4D X-Ray CT Reconstruction using Multi-Slice Fusion

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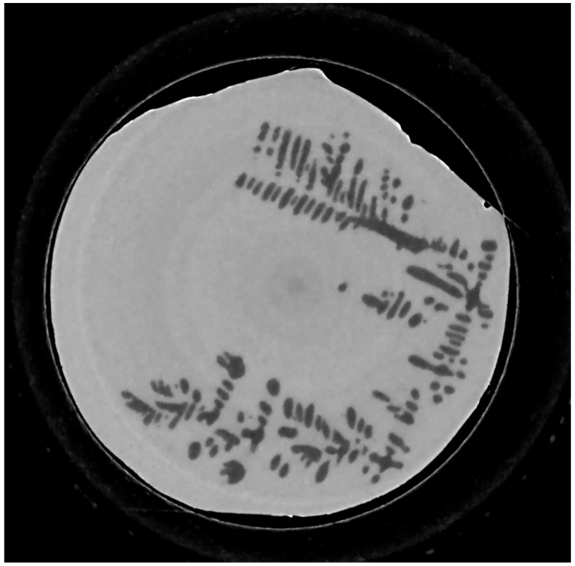
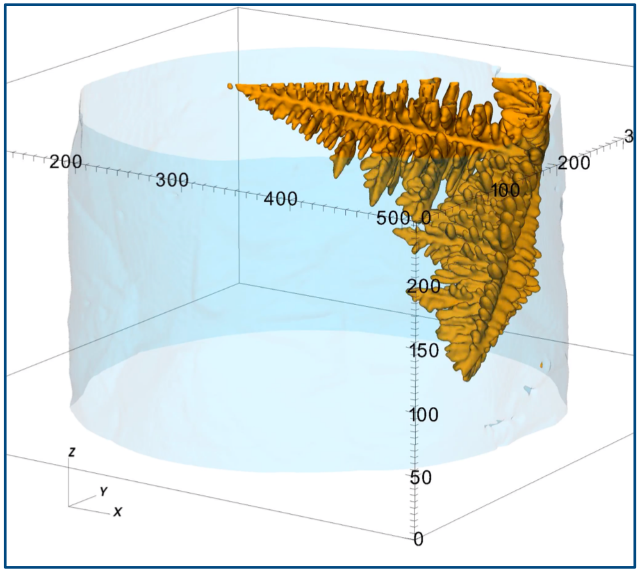
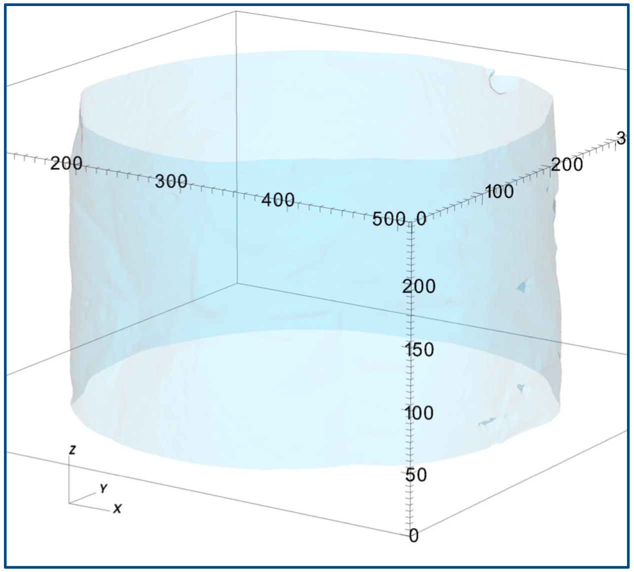
What is 4D (or High-D) Reconstruction?



2D: Image



3D: Volume



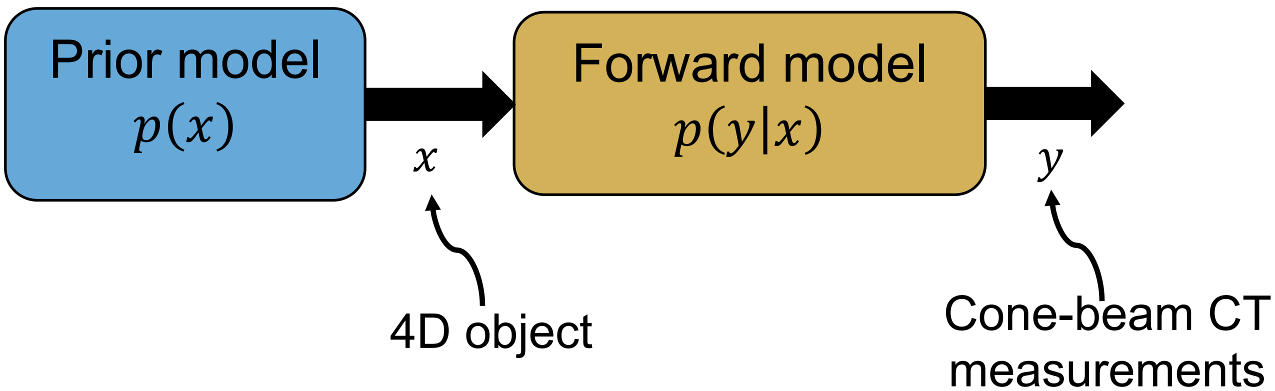
4D: Volume + time

- Reconstruct objects in many dimensions:
    - 4D: Space + time
    - 5D: Space + time + parameters (e.g., heart + respiration phase)

- Advantages:
    - Reduce data
    - Increase temporal resolution

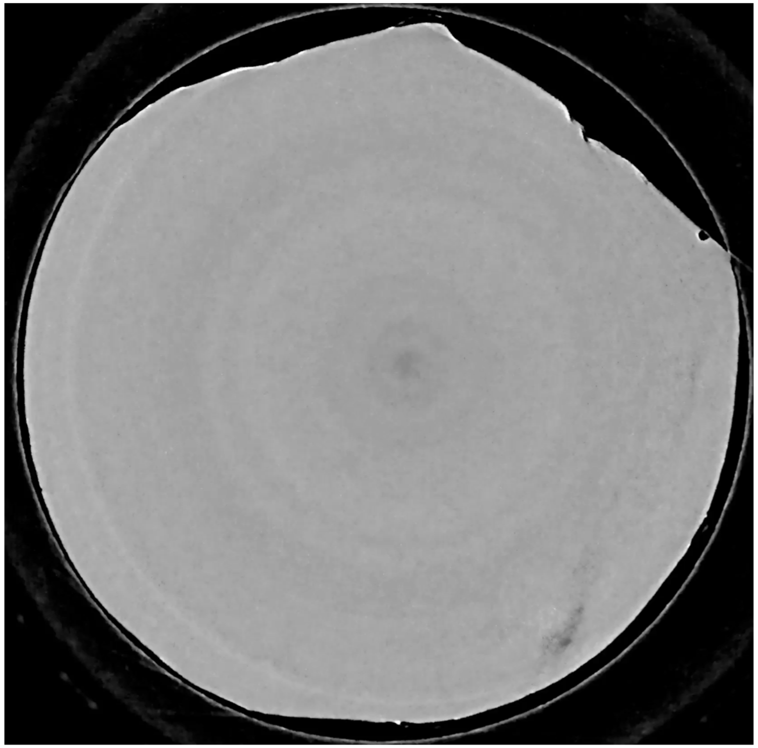
* Mohan, K. Aditya, et al. "TIMBIR: A method for time-space reconstruction from interlaced views." *IEEE Transactions on Computational Imaging* 1.2 (2015): 96-111.

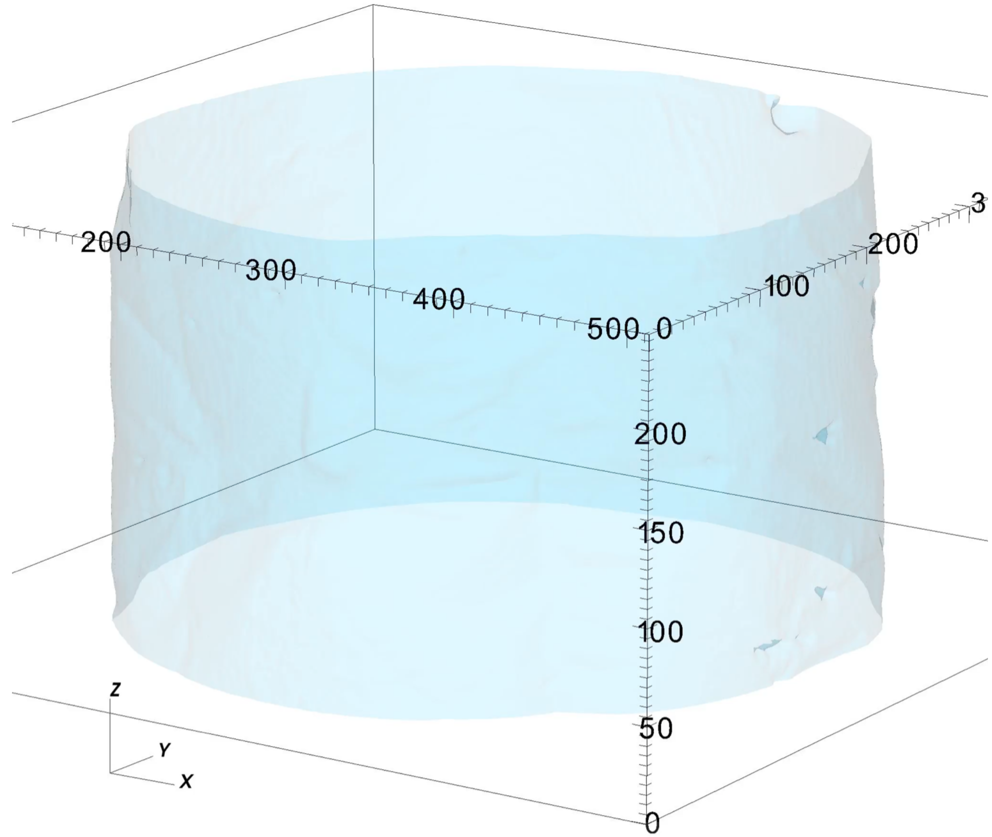
MBIR for 4D CT Reconstruction



- Forward model: $f(x) = -\log p(y|x)$
- 4D Prior model: $h(x) = -\log p(x)$
- 4D MBIR reconstruction: $\hat{x} \leftarrow \arg\min_{x} \{f(x) + h(x)\}$

Previous Work on 4D MBIR Reconstruction





TIMBIR:

- Showed 16x increase in temporal resolution
- Based on simple 4D MRF prior

Can we do better with advanced 4D priors?

