Radiative Gaussian Splatting for Efficient X-ray Novel View Synthesis

Yuanhao Cai, Yixun Liang, Jiahao Wang, Angtian Wang,
Yulun Zhang, Xiaokang Yang, Zongwei Zhou, and Alan Yuille

Johns Hopkins University,
HKUST (GZ), Shanghai Jiao Tong University

- Introduction
- Method
- Experiment

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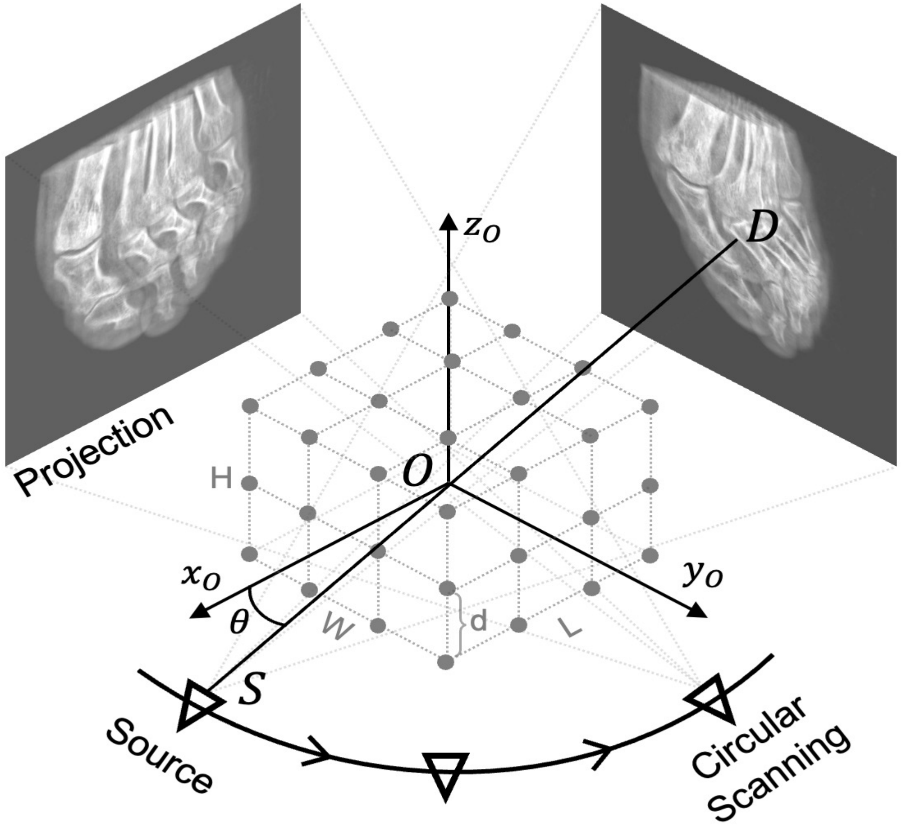
To reduce the harm of X-ray exposure, this work studies the low-dose X-ray reconstruction problem

- X-ray Novel View Synthesis
- Computed Tomography Reconstruction

Natural light imaging is based on the reflection off the surface of the object → anisotropic, view dependent

X-ray imaging is based on penetration and attenuation through the object → isotropic, view independent



