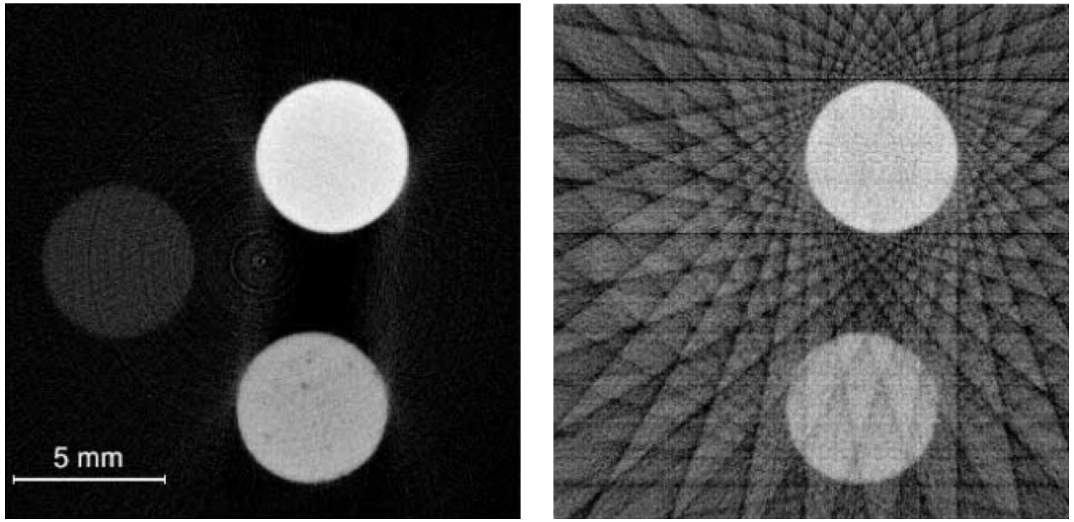
Noise in Computed Tomography (CT)

To reduce radiation of CT

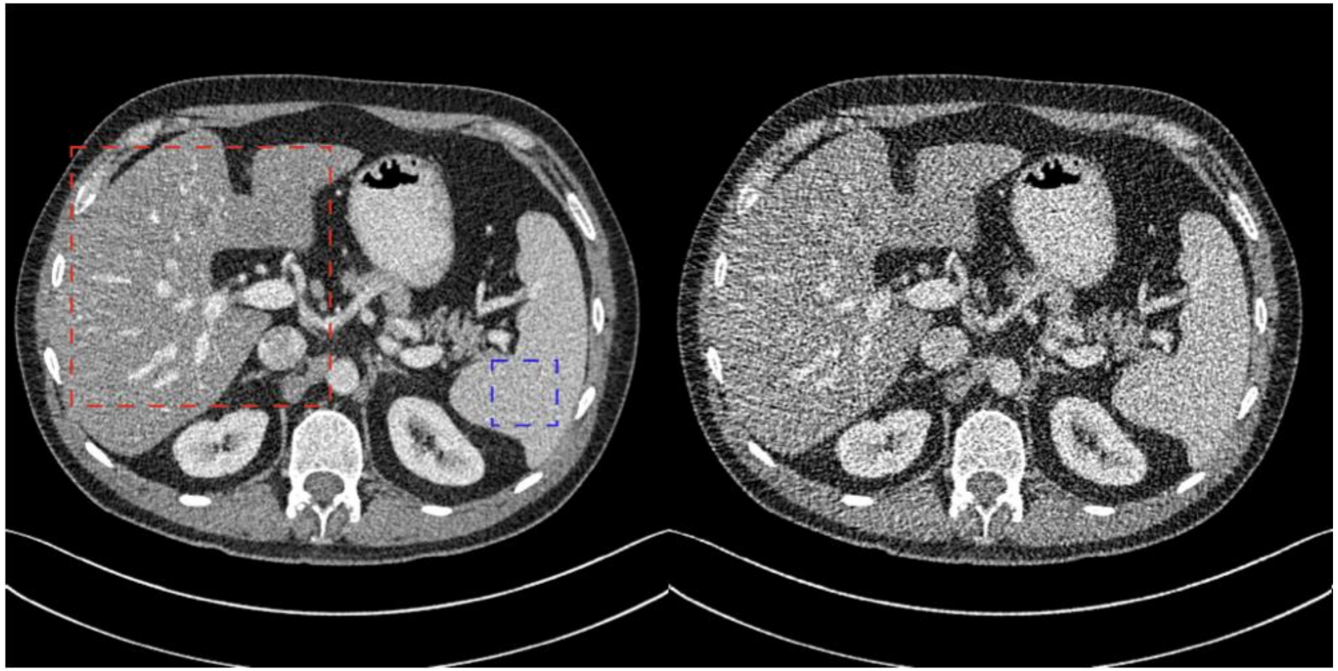
- Lower radiation amount, i.e., low dose CT

To improve scanning speed of CT

- Fewer projections



180 vs. 18 projections [Van Daatselaar et al, 2004]