* Mohan, K. Aditya, et al. "TIMBIR: A method for time-space reconstruction from interlaced views." *IEEE Transactions on Computational Imaging* 1.2 (2015): 96-111.

Designing Advanced 4D Prior Model

Challenges:

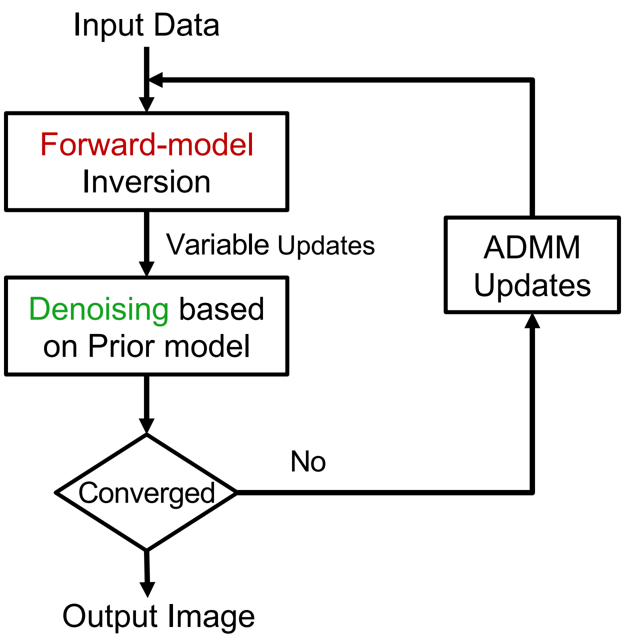
- 4D (or high-D) prior modeling is difficult!
- Curse of dimensionality: In 5D, each voxel has 242 neighbors!
- Prior model is often more computation than forward model!

Approach:

- Use CNNs to build advanced 4D prior model
- CNNs are fast and very effective at modeling complex data
- Heterogeneous CPU/GPU computing with TensorFlow libraries

How to Incorporate a CNN Prior?

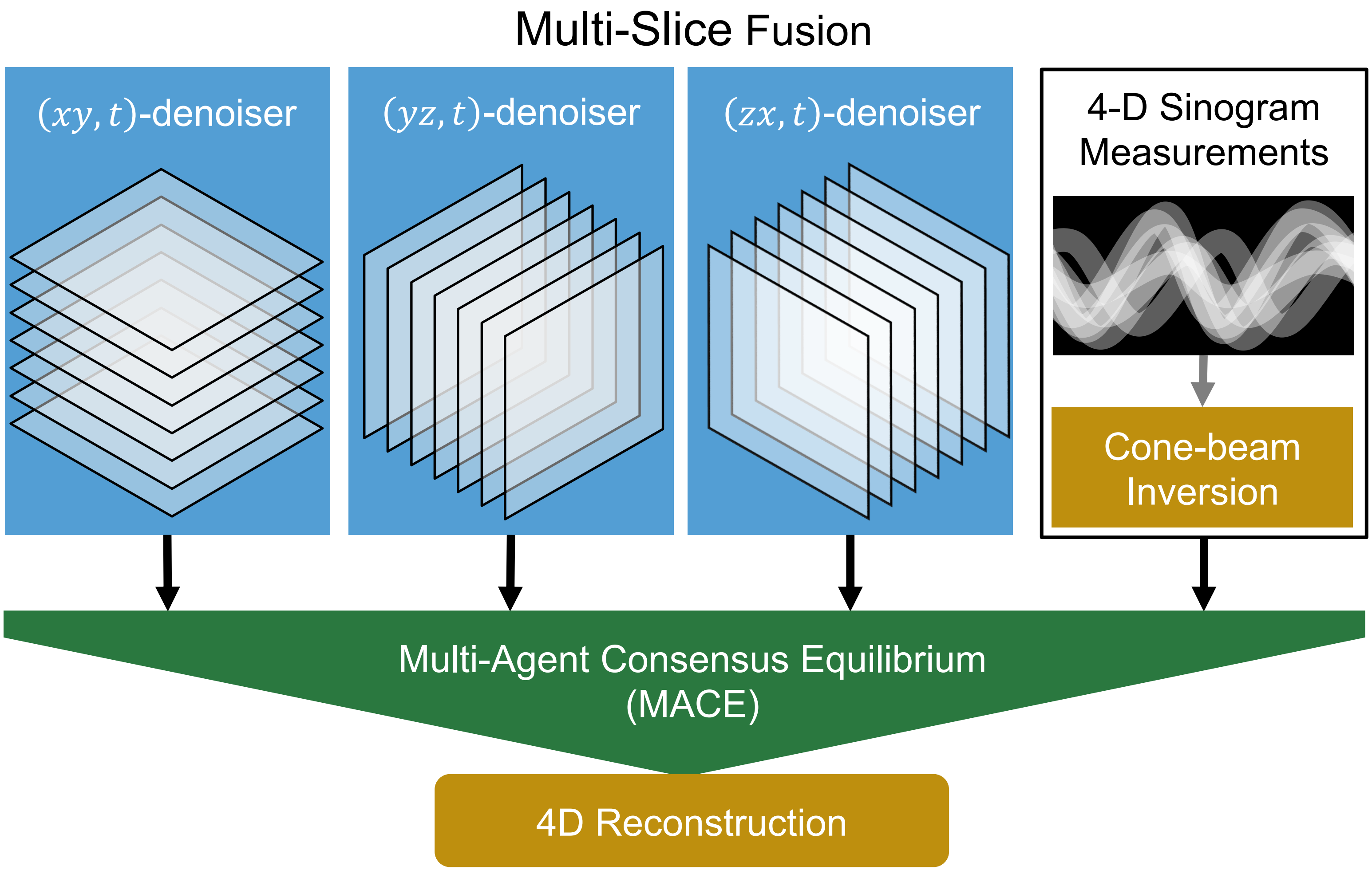
- Plug & Play Priors:
  - CNN denoiser functions as prior model
  - Variations: P&P-ADMM, RED, P&P-FISTA
  - Alternate reconstruction and denoising



- **Problem**: 4D CNN denoising is difficult
  - 4D convolutions require 6D kernels: computationally expensive
  - No GPU accelerated routines from major Deep Learning vendors
  - 4D training data difficult to obtain

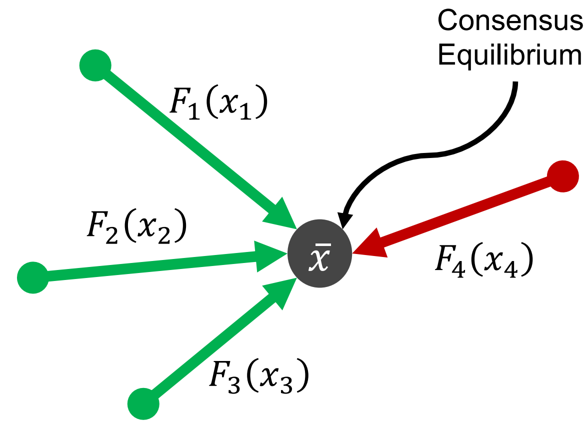
Can we build 4D prior from 2D convolutions?

Multi-Slice Fusion using MACE



- Fuse multiple low-D CNN denoisers to implement 4D prior
- Use 2D convolutions: fast and implementable
- No 4D training data required

Intro to MACE Model Fusion



How does MACE work?