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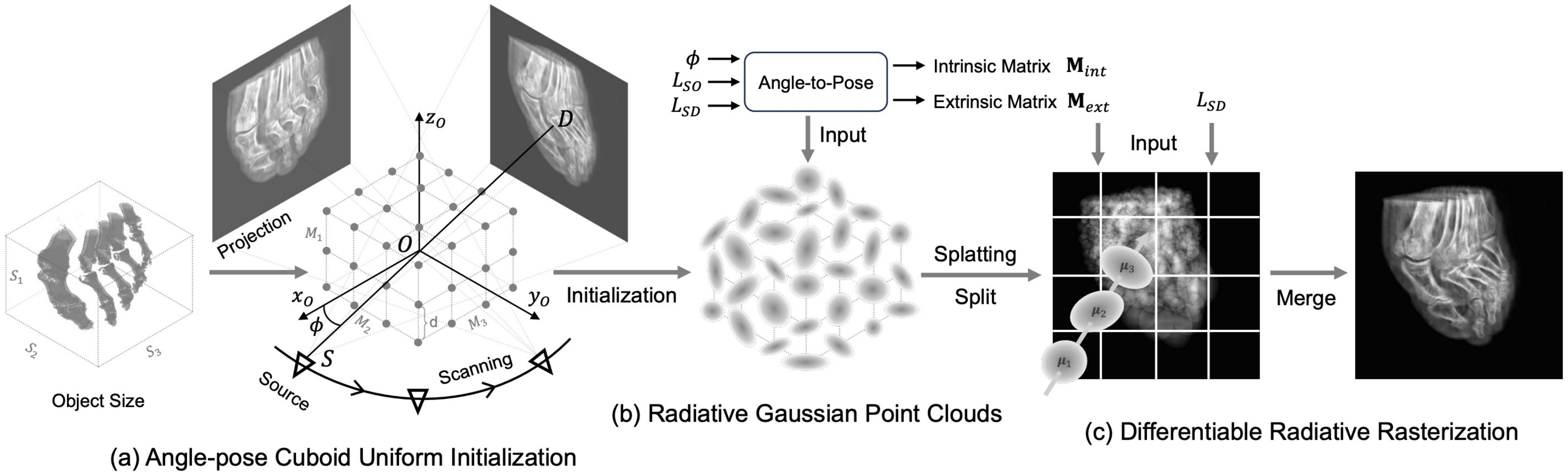
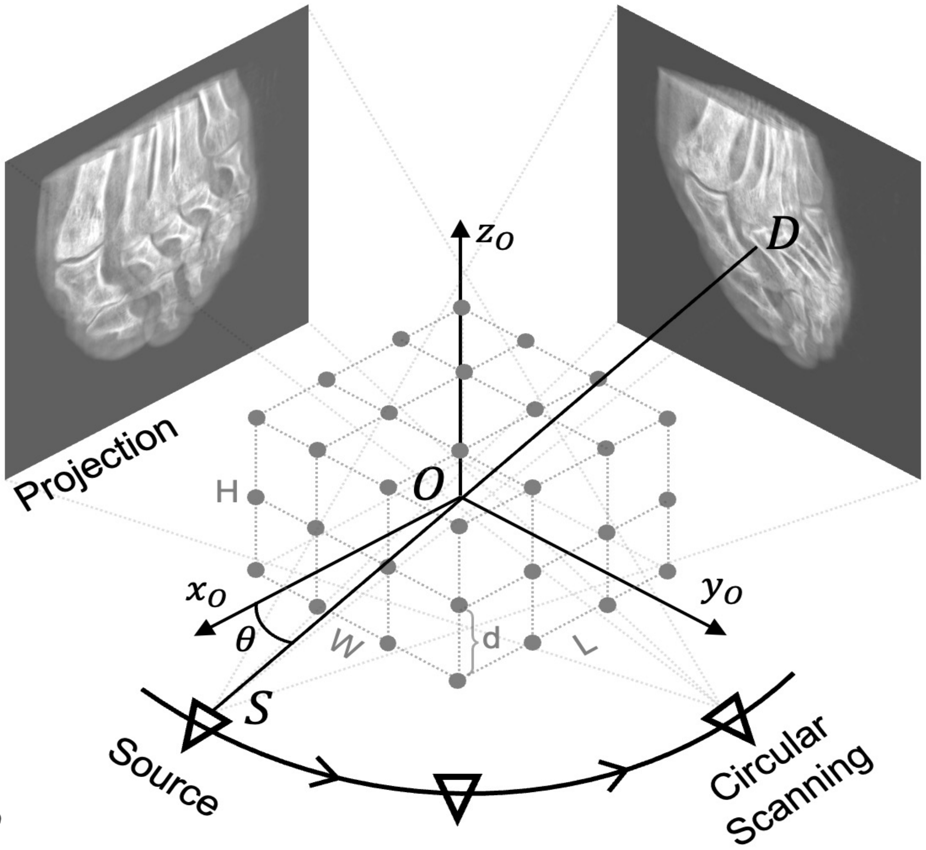


