GH-NAF: Grid-Adaptive Hash-Level–Attended Neural Attenuation Fields for Discrepancy-Aware CBCT

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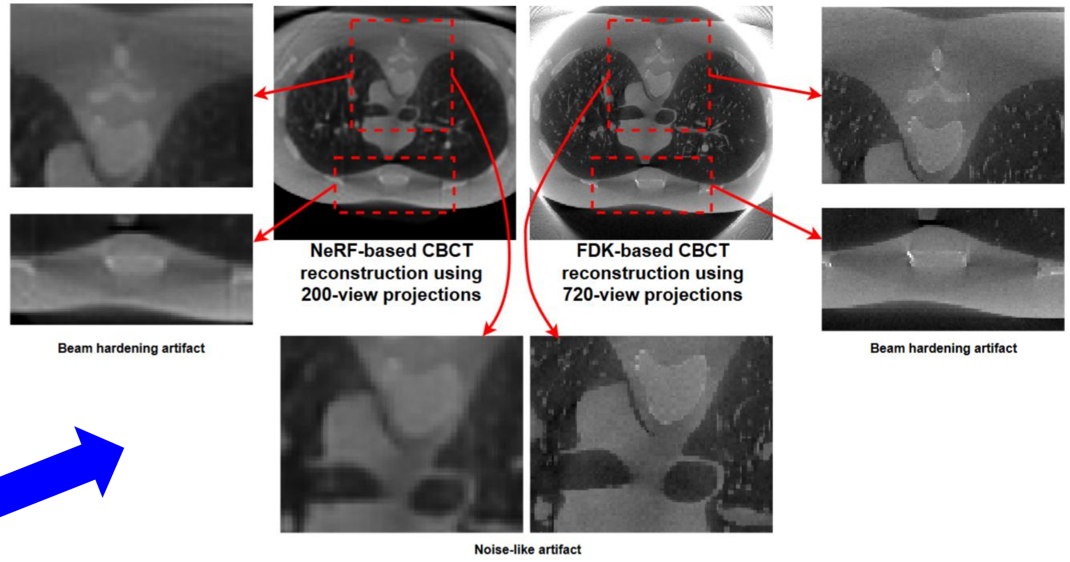
CVPR JUNE 3-7, 2026 DENVER COLORADO

Introduction

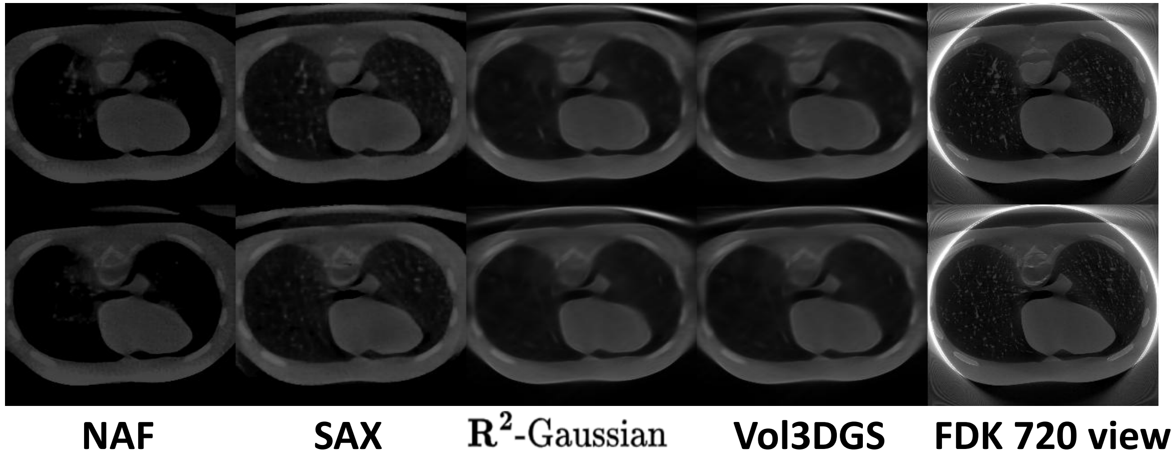
- Sparse-view CBCT reduces radiation exposure by reconstructing 3D volumes from limited X-ray projections.