- Generalization of Plug & Play
- Can fuse multiple models
- Can be viewed as a force balance equation

MACE equilibrium equations:

$$L(X) = G(X)$$

where

$$L(X) = \begin{bmatrix} F_1(x_1) \\ F_2(x_2) \\ F_3(x_3) \\ F_4(x_4) \end{bmatrix}, \qquad X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}; \quad G(X) = \begin{bmatrix} \bar{x} \\ \bar{x} \\ \bar{x} \\ \bar{x} \end{bmatrix}, \qquad \bar{x} = \frac{1}{2}\left(\frac{1}{3}\sum_{k=1}^{3} x_k + x_4\right)$$

Forward model agent

Prior model agents

Definition of Agents

- **Forward model** agent is a proximal map that fits the data:

$$F_4(x) = \underset{v \in \mathbb{R}^N}{\operatorname{argmin}} \left\{ -\log p(y|v) + \frac{\beta}{\sigma^2} \|v - x\|_2^2 \right\}$$

- **Prior model** agents are CNN denoising operators:
  - F_1 denoises in (x, y, t)
  - F_2 denoises in (x, z, t)
  - F_3 denoises in (y, z, t)
  - F_1, F_2, F_3 share same architecture and weights

- CNN denoisers are trained to remove AWGN noise
  - Does not represent measurement noise
  - Artificial noise within MACE framework

Computing MACE solution

Initial Reconstruction: $x_1 = x_2 = x_3 = x_4 \in \mathbb{R}^N$

$X \leftarrow W \leftarrow \begin{bmatrix} x_1 \\ \vdots \\ x_4 \end{bmatrix}$

while *not converged*

$X \leftarrow \tilde{L}(W; X)$

$Z \leftarrow G(2X - W)$

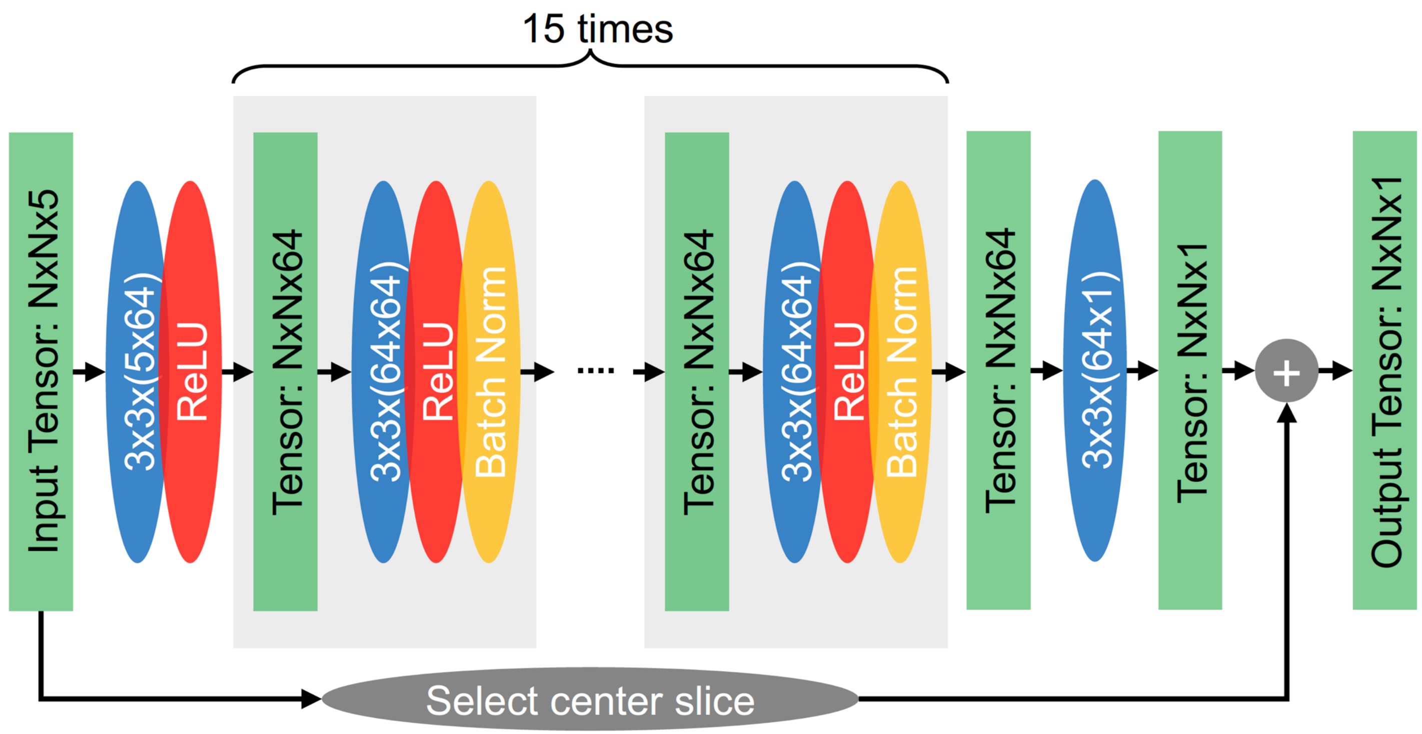
$W \leftarrow W + 2\,\rho(Z - X)$

Return(x_1)

Other details:

- Uses partial update of $L(W) \approx \tilde{L}(W; X)$ to reduce computation
- The parameter $\rho \in (0,1)$ can be adjusted to speed convergence
- Special case: two agents and $\rho = 0.5$ equivalent to ADMM
- CNN agents ran on GPUs, and inversion agents ran on CPUs

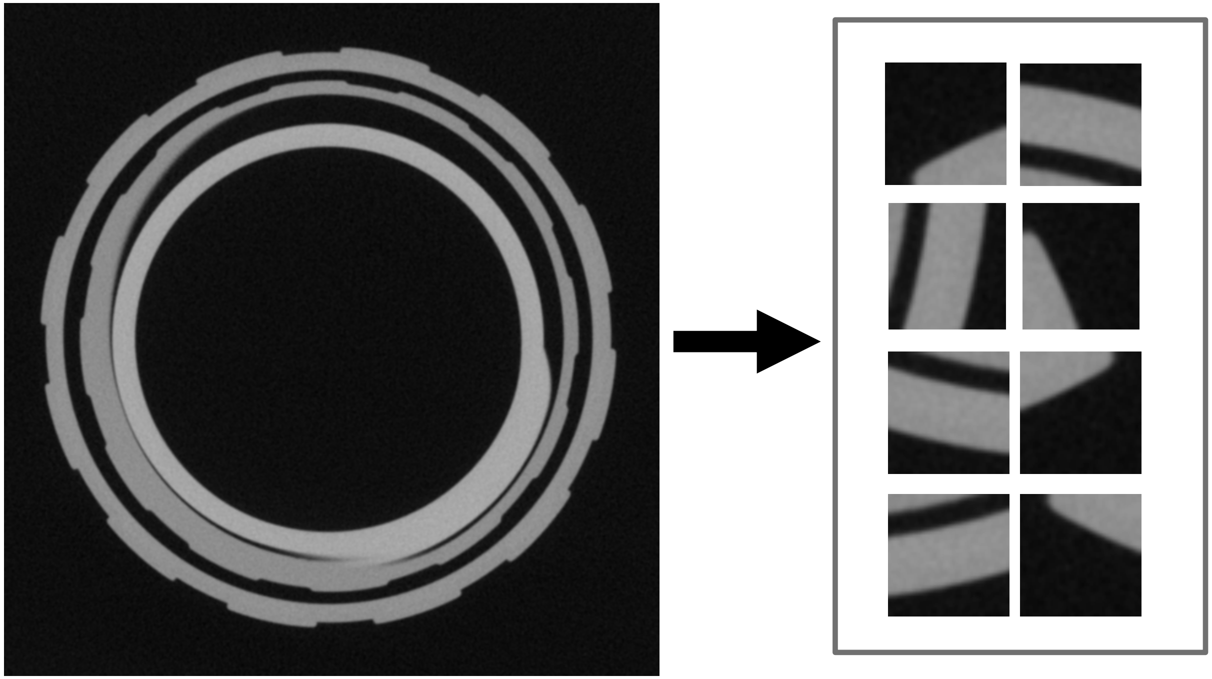
2.5D CNN Denoiser Architecture



Network Architecture

- 17 Layer residual network
- 2.5-D: Multiple 2-D slices passed as input channels
- Denoises center slice of 5 adjacent time points
- Denoises full volume with a moving window

Training CNN Denoisers



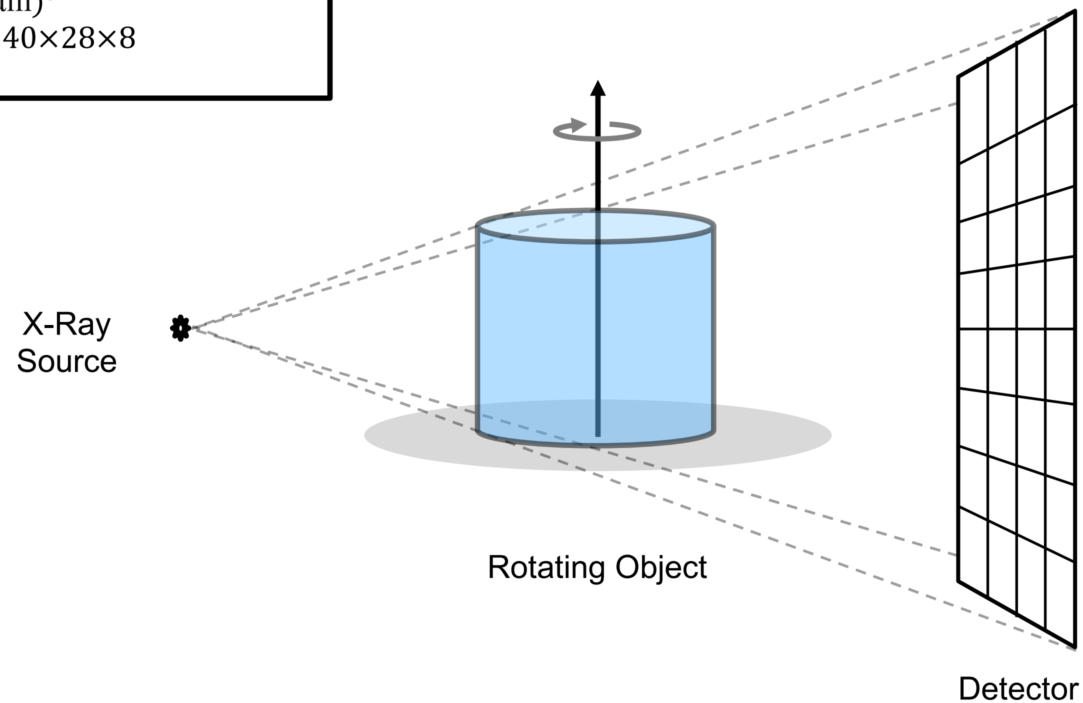
Typical CT volume

Patches of size $40 \times 40 \times 5$

1. Extract patches
2. Add synthetic AWGN noise to patches
3. Train CNN to remove noise

Simulated Experimental Setup

Source-Detector Distance	839 mm
Magnification	5.57
Cropped Detector Array	240×28, $(0.254\ \text{mm})^2$
Detector resolution at ISO	45.7 μm
Number of Views per Rotation	75
Voxel Size	$(45.7\ \mu\text{m})^3$
Reconstruction Size (x, y, z, t)	240×240×28×8