- Angle-pose Cuboid Uniform Initialization
- Radiative Gaussian Point Cloud Model
- Differentiable Radiative Rasterization

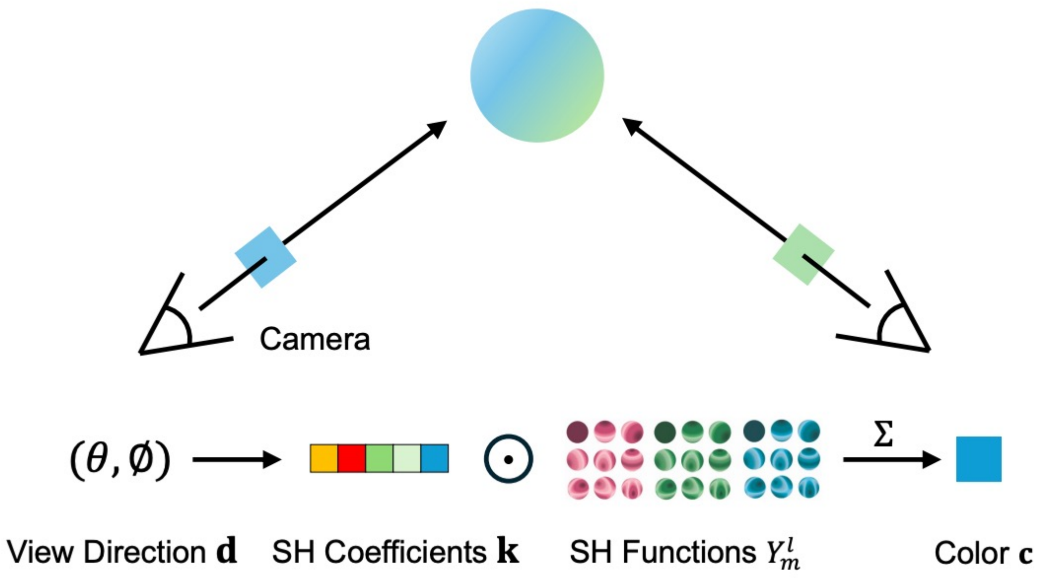
$$\mathbf{M}_{ext} = \begin{bmatrix} -\sin\phi & \cos\phi & 0 & 0 \\ 0 & 0 & -1 & 0 \\ -\cos\phi & -\sin\phi & 0 & L_{SO} \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{M}_{int} = \begin{bmatrix} L_{SD} & 0 & W/2 & 0 \\ 0 & L_{SD} & H/2 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

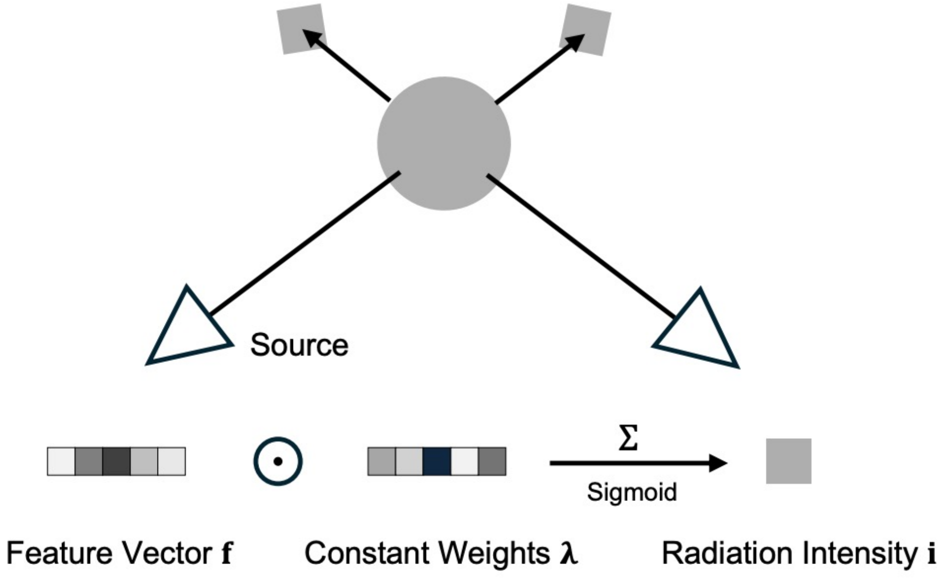
$$\mathcal{P} = \left\{ \left(\frac{n_1 S_1 d}{M_1}, \frac{n_2 S_2 d}{M_2}, \frac{n_3 S_3 d}{M_3}\right) \mid -[\frac{M_i}{2d}] - 1 \leq n_i \leq [\frac{M_i}{2d}] + 1,\ i = 1, 2, 3 \right\},$$