- However, real-world projections suffer from scatter, beam hardening, noise, and projection-domain discrepancy, causing shading artifacts and non-uniform attenuation.

- Existing NeRF/NAF-based methods uniformly fuse multi-resolution hash levels, which can entangle low- and high-frequency features under real projection discrepancy.

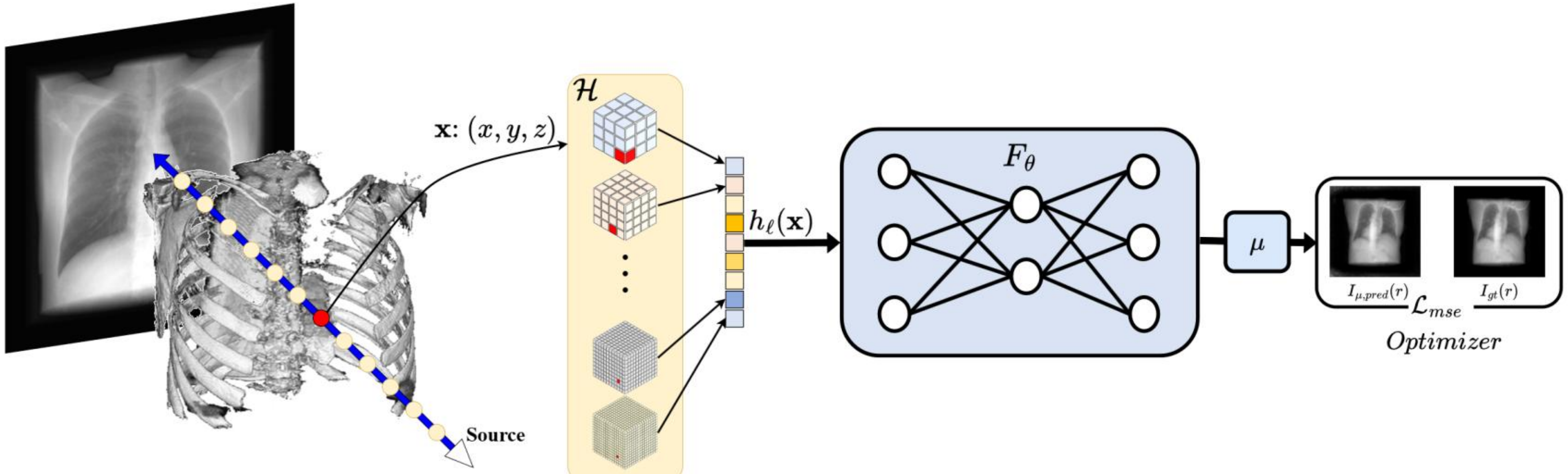


Result due to actual projection discrepancy



Introduction

Problem: uniform hash-level fusion entangles frequency



Uniform hash fusion

All hash-grid levels are aggregated witho ut considering local tissue structure.

Low- and high-frequency components b ecome entangled when projection discr epancy is present.