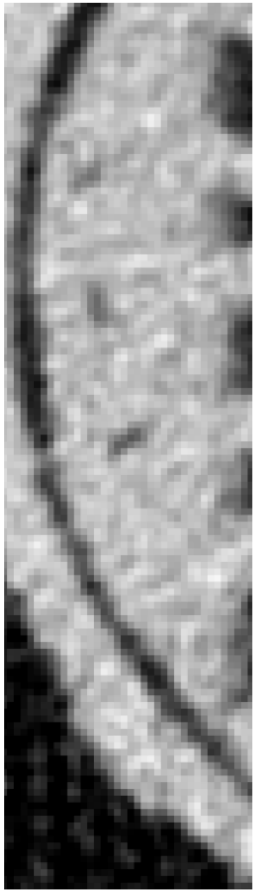


Procedure:

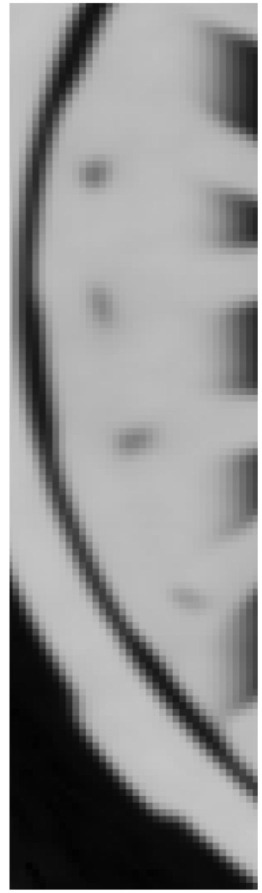
1. Generate 3D phantom
2. Translate 3D phantom to generate 4D phantom
3. Forward project phantom to generate sinograms
4. Reconstruct from sinograms
5. Compare with phantom

Simulated Results: Qualitative Comparison

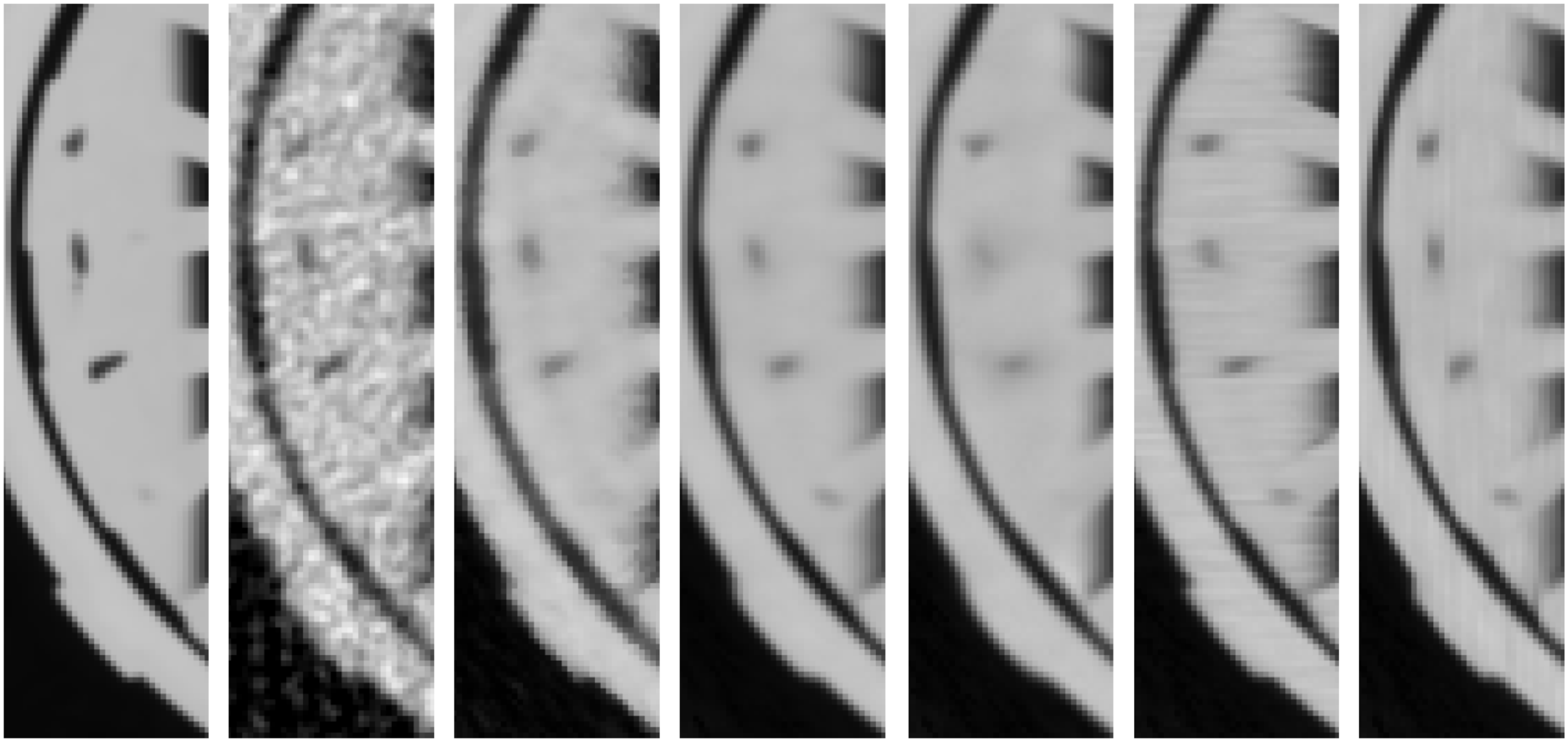

Phantom


FBP (3D)

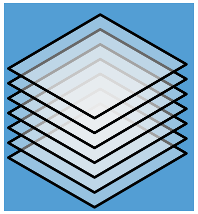

4D MBIR

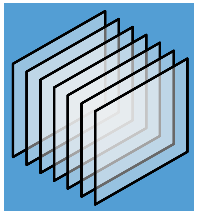

Multi-Slice Fusion

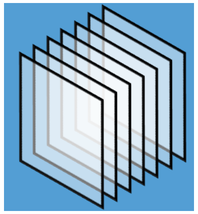
Simulated Results: Qualitative Comparison



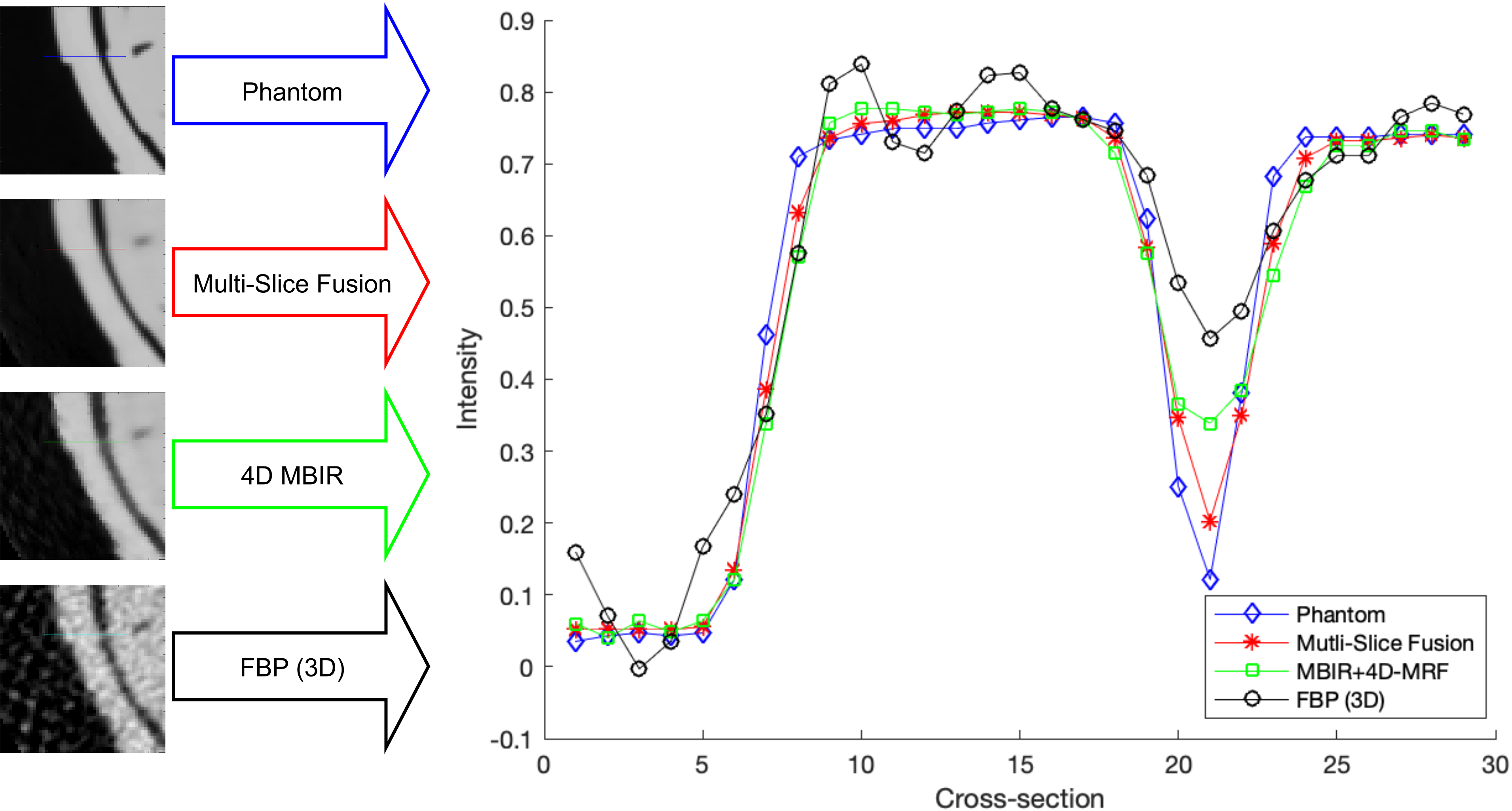
Phantom | FBP (3D) | 4D MBIR | Multi-Slice Fusion | CNN (xy, t) | CNN (yz, t) | CNN (zx, t)