Our method is SFM-free !



(a) Original RGB Gaussian Point Cloud



(b) Our Radiative Gaussian Point Cloud

$$\mathbf{c}(\mathbf{d}, \mathbf{k}) = \sum_{l=0}^{L} \sum_{m=-l}^{l} k_l^m \; Y_l^m(\theta, \phi),$$

$$\mathcal{G}_x = \{G_i(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i, \alpha_i, \mathbf{f}_i) \mid i = 1, 2, \ldots, N_p\},$$

$$\mathbf{i}(\mathbf{f}) = \mathrm{RIRF}(\mathbf{f}) = \mathrm{Sigmoid}(\boldsymbol{\lambda} \odot \mathbf{f}),$$

Use Spherical Harmonics – view dependent

Radiation Intensity Response Function – view dependent

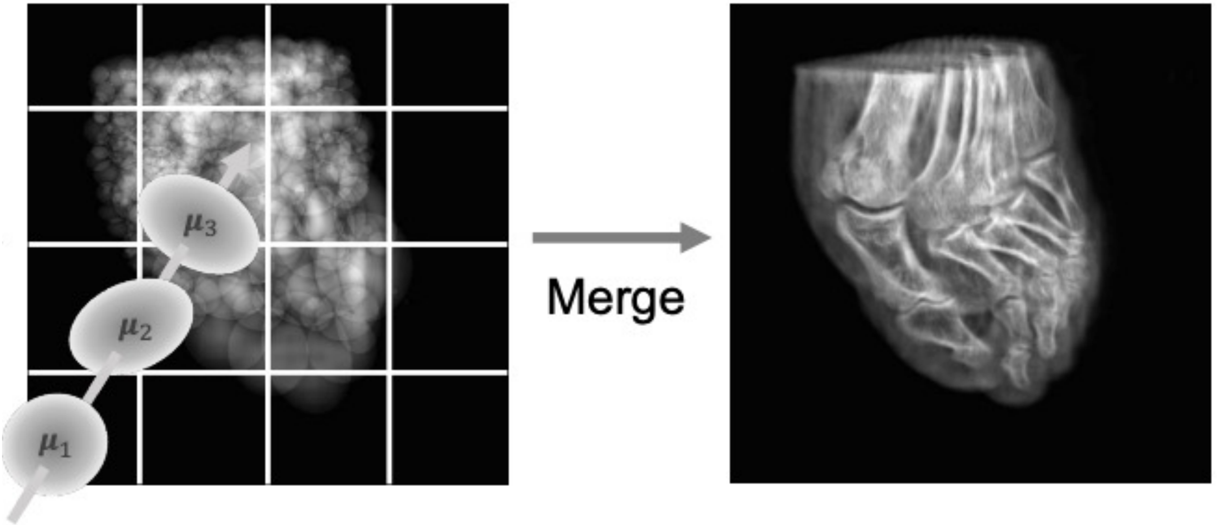
$$\mathbf{I} = F_{\mathrm{DRR}}(\mathbf{M}_{ext}, \mathbf{M}_{int}, \{G_i(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i, \alpha_i, \mathbf{f}_i) \mid i = 1, 2, \ldots, N_p\}),$$