Artifacts

Homogeneous tissues
→ spurious high-frequency textures

Boundaries
→ blurred or biased anatomy

Sparse projections
→ amplified low-frequency shading

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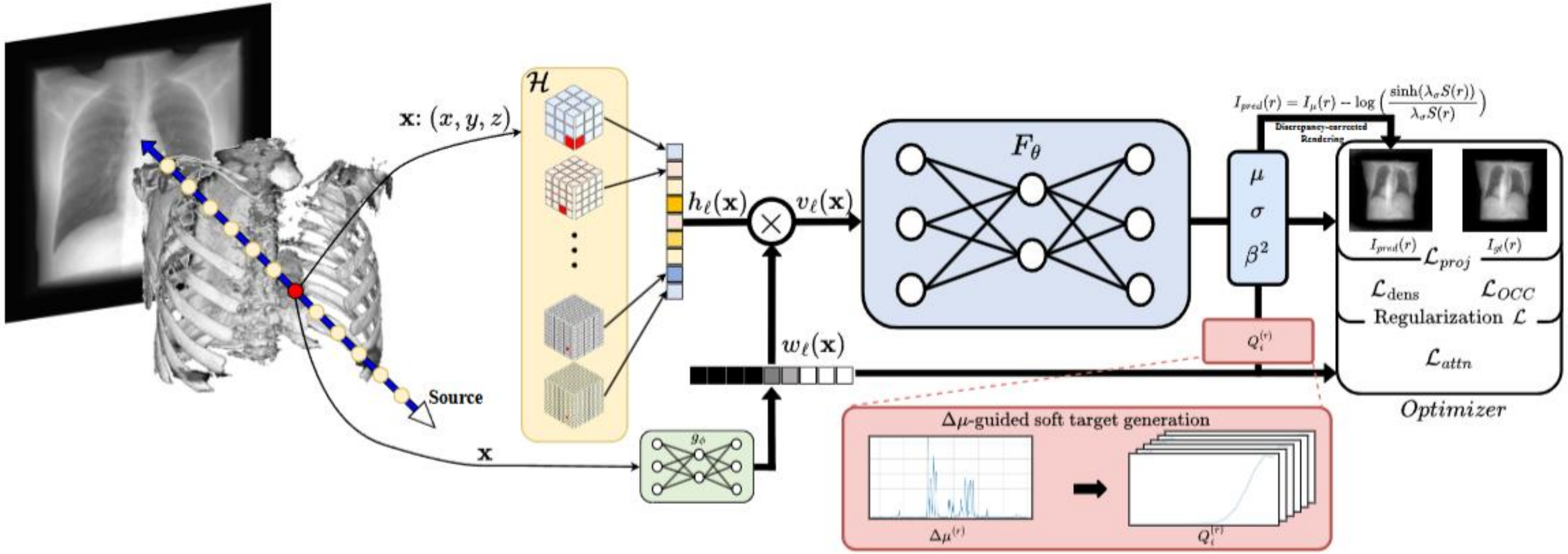

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GH-NAF insight

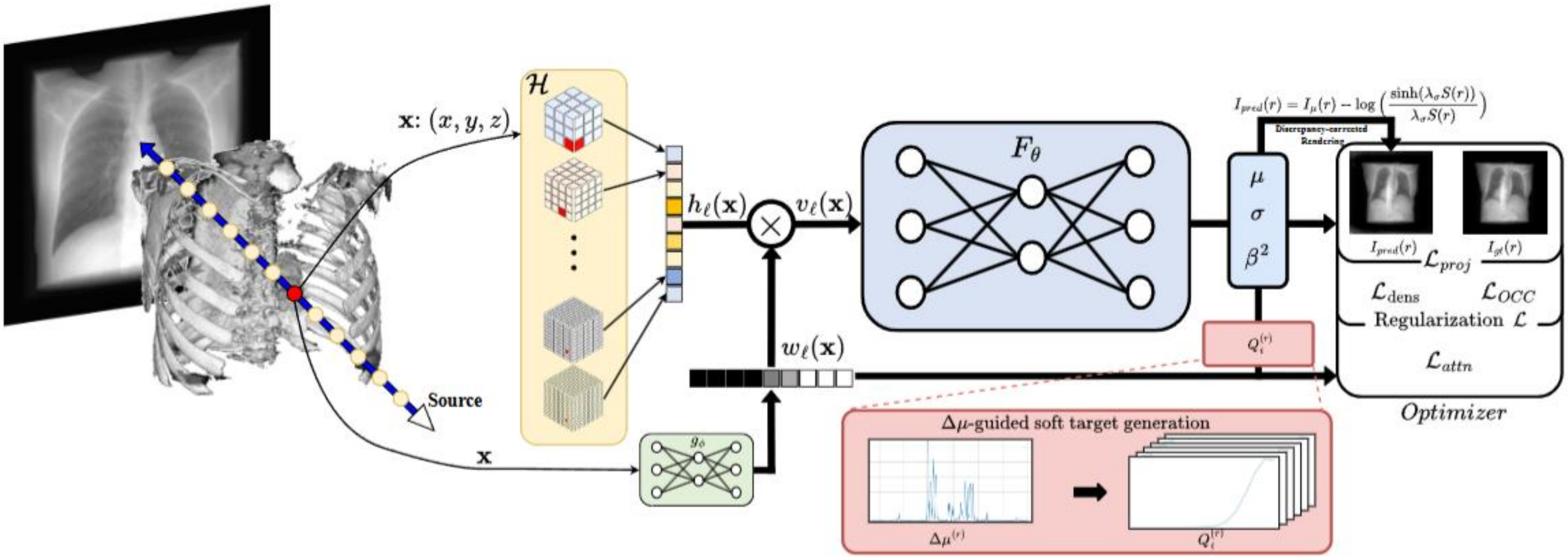
Make hash-level fusion grid-adaptive:

coarse levels for smooth regions

fine levels for boundaries

uncertainty downweights unreliable r
ays

Method



1. Hash-level attention
Adaptive level weights fuse coarse/fine features per spatial location.

2. Discrepancy-aware rendering
Predicts μ, σ, β^2 and corrects log-projection to match raw CBCT measurements.

3. Gradient-guided attention
Local attenuation gradients generate soft level targets; uncertainty modulates supervision.

4. Optimizer
Jointly optimizes projection matching, attention alignment, and density/occlusion regularization for stable sparse-view reconstruction.

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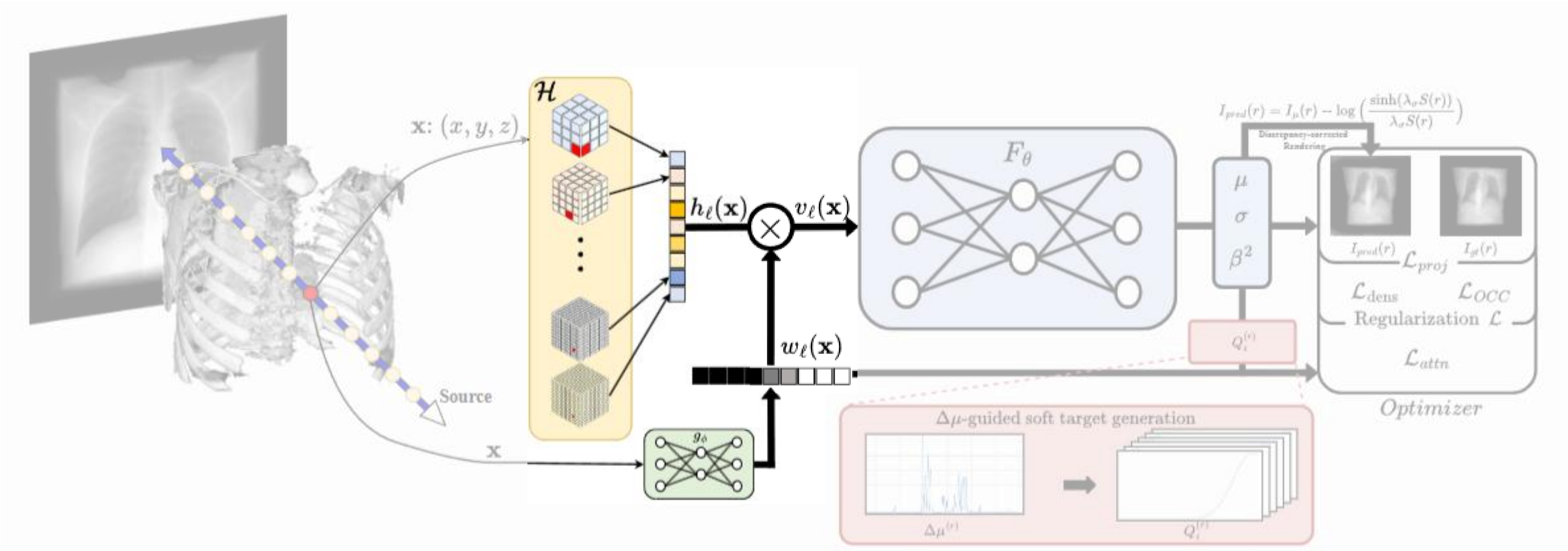