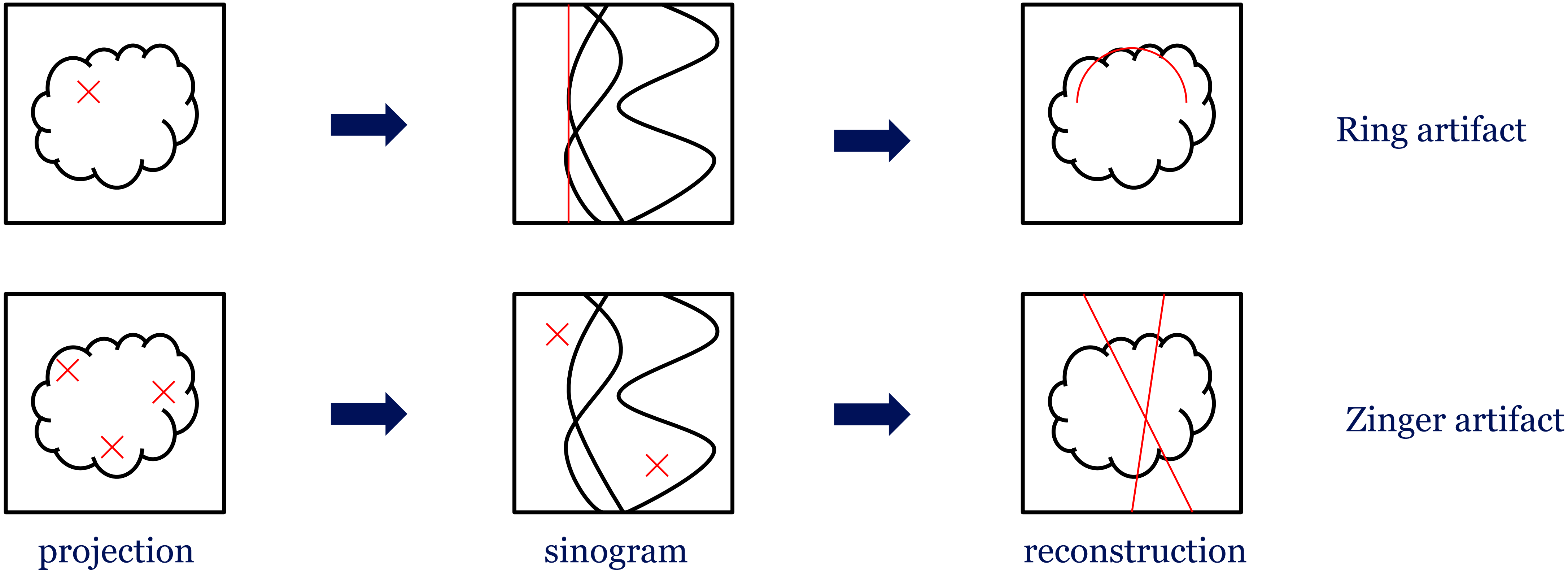
Normal dose vs. low dose [Yang et al, 2018]

Background

Artifacts in Computed Tomography (CT)

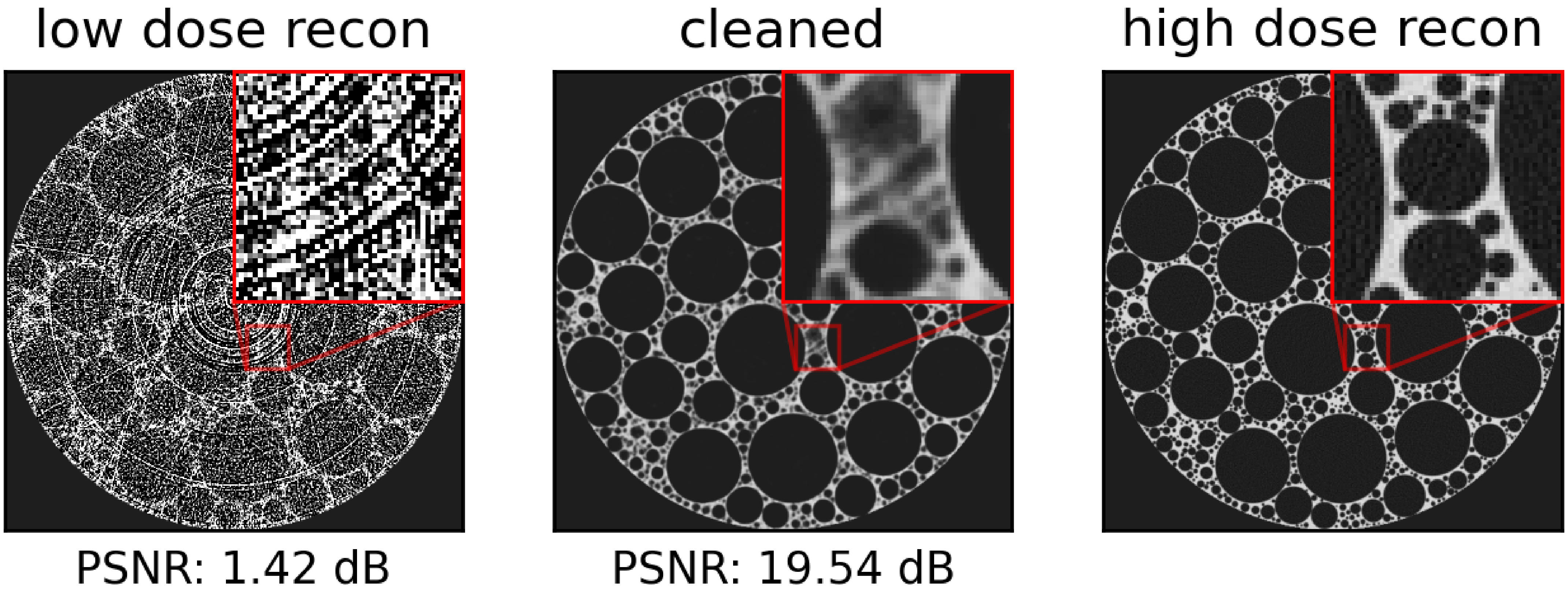
Systematic errors in some certain fixed detector elements (miscalibrated or defective) -> ring artifact