$$P(\mathbf{x}|\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) = \exp\big(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_i)^\top \boldsymbol{\Sigma}_i^{-1}(\mathbf{x} - \boldsymbol{\mu}_i)\big).$$

$$\widetilde{\mathbf{t}}_i = \begin{bmatrix} \mathbf{t}_i \\ 1 \end{bmatrix} = \mathbf{M}_{ext}\ \widetilde{\boldsymbol{\mu}}_i = \mathbf{M}_{ext} \begin{bmatrix} \boldsymbol{\mu}_i \\ 1 \end{bmatrix}, \quad \widetilde{\mathbf{u}}_i = \begin{bmatrix} \mathbf{u}_i \\ 1 \end{bmatrix} = \mathbf{M}_{int}\ \widetilde{\mathbf{t}}_i = \mathbf{M}_{int} \begin{bmatrix} \mathbf{t}_i \\ 1 \end{bmatrix},$$

$$\boldsymbol{\Sigma}_i^{'} = \mathbf{J}_i \mathbf{W}_i \boldsymbol{\Sigma}_i \mathbf{W}_i^\top \mathbf{J}_i^\top,$$

$$\mathbf{J}_i = \begin{bmatrix} \frac{L_{SD}}{t_z} & 0 & -\frac{L_{SD}\ t_x}{t_z^2} \\ 0 & \frac{L_{SD}}{t_z} & -\frac{L_{SD}\ t_y}{t_z^2} \\ 0 & 0 & 0 \end{bmatrix}, \qquad \mathbf{W}_i = \begin{bmatrix} -\sin\phi & \cos\phi & 0 \\ 0 & 0 & -1 \\ -\cos\phi & -\sin\phi & 0 \end{bmatrix},$$