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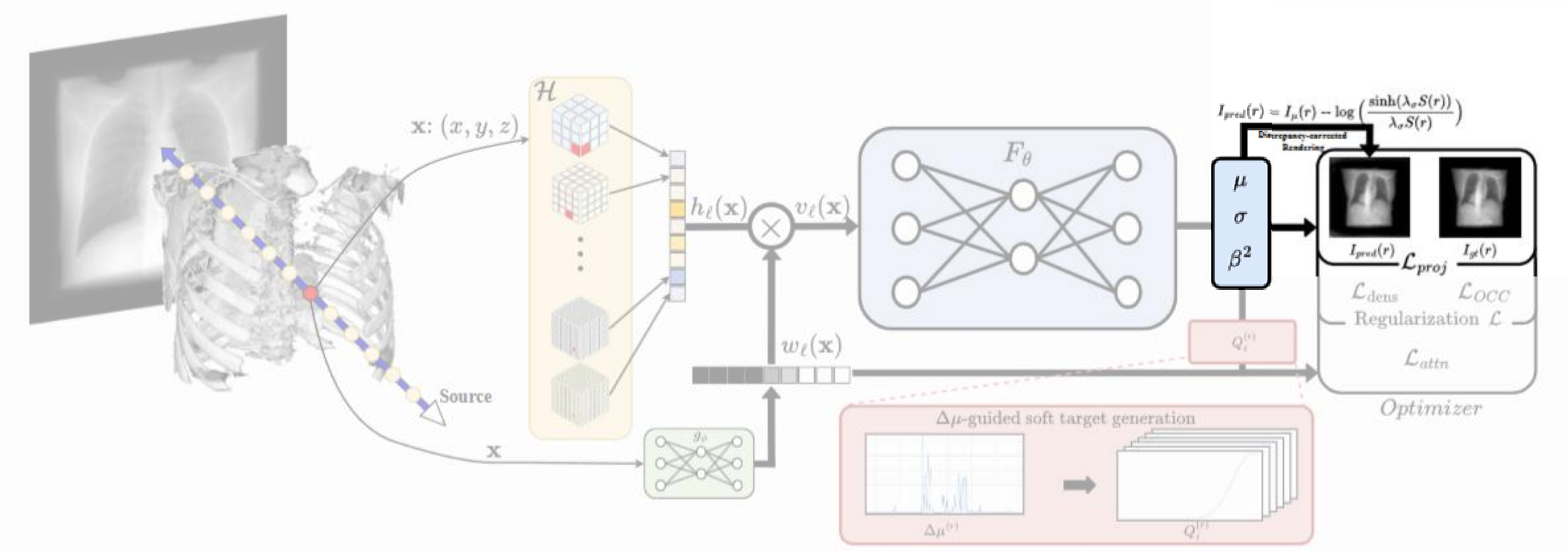

