6DGS: Enhanced Direction-Aware Gaussian Splatting for Volumetric Rendering

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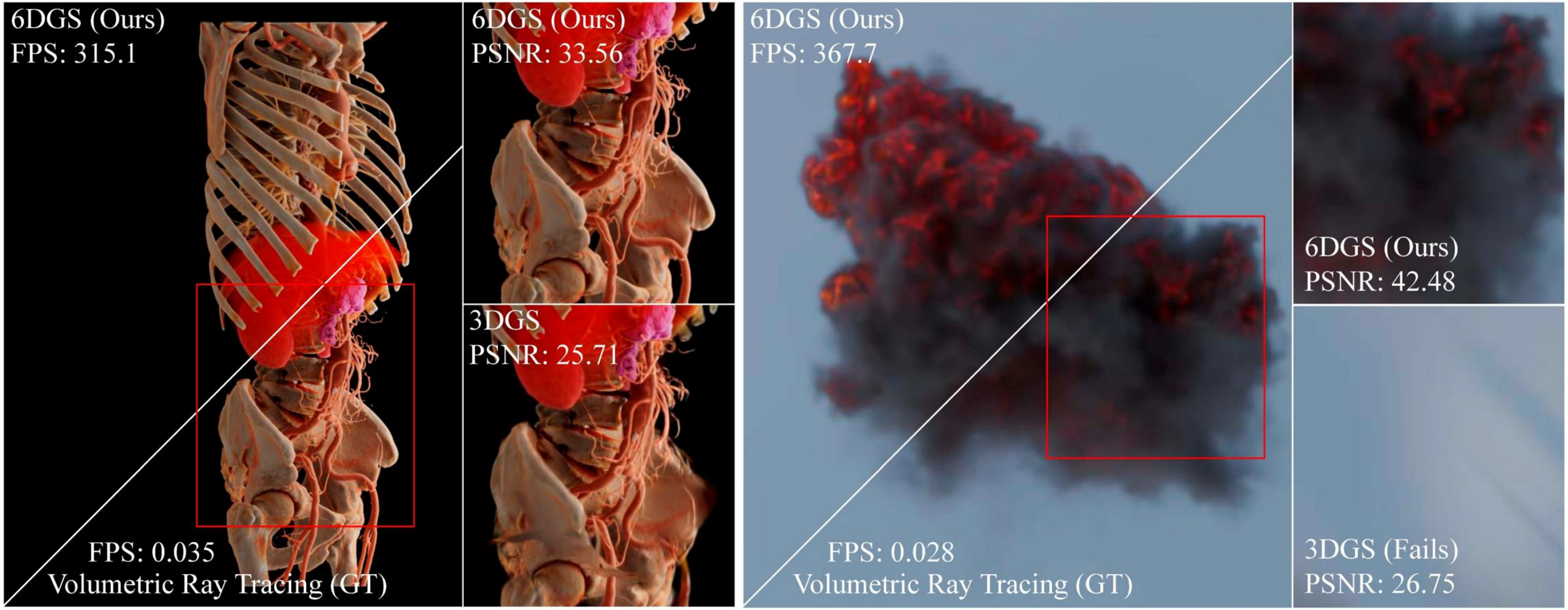
Real-time Rendering of View-dependent Effects



Motivations

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- **Real-Time Rendering Challenge:** Achieve high-quality, physically-based rendering in real time, especially when handling view-dependent effects like specular highlights and reflections.
- **Shortcomings of 3DGS:** Existing 3D Gaussian splatting accelerates rendering but struggles to model view-dependent phenomena due to its purely spatial representation.
- **Inefficiencies in N-DG:** Although N-D Gaussian can better capture view-dependent effects, the current representation and optimization schemes are suboptimal and inefficient.
- **Enhanced Modeling Needs:** There is a need to improve the representation, leveraging additional directional information to better capture fine details and complex lighting interactions.
- **Seamless Integration:** A solution that remains compatible with the 3DGS framework is desirable, enabling easy adoption and immediate performance benefits without extensive modifications.