Prominent bright spots in projections-> zinger artifact

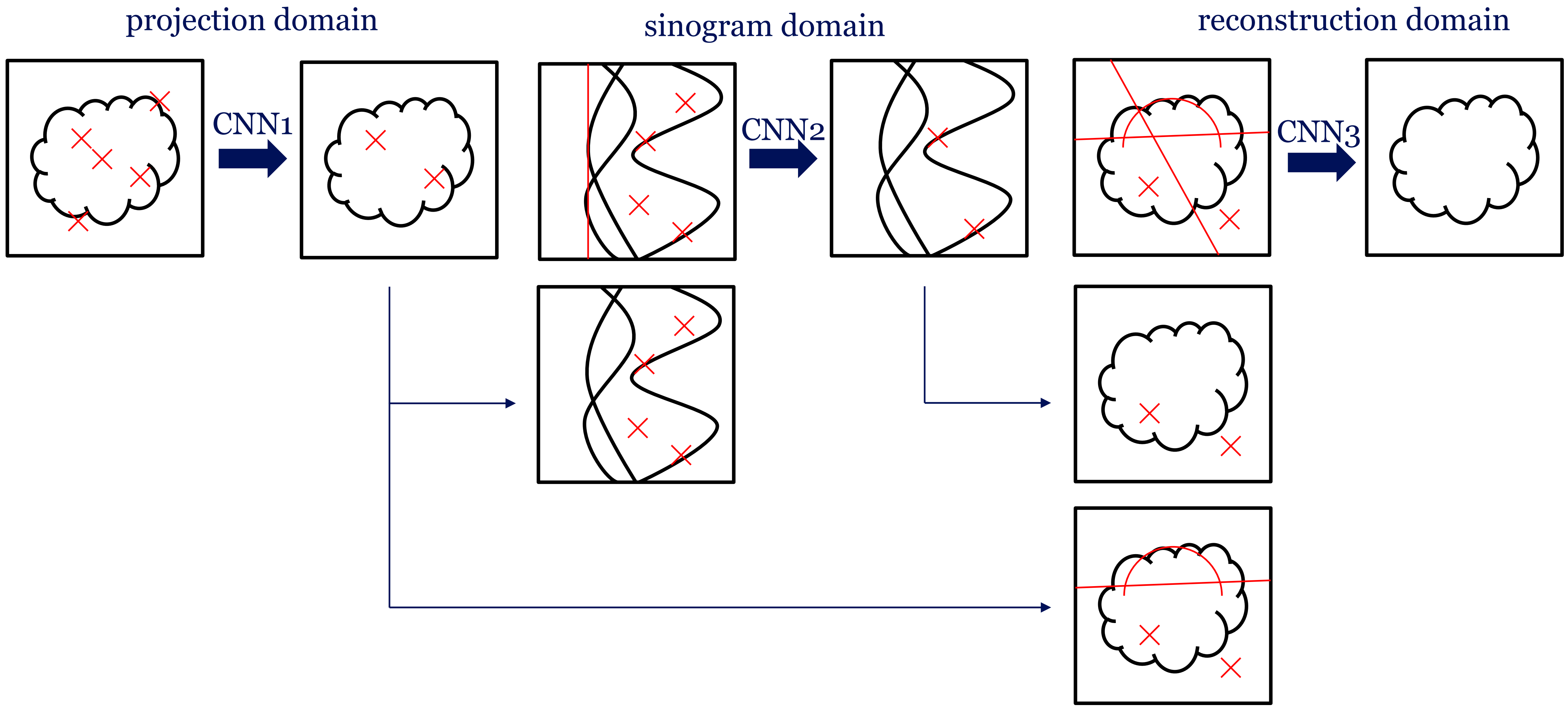


Problem

- A lot of deep-learning denoising techniques exist for reconstruction domain. [Marcos et al., 2020] [Bepler et al. 2020] [Chen et al., 2016]
- But with high noise level and certain artifacts, those techniques could yield to suboptimal result.
- Full potential of CT is not used.