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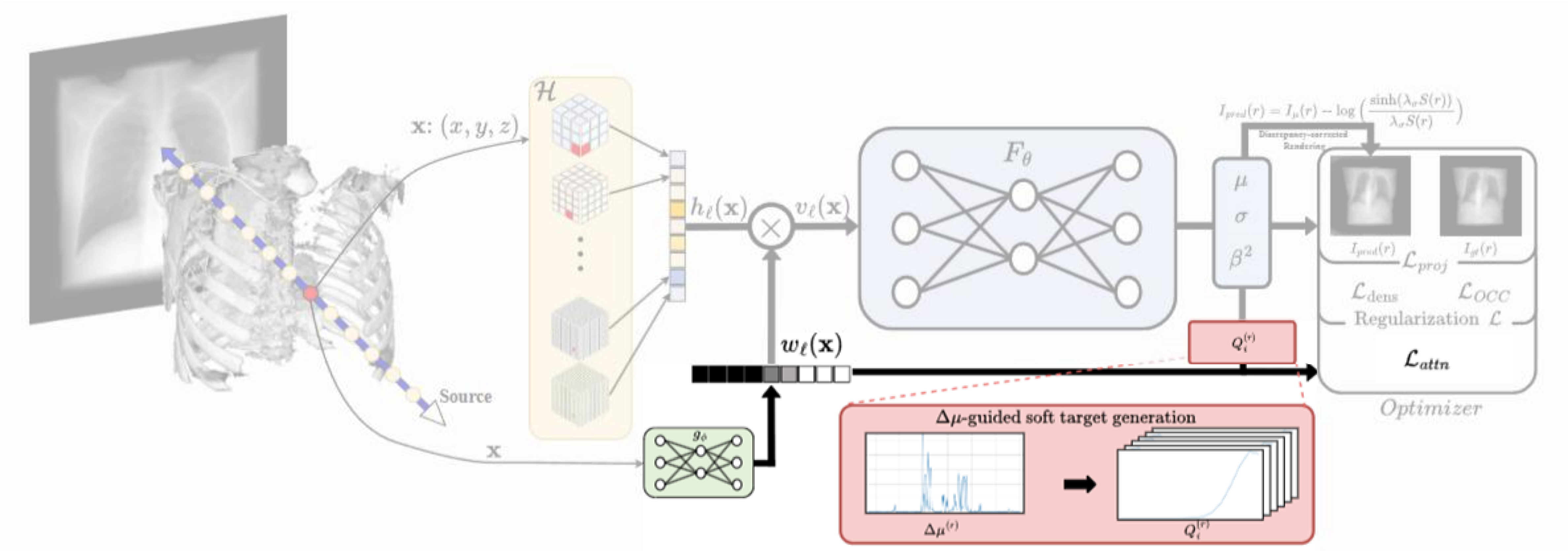

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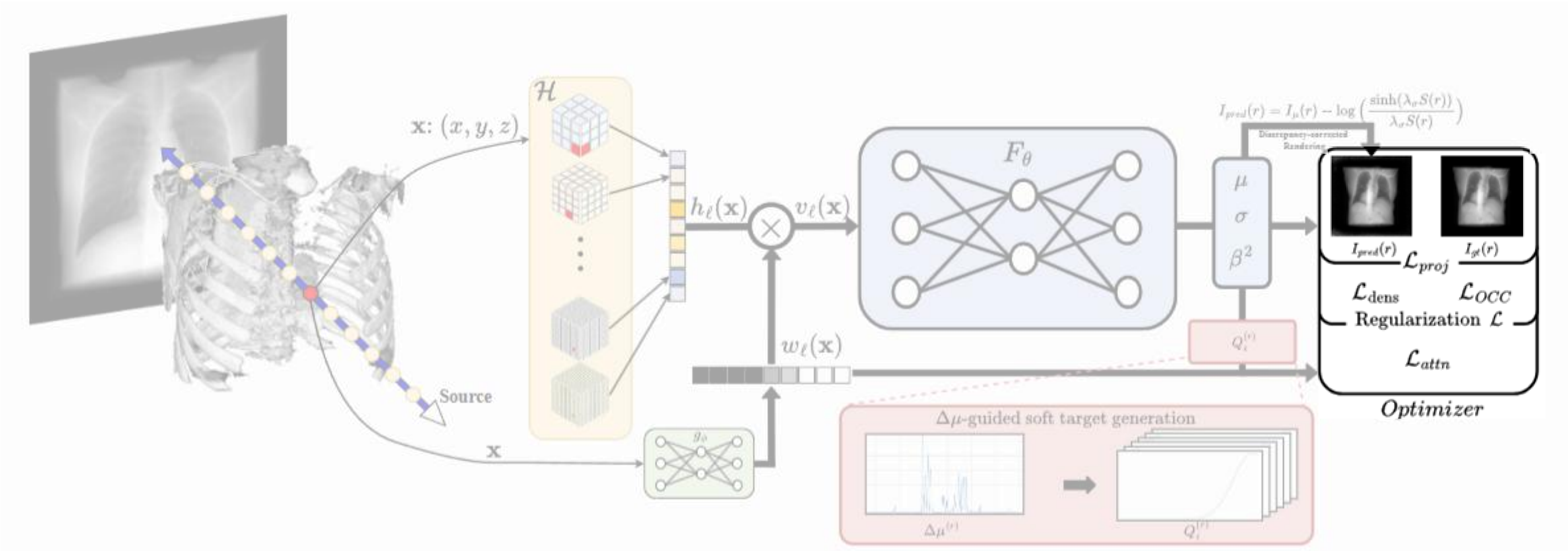