Simulated Results: Cross-Section



Multi-Slice Fusion: most accurate reconstruction of gap

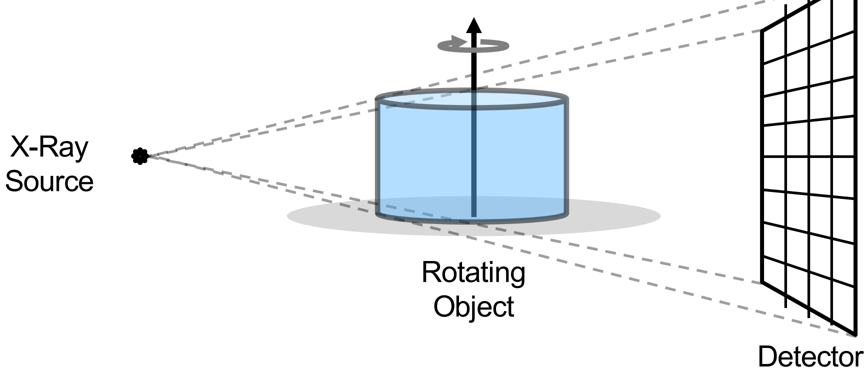
Simulated Results: Quantitative Metrics

Method	PSNR(dB)	SSIM
FBP	19.690	0.609
MBIR+4D-MRF	25.837	0.787
Multi-Slice Fusion	**29.071**	**0.943**
MBIR+$H_{xy,t}$	29.026	0.922
MBIR+$H_{yz,t}$	28.040	0.932
MBIR+$H_{zx,t}$	28.312	0.926

- PSNR and SSIM is computed for each method with respect to the phantom
- Multi-Slice Fusion achieves highest PSNR and SSIM metrics

Experimental Setup

Scanner Model	North Star Imaging X50
Source-Detector Distance	839 mm
Magnification	5.57
Cropped Detector Array	731×91, $(0.254\text{ mm})^2$
Detector resolution at ISO	45.7 µm
Number of Views per Rotation	150
Voxel Size	$(45.7\ \mu\text{m})^3$
Reconstruction Size (x, y, z, t)	$731\times731\times91\times16$

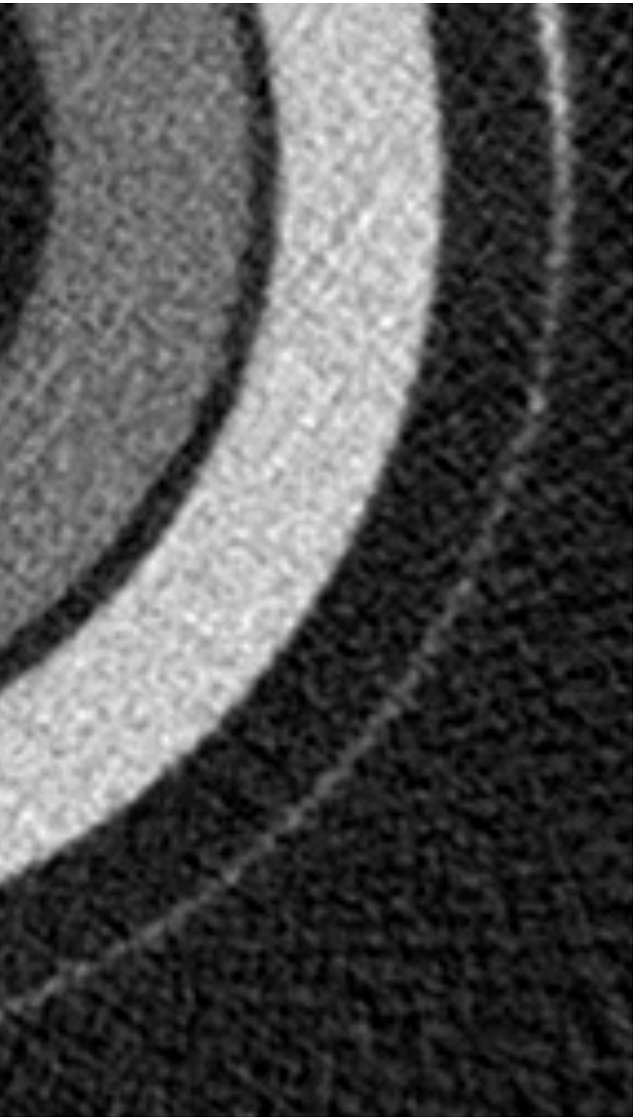


Other details:

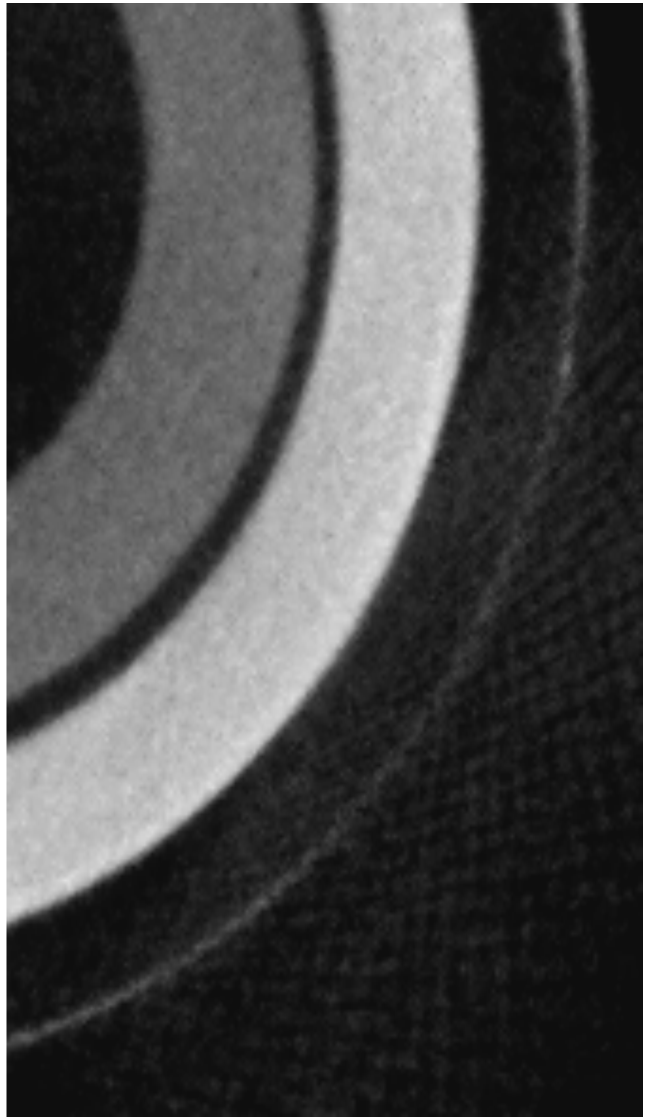
- Object held in place by fixtures: artifacts
- All 4D results undergo preprocessing to correct for jig artifacts

Results: Dynamic 3D Rendering

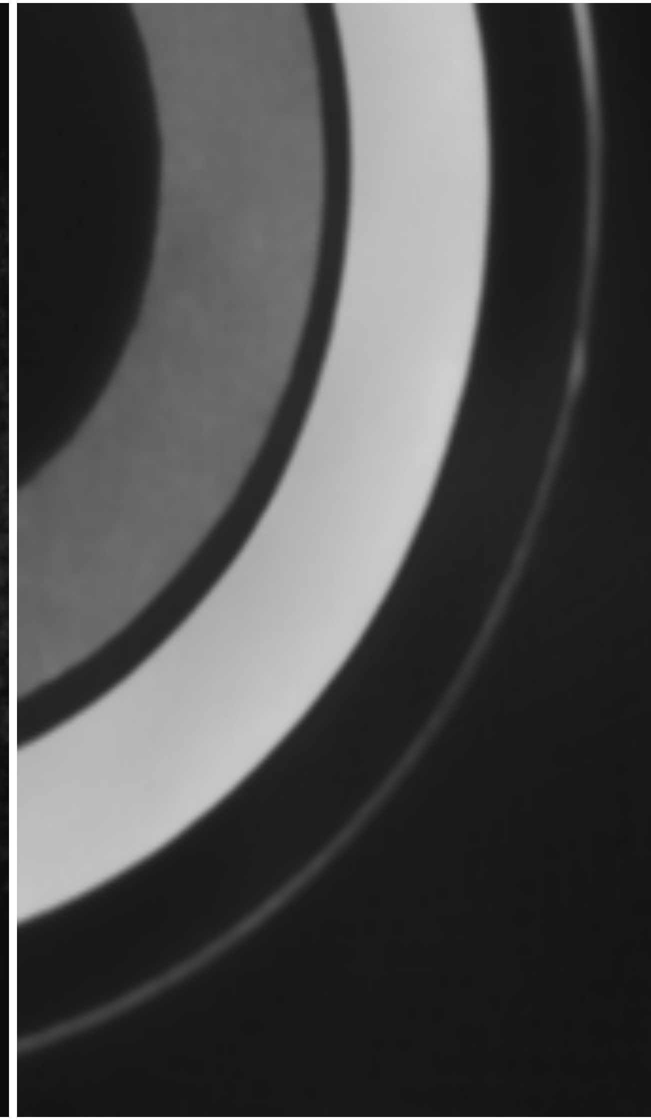
Results: Qualitative Comparison



FBP (3D)