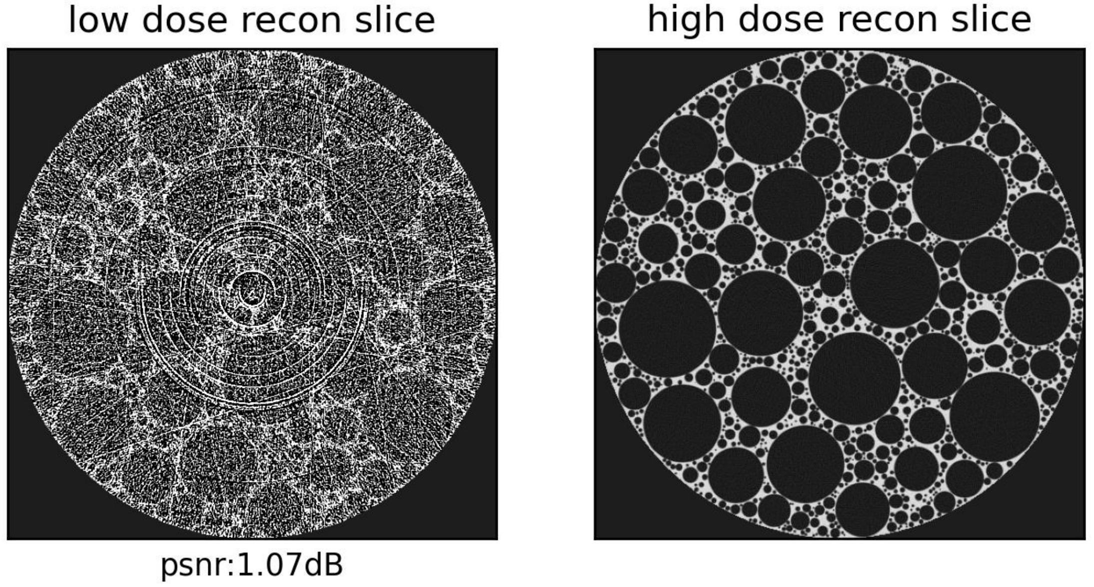


Algorithm

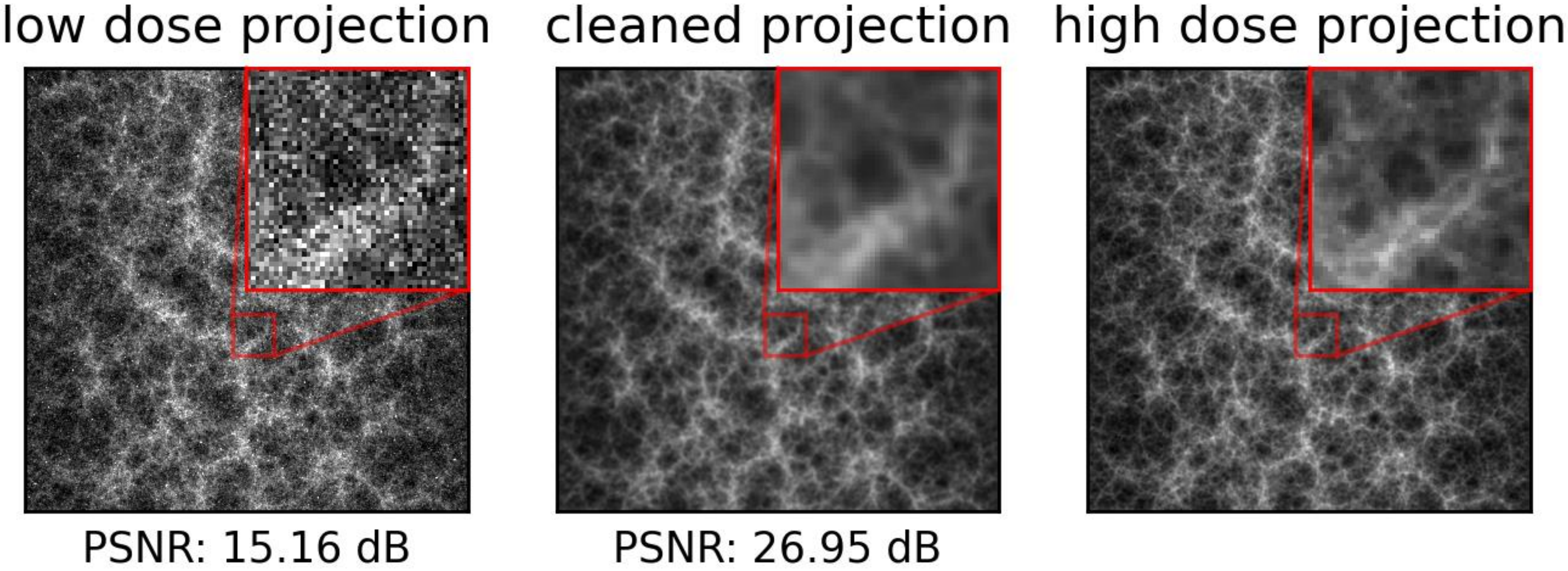

projection domain
sinogram domain
reconstruction domain
CNN1
CNN2
CNN3

Algorithm – Experiment Setup

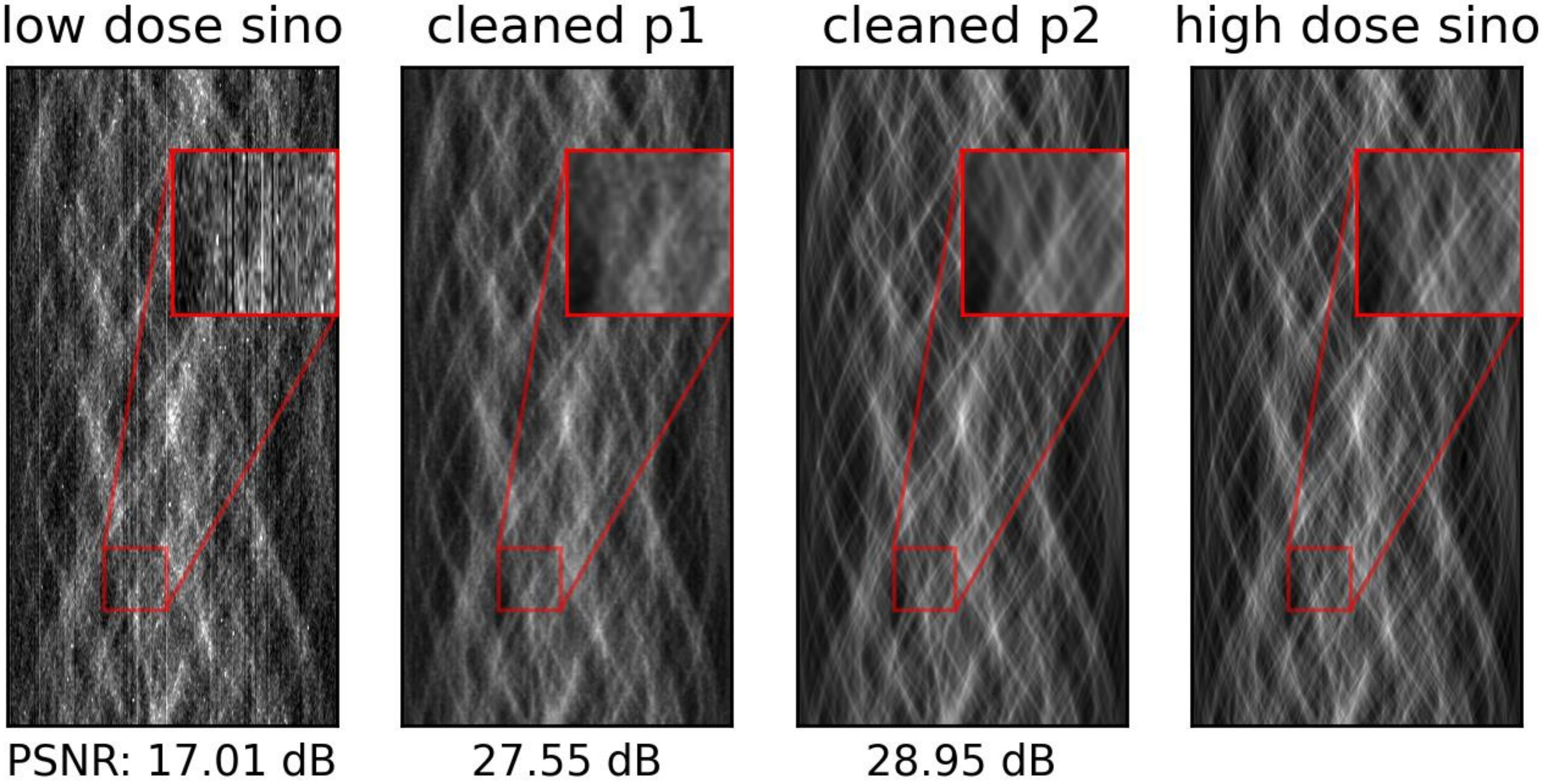
- For each stage, Unet [Ronneberger, 2015] with reduced channels or MSD-Net [D. M. Pelt & J. A. Sethian, 2017] is used
- Training with augmentation due to limited training examples, and early stopping
- Simulated foam phantom [D. M. Pelt et al., 2022] with ASTRA Toolbox [W. van Aarle et al., 2016]
  - Low dose: fewer projections, add poisson noise, ring and zinger artifacts
  - High dose: noise-free
- Parallel beam, reconstruction with FBP