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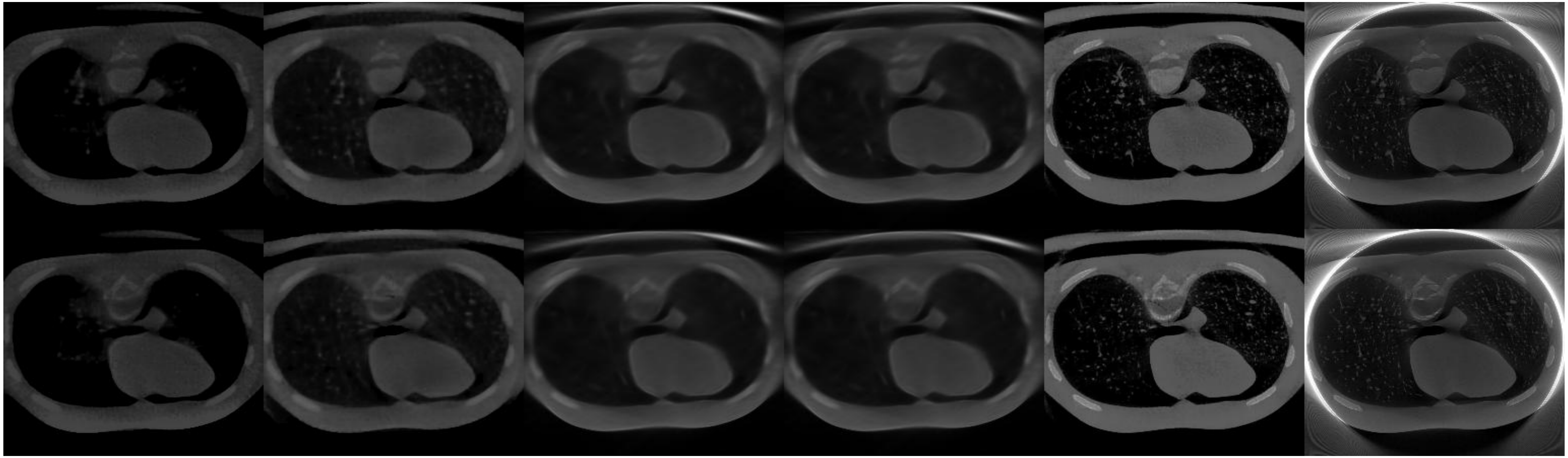
Experiment

Real chest phantom qualitative comparison under pronounced projection discrepancy, including Gaussian failure