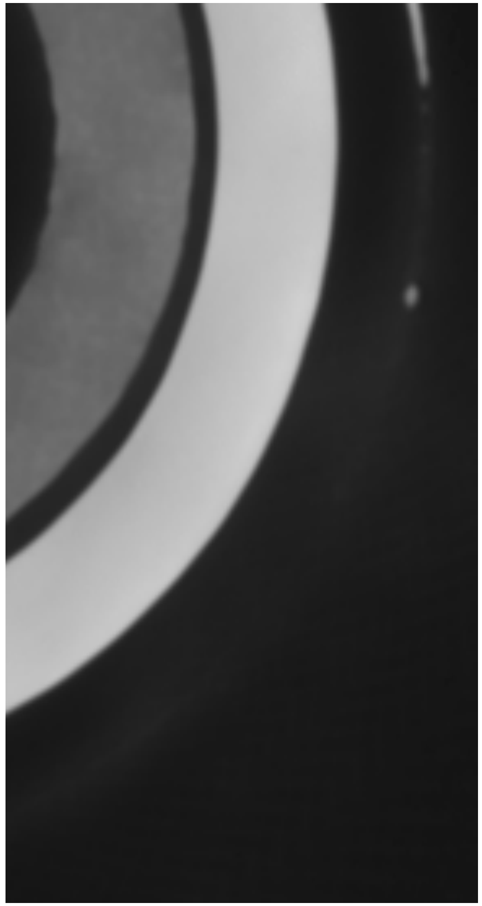
4D MBIR
(MBIR with 4D MRF prior model)



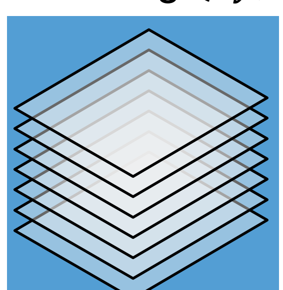
Multi-Slice Fusion

Results: Effect of Model Fusion

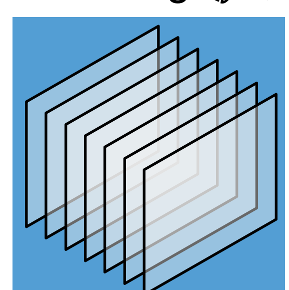
Multi-Slice Fusion

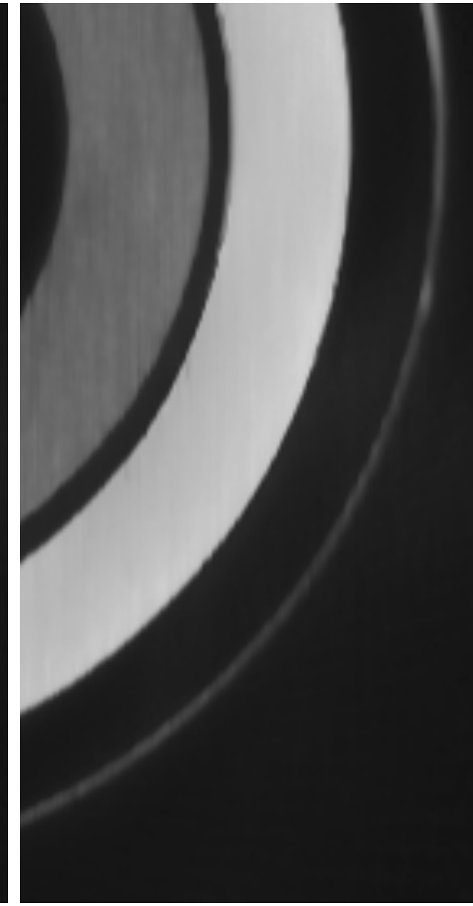


CNN along (xy, t)

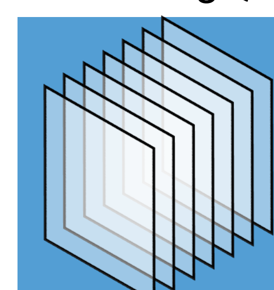


CNN along (yz, t)

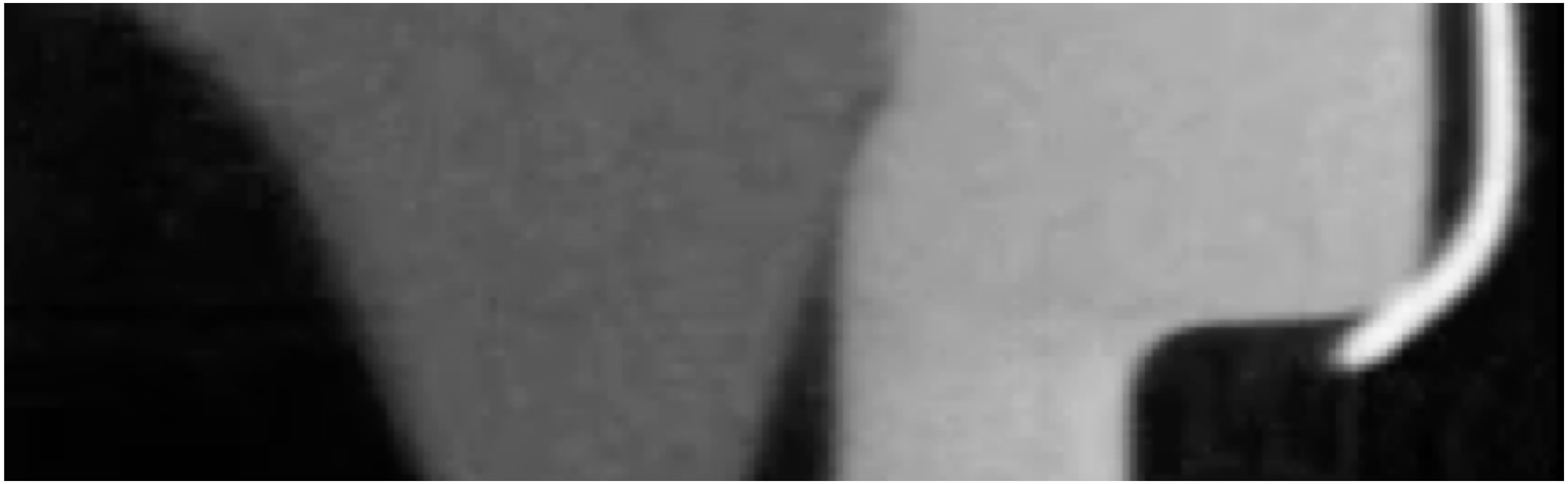




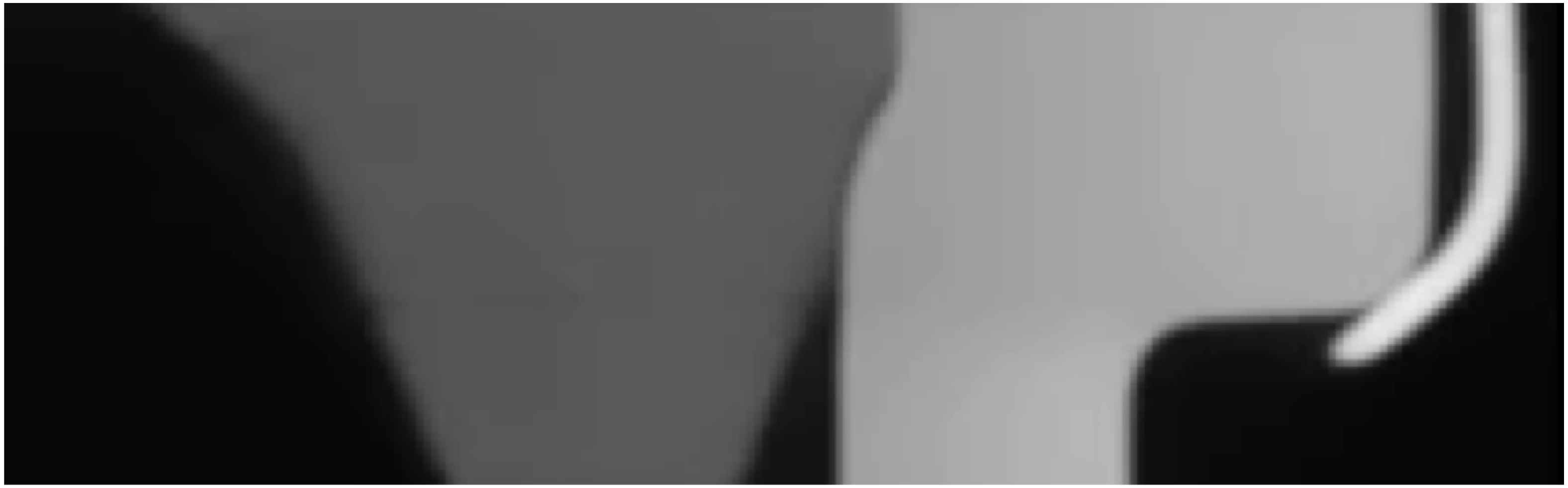
CNN along (zx, t)