Result – projection domain

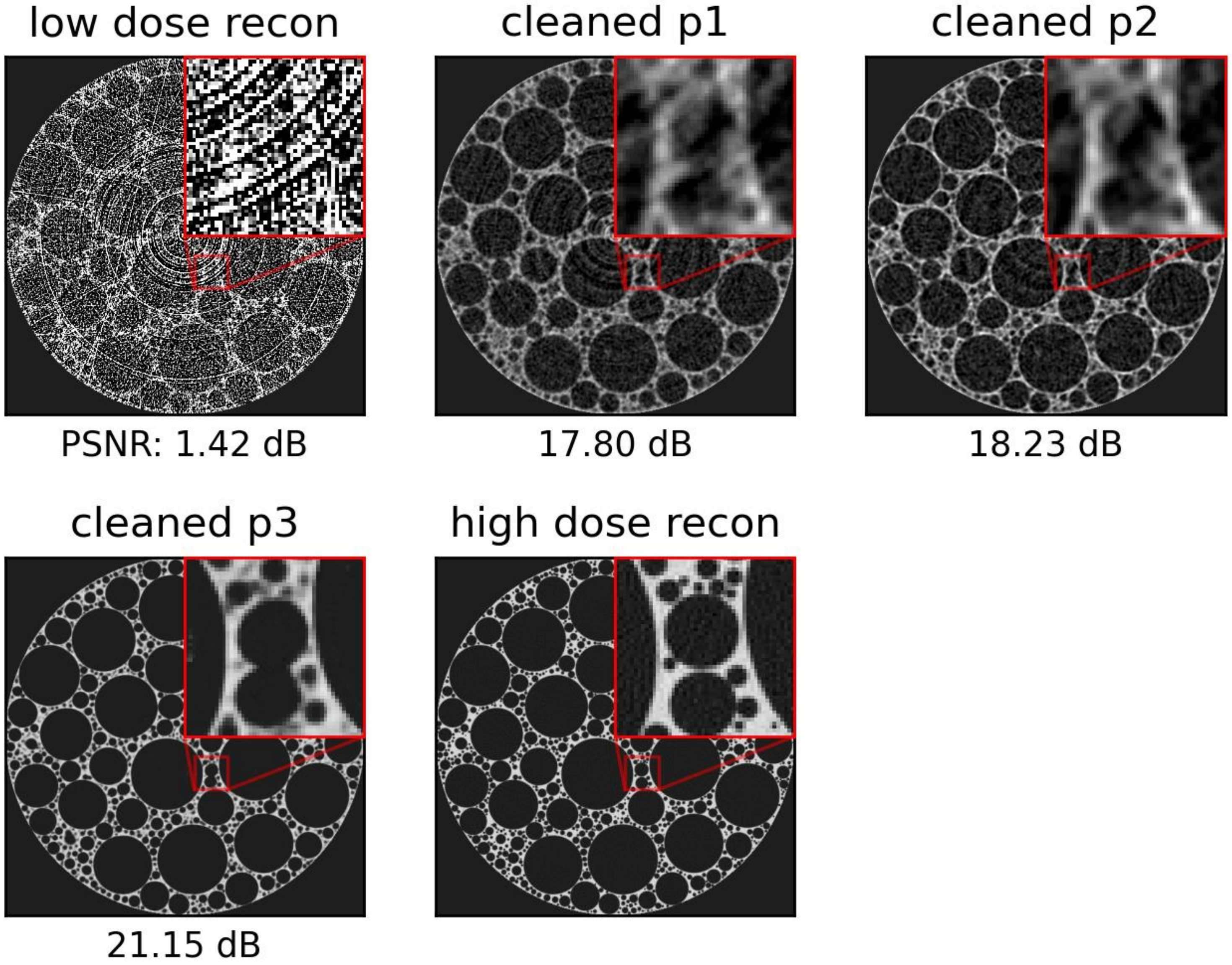


Result – sinogram domain



Result – reconstruction domain

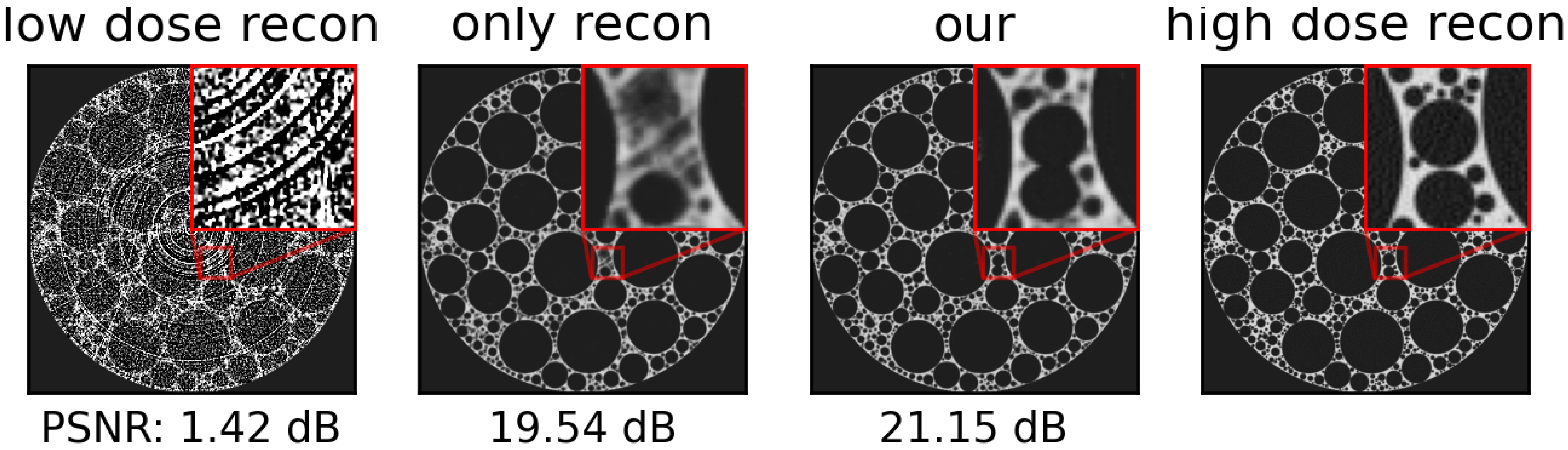
- Noise is reduced gradually
- Effective against ring/zinger artifacts
- Ring/Zinger artifacts are easier to be removed in projection and sinogram domain