(c) Differentiable Radiative Rasterization

Image Coordinate System —> Camera Coordinate System —> World Coordinate System

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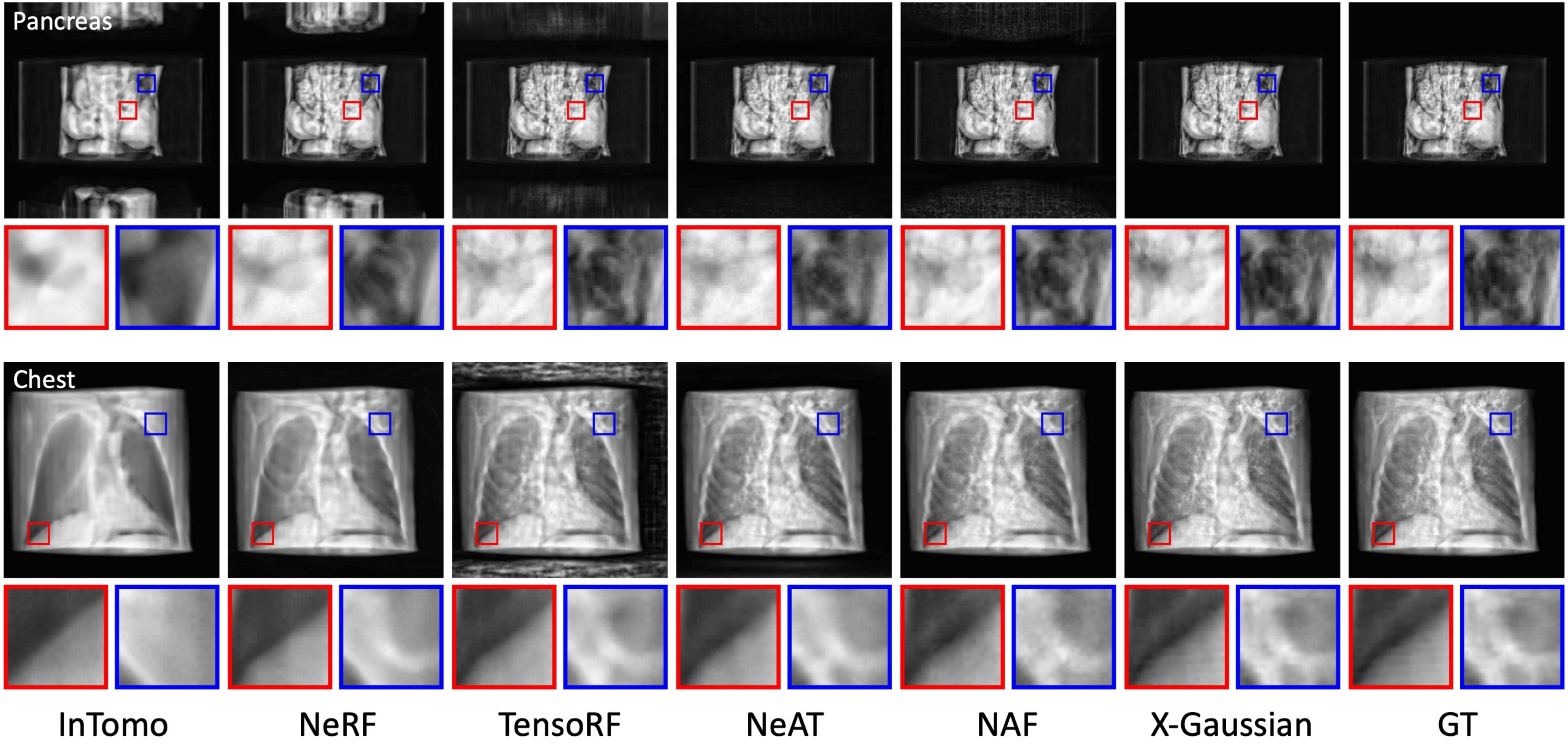
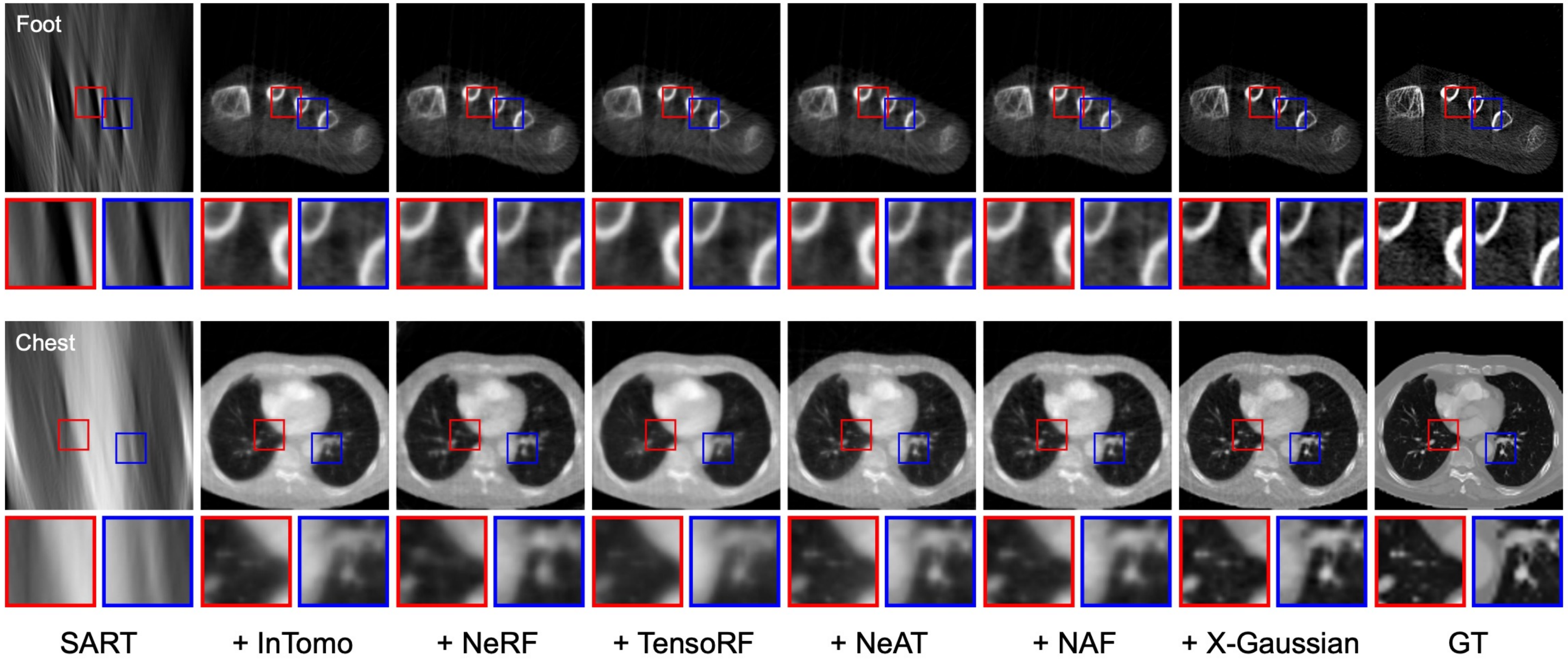
Method	Infer Speed	Train Time	Chest	Foot	Head	Abdomen	Pancreas	Average
InTomo [58]	0.62 fps	125 min	28.948 0.9915	39.482 0.9979	34.832 0.9977	27.641 0.9646	20.031 0.8537	30.187 0.9611
NeRF [37]	0.14 fps	313 min	36.157 0.9988	41.053 0.9989	29.760 0.9991	24.620 0.9559	19.853 0.8560	30.289 0.9617
TensoRF [10]	0.77 fps	178 min	23.609 0.9402	37.728 0.9929	34.429 0.9879	27.382 0.8730	29.235 0.8031	30.477 0.9194
NeAT [42]	1.78 fps	69 min	40.765 0.9990	38.236 0.9963	27.738 0.9295	26.741 0.8563	37.526 0.9017	34.201 0.9366
NAF [60]	2.01 fps	63 min	42.366 0.9993	38.353 0.9913	30.174 0.9531	37.590 0.9855	36.228 0.8844	36.942 0.9627
X-Gaussian	**148 fps**	**9 min**	**43.887** **0.9998**	**42.153** **0.9997**	**41.579** **0.9997**	**45.762** **0.9999**	**43.640** **0.9976**	**43.404** **0.9993**