Results: Qualitative Comparison (Time-Space)

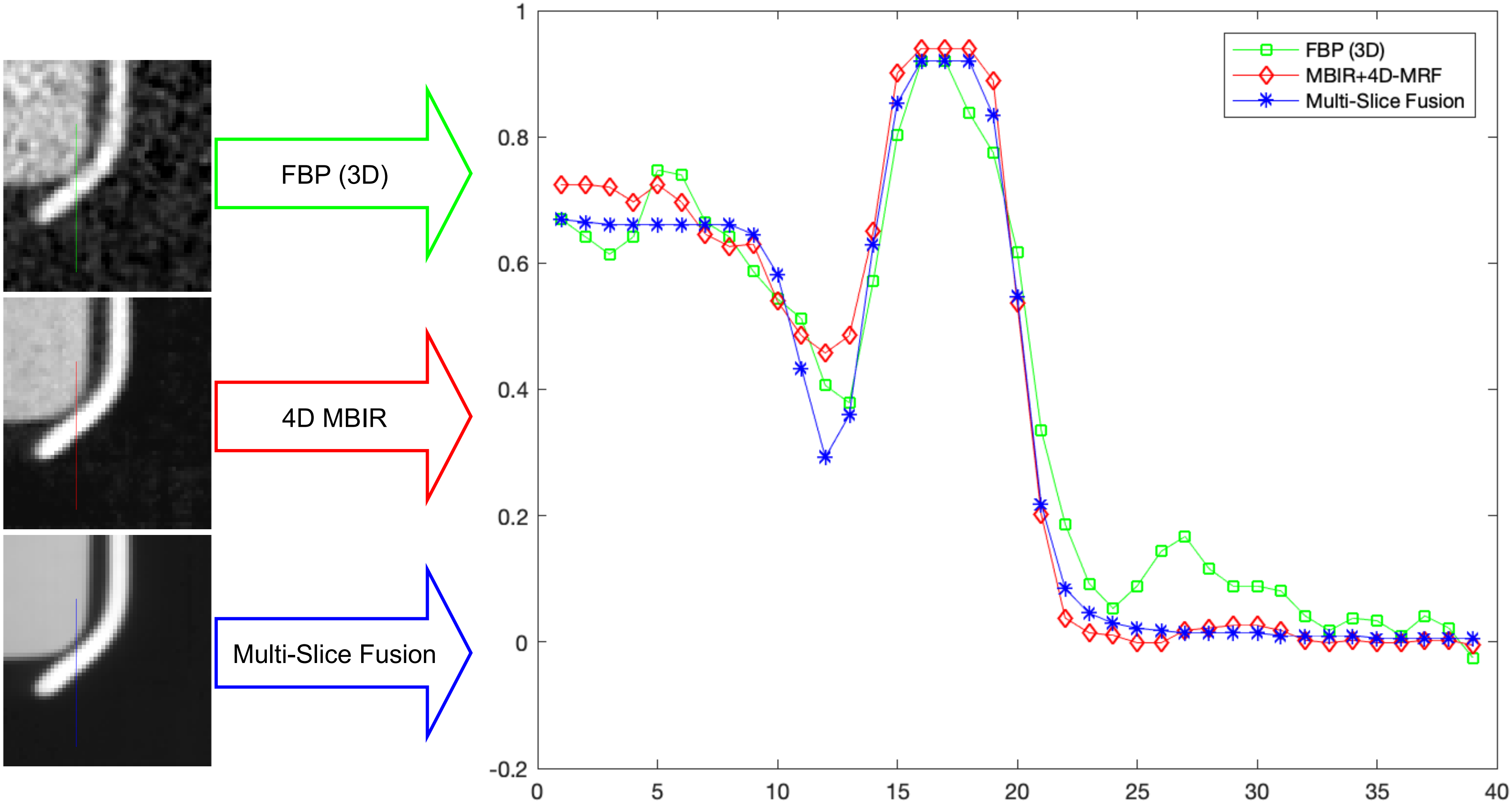


4D MBIR
(MBIR with 4D MRF prior model)

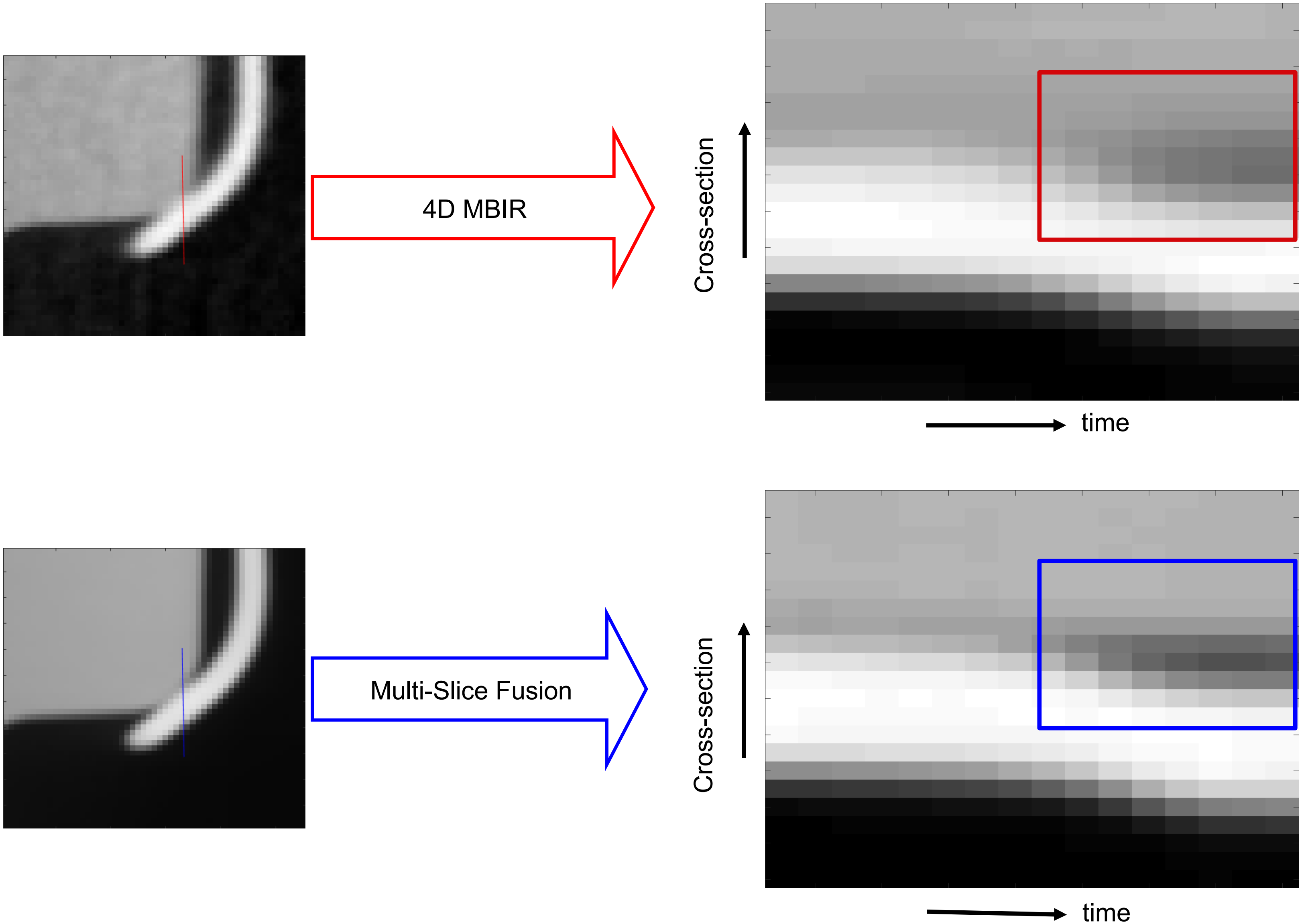


Multi-Slice Fusion
(Uses three 2.5D CNN priors with MACE model fusion)