Result – reconstruction domain

Compare with supervised learning only in reconstruction domain

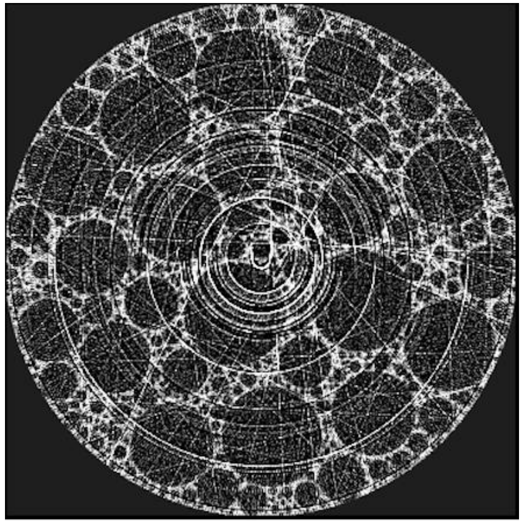
CNN with equal training parameters as CNNs for 3 stages in total, same training strategy



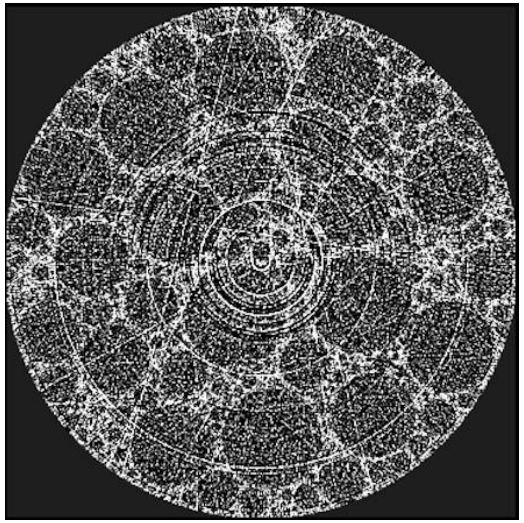
Result – different Poisson level

Poisson noise + ring + zinger

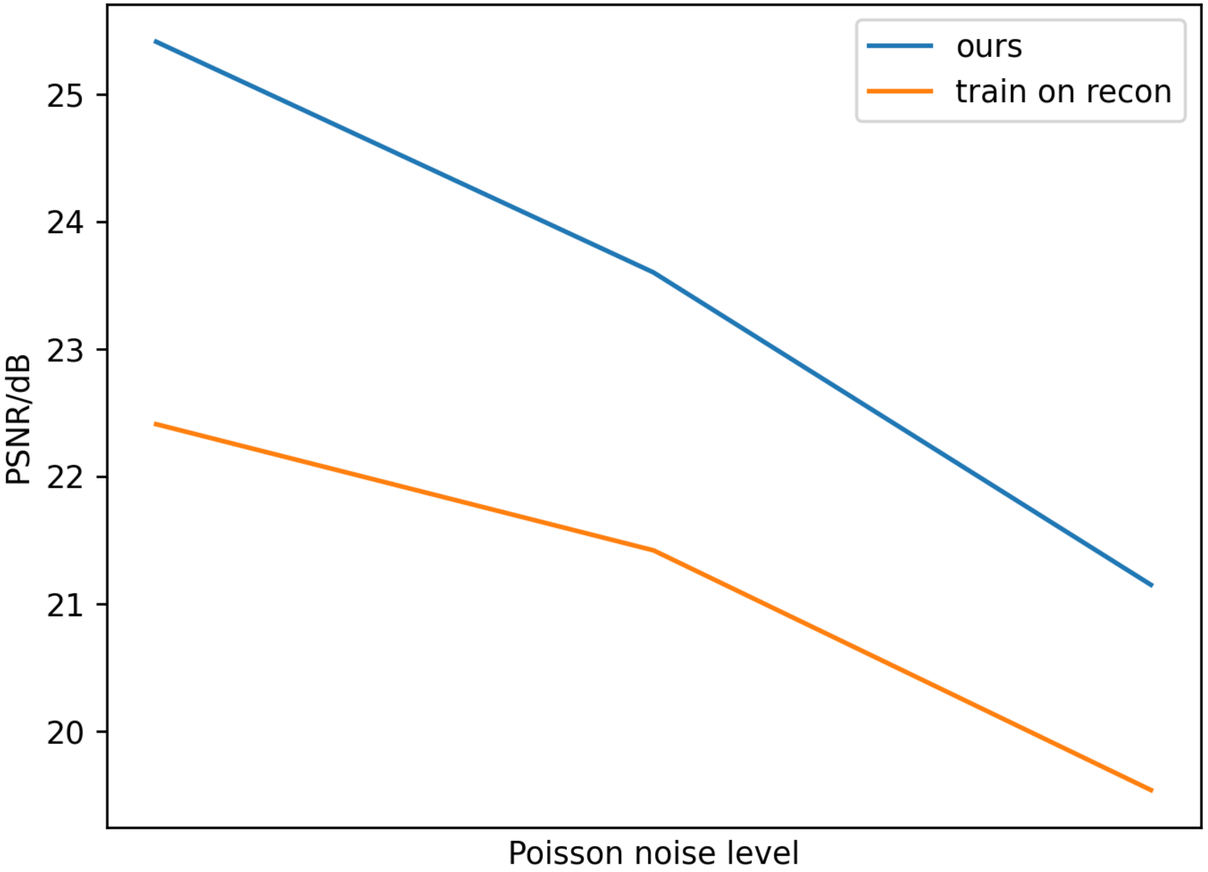
- Fixed ring and zinger artifact, and different Poisson noise level