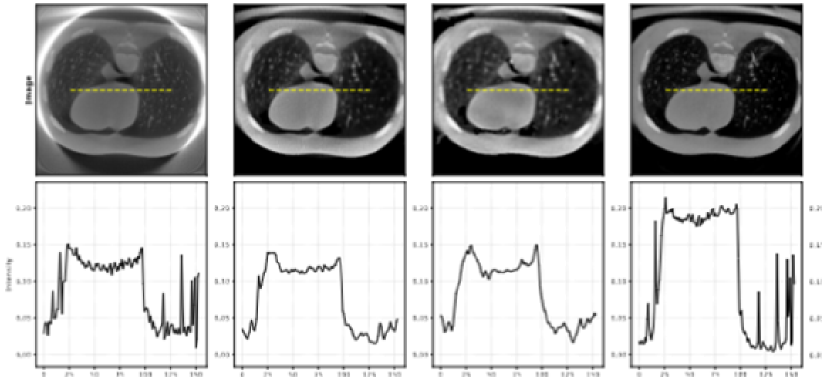


NAF SAX R^2-Gaussian Vol3DGS GH-NAF FDK 720 view

Chest phantom MANIQA, NeRF baselines only

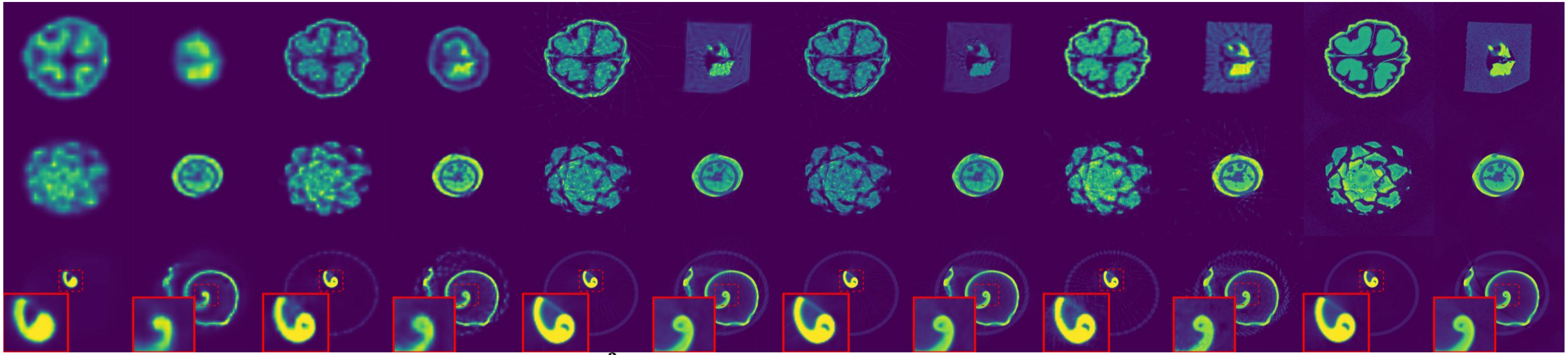
Model	Views			
	100	125	150	200
NAF	0.252	0.296	0.292	0.260
SAX	0.268	0.268	0.353	0.322
GH-NAF (ours)	**0.338**	**0.414**	**0.392**	**0.393**

Comparison of intensity distributions



Experiment

FIPS datasets qualitative comparison



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FIPS SSIM/PSNR

Model	views	Seashell PSNR	Seashell SSIM	Walnut PSNR	Walnut SSIM	Pine PSNR	Pine SSIM
NAF	25	36.29	0.950	40.34	0.960	38.93	0.963
	50	36.55	0.983	43.42	0.981	43.44	0.980
SAX	25	39.50	**0.982**	43.68	0.983	42.13	0.984
	50	42.08	0.988	47.11	0.992	43.47	0.989
R^2-Gaussian	25	**41.90**	0.953	45.24	0.968	**45.23**	0.971
	50	45.35	0.971	**49.02**	0.980	**47.90**	0.979
Vol3DGS	25	41.55	0.948	44.68	0.965	45.08	0.970
	50	45.05	0.969	48.64	0.979	47.29	0.977
GH-NAF (ours)	25	39.91	0.972	**46.54**	**0.991**	43.84	**0.989**
	50	**42.66**	**0.988**	48.95	**0.994**	46.30	**0.991**

Quantitative results in synthetic dataset

View	FDK PSNR	FDK SSIM	SART PSNR	SART SSIM	ASD-POC PSNR	ASD-POC SSIM	NAF PSNR	NAF SSIM
15	21.53	0.2727	30.44	0.8134	29.67	0.8160	31.72	0.9162
30	25.66	0.4102	34.13	0.8821	33.17	0.8905	35.94	0.9562
50	28.69	0.5455	37.48	0.9300	36.30	0.9333	37.15	0.9662

View	SAX PSNR	SAX SSIM	R^2-gaussian PSNR	R^2-gaussian SSIM	Vol3DGS PSNR	Vol3DGS SSIM	GH-NAF (Ours) PSNR	GH-NAF (Ours) SSIM
15	32.69	0.9248	**34.34**	0.8954	33.55	0.8854	33.56	**0.9341**
30	36.25	0.9605	**38.72**	0.9446	38.69	0.9449	37.31	**0.9682**
50	38.40	0.9755	**40.51**	0.9593	40.16	0.9575	39.82	**0.9815**

Thank you

Code