Results: Cross-Section

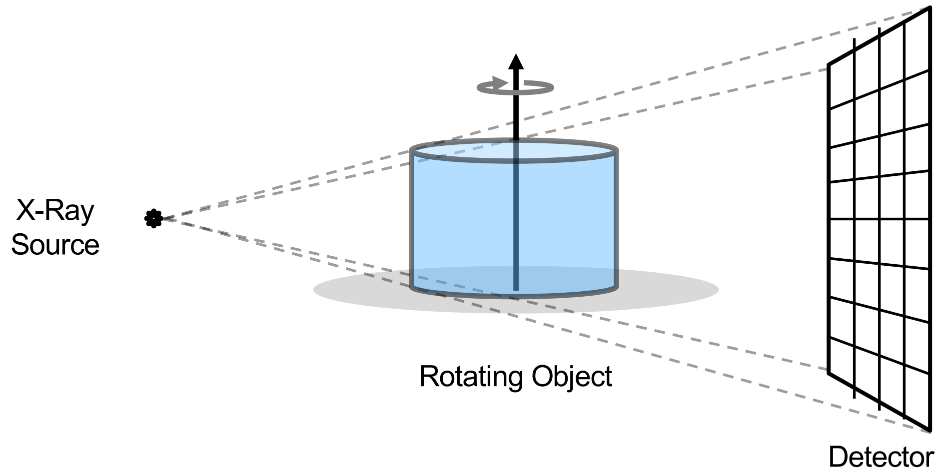


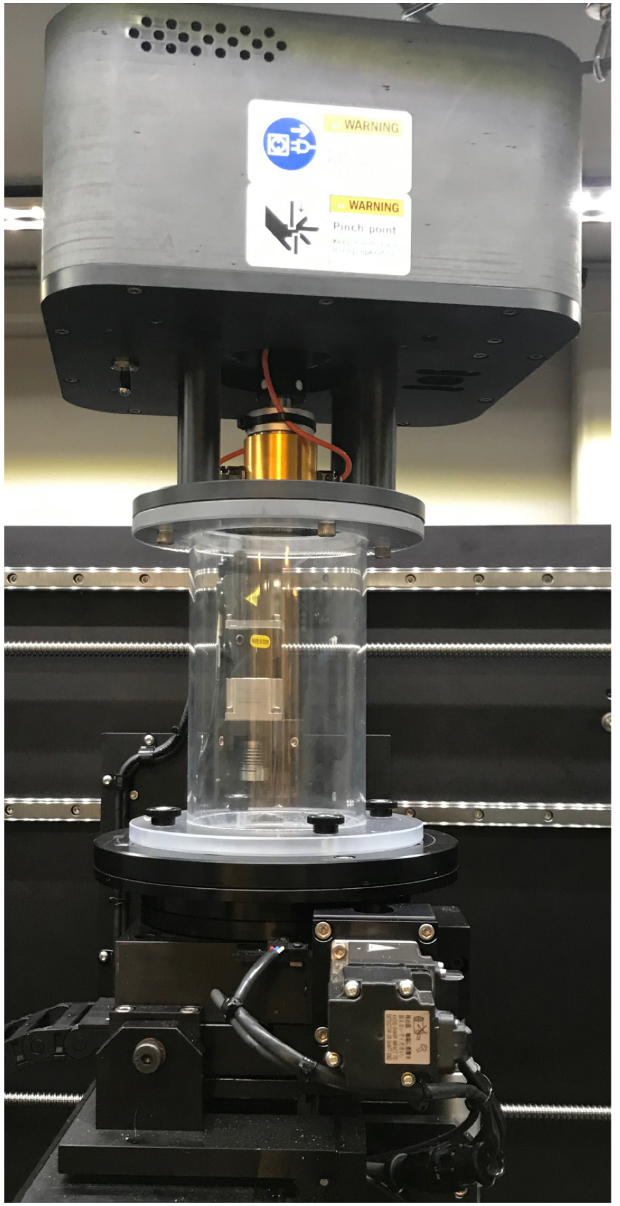
Results: Temporal Resolution



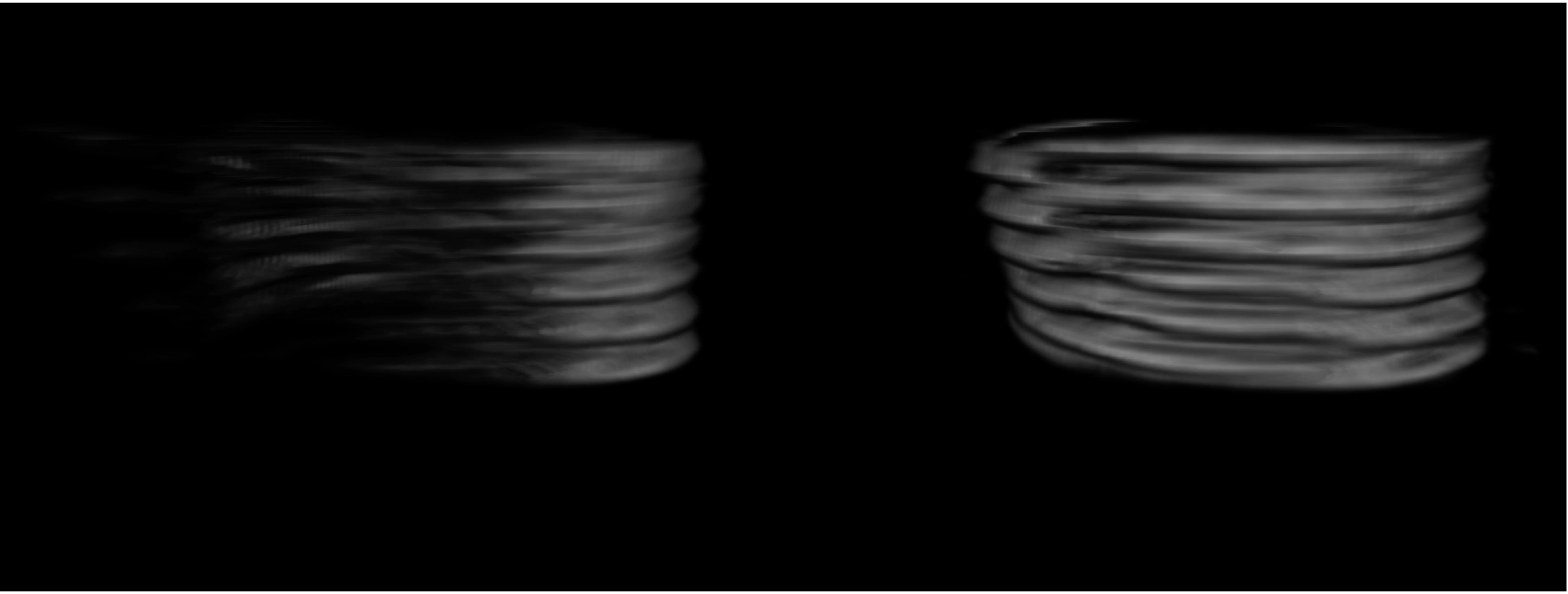
Experimental Setup: Narrow Angle CT

Scanner Model	North Star Imaging X50
Source-Detector Distance	694 mm
Magnification	2.83
Cropped Detector Array	$300{\times}768$, $(0.254\text{ mm})^2$
Detector resolution at ISO	89 μm
Number of Views per Rotation	144
Voxel Size	$(89\ \mu\text{m})^3$
Reconstruction Size (x, y, z, t)	$300{\times}300{\times}768{\times}12$





Results: Narrow Angle CT



FBP (3D)

Multi-Slice Fusion

Each frame reconstructed from disjoint view-sets of 90-degrees

Conclusion

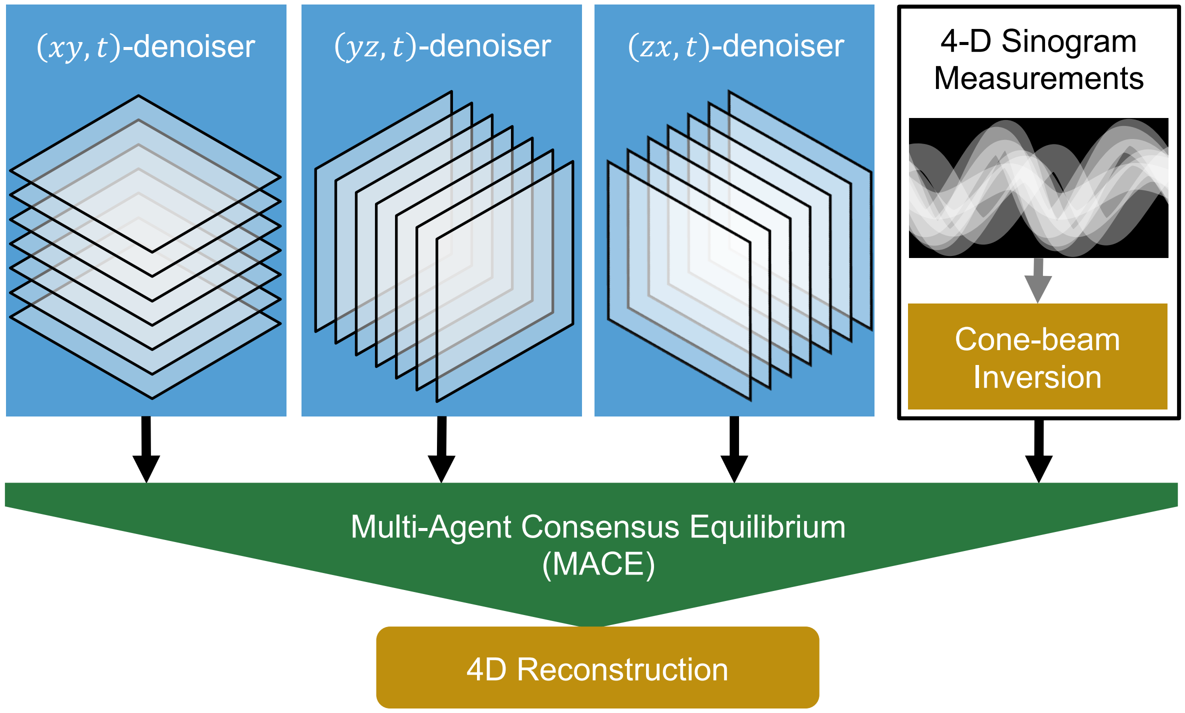


Image Quality can be dramatically improved with:

- 4D reconstruction
- Advanced CNN priors

Multi-slice fusion using MACE:

- Makes high-D priors practical to implement
- Results in smooth reconstruction along all dimensions