Our 6DGS Compatible with the Existing 3DGS Pipeline

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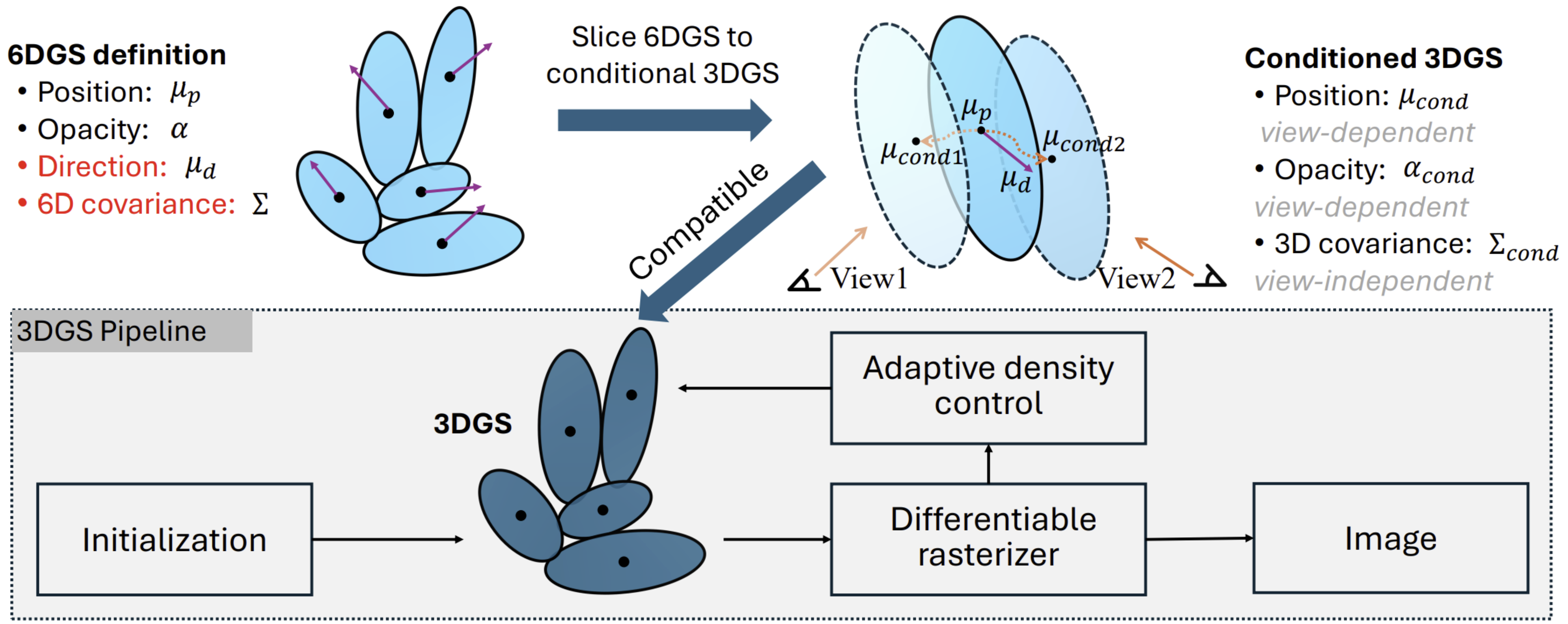

Experiments

Datasets:

- public Synthetic NeRF dataset (Mildenhall et al., 2020)
- custom 6DGS-PBR dataset (physically-based rendering)
- Three real-world datasets in Supplementary
  - Deep Blending (Hedman et al., 2021),
  - Tanks & Temples (Knapitsch et al., 2017)
  - Shiny (Wizadwongsa et al., 2021)