On the novel view synthesis task, our X-Gaussian is 6.5 dB higher and 73 x faster in model inference speed.



Our X-Gaussian can reconstruct more structural details

Method	+ None		+ InTomo [58]		+ NeRF [37]		+ TensoRF [10]		+ NeAT [42]		+ NAF [60]		+ X-Gaussian	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
FDK	7.41	0.093	20.31	0.498	20.57	0.502	20.61	0.501	20.94	0.511	21.28	0.523	**22.60**	**0.584**
Δ FDK	0	0	12.90	0.405	13.16	0.409	13.20	0.408	13.52	0.418	13.87	0.430	**15.19**	**0.491**
SART	17.24	0.528	26.28	0.859	26.78	0.853	27.06	0.867	27.31	0.869	27.84	0.879	**30.25**	**0.907**
Δ SART	0	0	9.04	0.331	9.54	0.325	9.82	0.339	10.07	0.341	10.60	0.351	**13.01**	**0.379**
ASD-POCS	17.03	0.525	25.44	0.847	26.58	0.857	26.93	0.868	26.95	0.865	27.91	0.880	**30.56**	**0.926**
Δ ASD-POCS	0	0	8.41	0.322	9.55	0.332	9.90	0.343	9.92	0.340	10.88	0.355	**13.53**	**0.401**



On the sparse-view CT reconstruction task. Our method significantly boosts the performance of traditional methods By over 10 dB

X-Gaussian

Code, models, and data are publicly available at

https://github.com/caiyuanhao1998/SAX-NeRF