PSNR: 5.26 dB



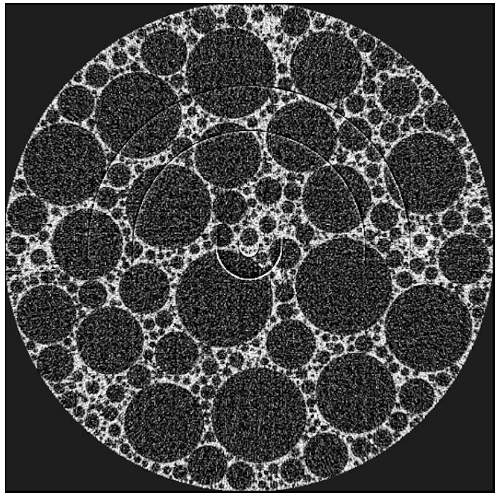
PSNR: 1.42 dB



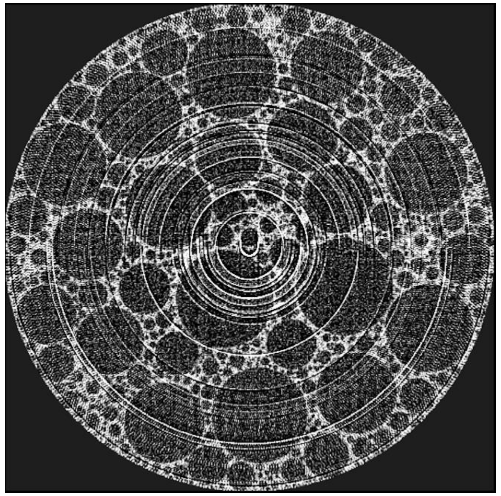
Result – different ring artifact level

Poisson noise + ring

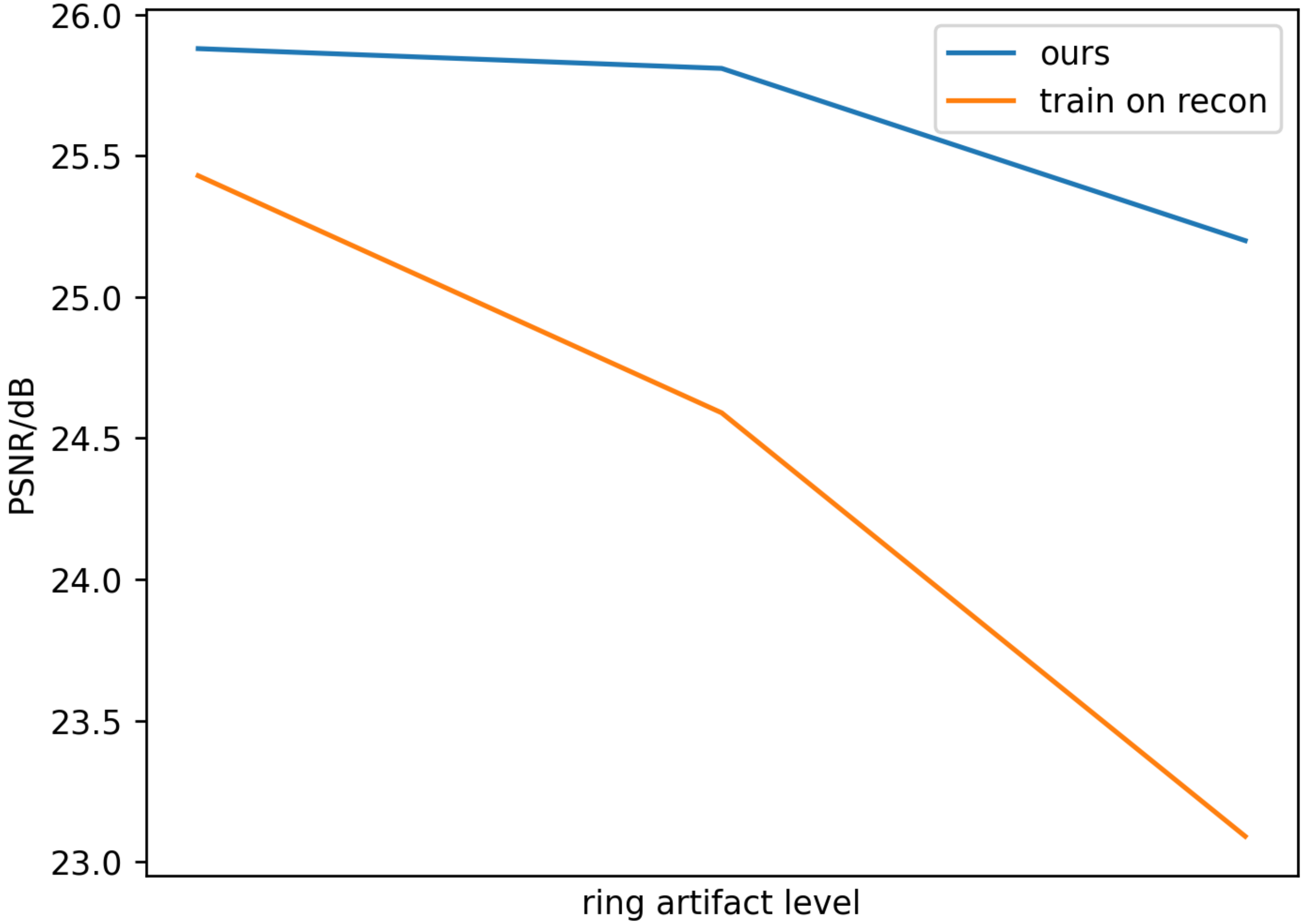
- Fixed Poisson noise and different ring artifact level