Results – Qualitative on 6DGS-PBR

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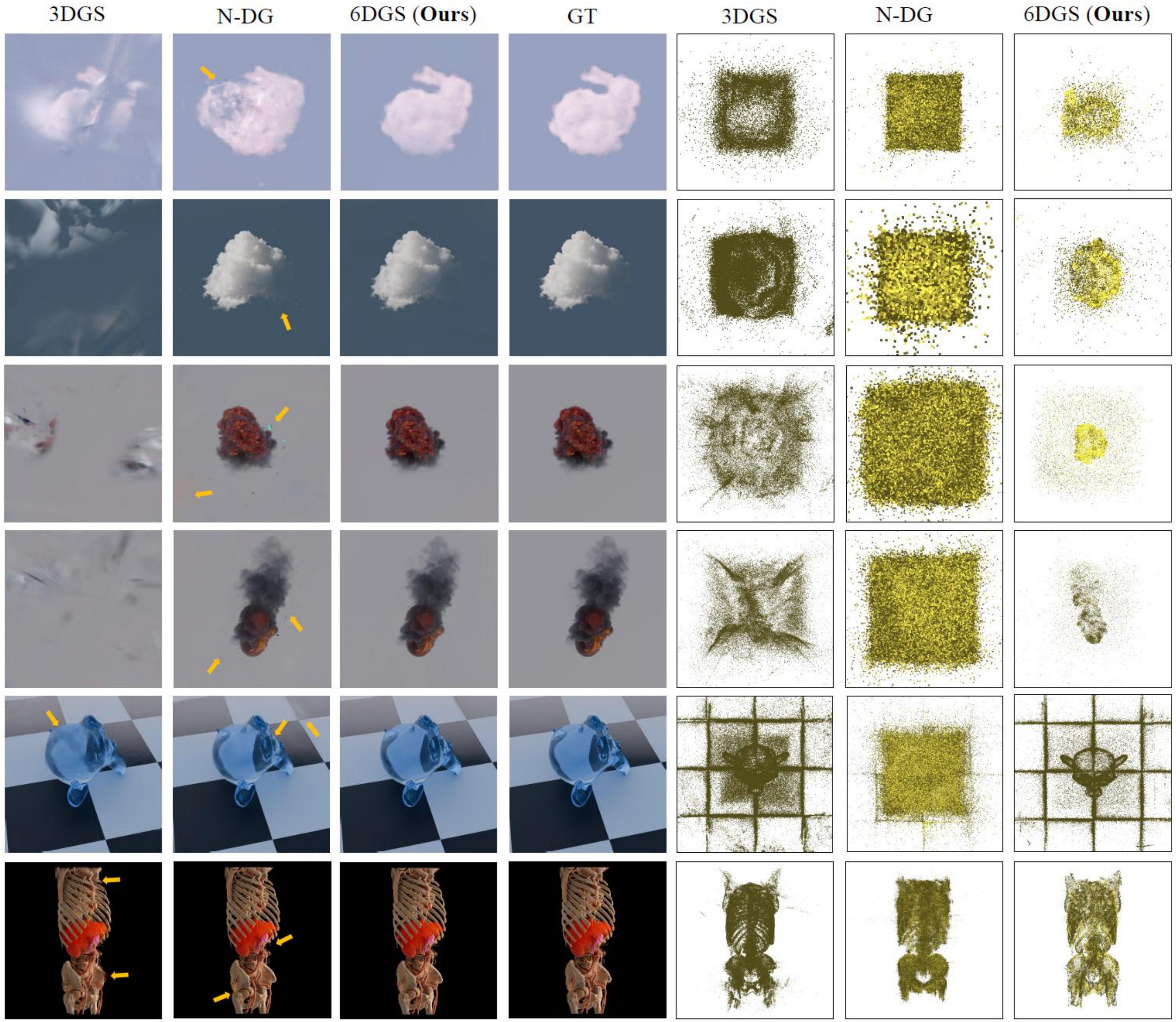

Results – Quantitative on 6DGS-PBR

	3DGS			N-DG			**6DGS (Ours)**		
	PSNR↑	SSIM↑	# points↓	PSNR↑	SSIM↑	# points↓	PSNR↑	SSIM↑	# points↓
bunny-cloud	30.75	0.988	21,074	35.48	0.990	530,711	**41.57**	**0.993**	**6,660**
cloud	29.70	0.972	58,233	**42.40**	**0.991**	98,149	40.41	**0.991**	**12,657**
explosion	26.75	0.953	51,140	40.16	0.989	207,778	**42.48**	**0.991**	**17,133**
smoke	28.55	0.969	60,533	**41.61**	**0.992**	212,050	40.61	**0.992**	**10,762**
suzanne	23.70	0.901	270,001	26.00	0.921	232,145	**27.03**	**0.928**	**174,746**
ct-scan	25.71	0.917	229,683	30.96	0.952	1,073,082	**33.56**	**0.965**	**182,981**
avg	27.53	0.950	115,111	36.10	0.973	392,319	**37.61**	**0.977**	**67,490**