PSNR: 10.69 dB



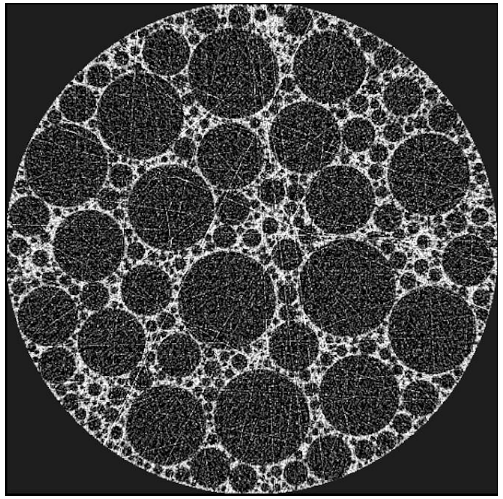
PSNR: 6.24 dB



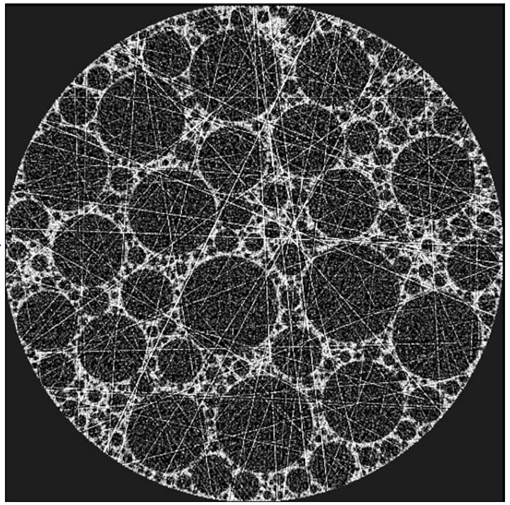
Result – different zinger artifact level

Poisson noise + zinger

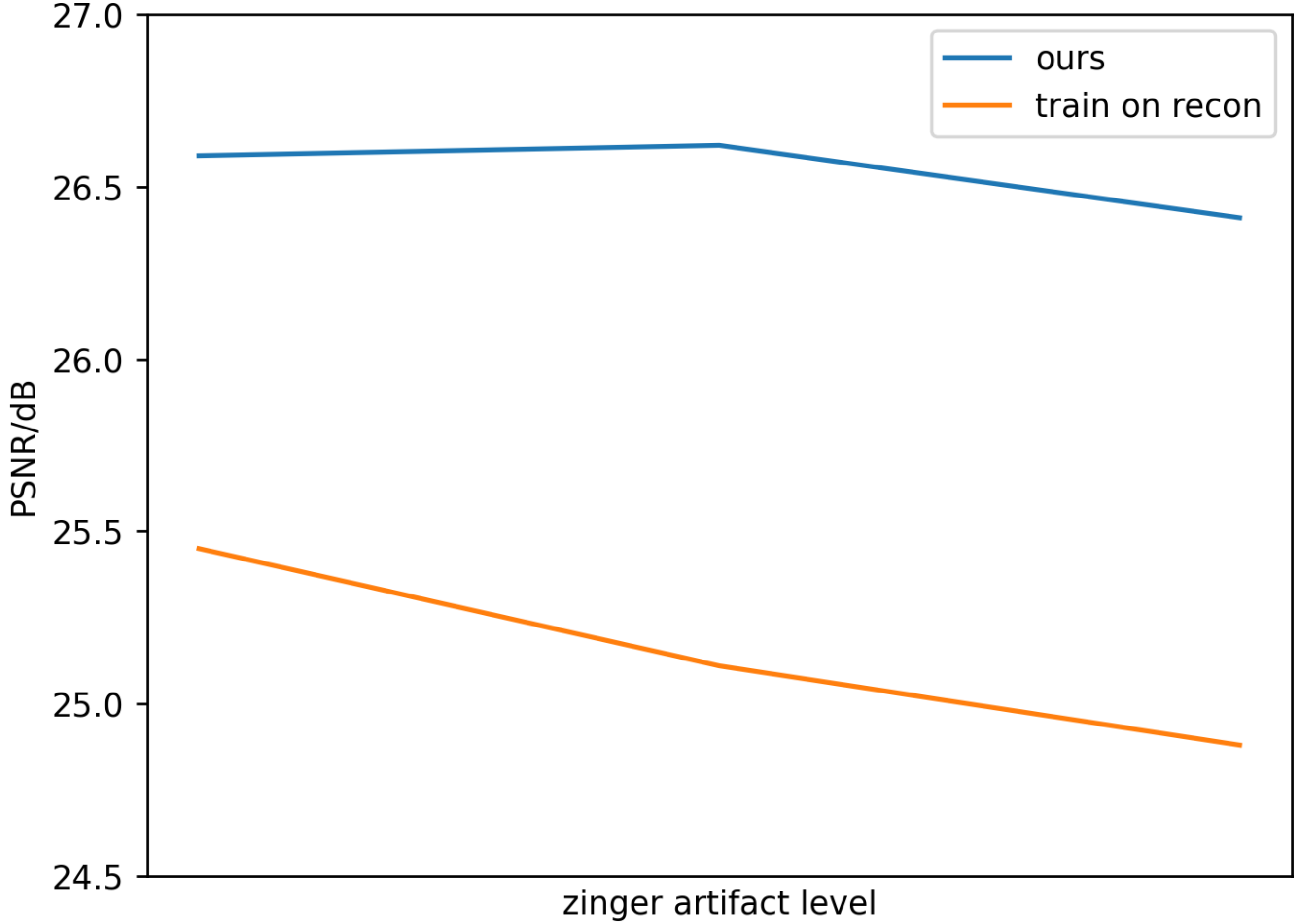
- Fixed Poisson noise and different zinger artifact level



PSNR: 10.78 dB



PSNR: 8.85 dB



Summary

- Beside Poisson noise, our denoising strategy could also remove ring and zinger artifacts
- Ring and zinger is easier to be removed in projection and sinogram domain
- Limits:
  - Only tested on simulated data, Difficult to acquire two (similar) phantoms in practice
- Expanding this algorithm to self-supervised denoising
- Also works for cone beam, the performance is slightly worse than parallel beam case

Thank you!

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j.shi@liacs.leidenuniv.nl