	bunny-cloud	cloud	explosion	smoke	suzanne	ct-scan	avg
Image size	1408	1408	1024	1536	1408	1024	N/A
3DGS	49.1	74.4	**161.9**	96.7	42.0	259.7	114.0
N-DG	27.0	90.7	65.6	50.4	**46.9**	13.3	49.0
6DGS (Ours)	**178.4**	**178.2**	120.2	**138.6**	34.7	**276.8**	**154.5**
6DGS-flash (Ours)	**315.3**	**318.0**	**367.7**	**345.5**	**295.9**	**315.1**	**326.3**

Results – Quantitative on Synthetic NeRF

	3DGS			N-DG			**6DGS (ours)**		
	PSNR↑	SSIM↑	# points↓	PSNR↑	SSIM↑	# points↓	PSNR↑	SSIM↑	# points↓
chair	**35.91**	**0.987**	272,130	30.87	0.956	**108,091**	35.49	0.986	223,747
drums	26.15	**0.955**	346,245	24.37	0.927	**106,756**	**26.45**	0.953	250,267
ficus	**34.49**	**0.987**	295,997	29.82	0.965	**59,052**	33.45	0.984	197,741
hotdog	37.72	**0.985**	147,098	33.89	0.971	**82,261**	**37.90**	**0.985**	102,451
lego	**35.79**	**0.983**	322,704	29.85	0.948	**151,291**	35.25	0.980	233,227
materials	29.98	0.960	282,334	26.86	0.938	**77,206**	**30.71**	**0.967**	222,209
mic	35.47	**0.992**	310,608	29.99	0.968	**40,848**	**36.13**	**0.992**	272,052
ship	30.52	**0.905**	328,053	26.35	0.862	337,294	**30.72**	0.903	**270,163**
avg	33.25	**0.969**	288,146	29.00	0.942	**120,350**	**33.26**	**0.969**	221,482

Results – Ablation Study

		bunny-cloud	cloud	explosion	smoke	suzanne	ct-scan	avg
PSNR	No-SH	38.13	37.39	41.05	38.52	26.76	33.27	35.85
	No-f_{opa}	38.15	36.16	35.49	35.52	24.88	29.65	33.31
	No-λ_{opa}	39.12	39.86	40.55	36.88	26.92	32.99	36.05
	$\tau = 0.005$	40.15	40.46	**43.14**	**41.04**	27.09	33.45	37.56
	$\lambda_{\text{opa}} = 0.35$	40.47	**40.73**	42.69	40.45	**27.15**	33.42	37.49
	learnable-λ_{opa}	**41.57**	40.42	42.48	40.61	27.03	**33.56**	**37.61**
# points	No-SH	**6,196**	**11,356**	16,465	**9,929**	**171,472**	177,204	65,437
	No-f_{cond}	11,698	31,999	39,736	35,023	349,716	320,879	131,509
	No-λ_{opa}	4,860	11,736	**13,582**	10,540	158,041	**154,997**	**58,959**
	$\tau = 0.005$	63,042	51,883	61,507	49,422	301,614	405,332	155,467
	$\lambda_{\text{opa}} = 0.35$	6,830	12,454	17,051	10,570	172,373	181,539	66,803
	learnable-λ_{opa}	6,660	12,657	17,133	10,762	174,746	182,981	67,490

Conclusion

- Introduced 6D Gaussian Splatting (6DGS) to integrate directional information and enhance the modeling of position and opacity.
- Achieved superior rendering quality and real-time performance with significantly fewer Gaussian points compared to existing methods.
- Demonstrated compatibility with the established 3DGS framework, enabling seamless integration into current systems.
- Provided a theoretical analysis of conditional Gaussian parameters, offering insights into view-dependent effects.
- Validated the approach through extensive experiments on both custom physically-based rendering datasets and public datasets.
- Future work will extend the framework to dynamic scenes, enabling efficient real-time rendering of moving objects.

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