1 Extended Experimental

This supplementary material provides extended experimental results to fully verify the performance and robustness of our method, including quantitative comparisons under two lighting conditions and qualitative visual comparisons.

1.1 Quantitative Comparisons Under Non-Uniform and Uniform Lighting Conditions

To comprehensively evaluate our method's performance across lighting scenarios, we conduct experiments on the MipNeRF360-varying and LOM datasets under non-uniform (challenging varying exposure) and uniform (standard normal illumination) conditions, comparing against four SOTA baselines: 3DGS (foundational 3D Gaussian Splatting), Aleth-NeRF (illumination adaptation via concealing field), GS-W (Gaussian feature decoupling), and Luminance-GS (view-adaptive curve adjustment). For objective evaluation, we adopt three core metrics—PSNR (pixel-level fidelity, higher is better), SSIM (structural consistency, higher is better), and LPIPS (subjective perceptual quality, lower is better)—which jointly reflect each method's comprehensive performance in low-level pixel matching and high-level perceptual realism.

Scene	Metric	Non-Uniform Lighting					Uniform Lighting				
		3DGS	Aleth-NeRF	GS-W	Luminance-GS	Ours	3DGS	Aleth-NeRF	GS-W	Luminance-GS	Ours
"bicycle"	PSNR ↑	**18.523**	12.943	15.616	18.383	18.237	25.246	*	25.092	16.442	**26.365**
	SSIM ↑	0.514	0.195	0.563	0.646	**0.691**	0.771	*	0.675	0.720	**0.808**
	LPIPS ↓	0.396	0.796	0.371	0.330	**0.274**	0.205	*	0.285	**0.179**	0.204
"garden"	PSNR ↑	20.187	12.685	20.482	20.984	**21.526**	27.410	*	28.184	21.210	**28.549**
	SSIM ↑	0.736	0.229	0.756	0.791	**0.807**	0.868	*	0.843	0.884	**0.893**
	LPIPS ↓	0.203	0.813	0.212	0.195	**0.191**	0.103	*	0.075	**0.068**	0.096
"counter"	PSNR ↑	15.098	12.454	15.892	16.850	**17.341**	28.700	*	28.272	15.502	**29.373**
	SSIM ↑	0.527	0.324	0.624	0.645	**0.739**	0.905	*	0.894	0.731	**0.920**
	LPIPS ↓	0.368	0.780	0.337	0.302	**0.224**	0.204	*	0.071	0.126	**0.080**
"bike"	PSNR ↑	18.447	9.378	**26.747**	20.358	22.371	29.641	*	25.641	27.657	**31.591**
	SSIM ↑	0.547	0.254	0.851	0.754	**0.858**	0.899	*	0.801	0.888	**0.915**
	LPIPS ↓	0.328	0.751	0.278	0.368	**0.219**	**0.141**	*	0.303	0.146	0.147
"buu"	PSNR ↑	14.472	13.288	**27.012**	16.486	26.119	34.367	*	32.942	26.307	**34.553**
	SSIM ↑	0.634	0.633	0.895	0.741	**0.916**	**0.950**	*	0.936	0.929	0.949
	LPIPS ↓	0.407	0.639	0.199	0.376	**0.176**	0.131	*	0.142	0.112	**0.109**
"shrub"	PSNR ↑	16.582	12.229	19.173	16.161	**19.845**	23.767	*	**27.524**	16.878	23.923
	SSIM ↑	0.449	0.169	0.557	0.667	**0.714**	0.791	*	0.737	0.710	**0.797**
	LPIPS ↓	0.374	0.713	0.289	0.207	**0.204**	0.150	*	0.200	**0.131**	0.144

Table 1: Quantitative Results on MipNeRF360-varying and LOM Dataset (Non-Uniform vs. Uniform Lighting). The best performance for each row is highlighted in red bold font.

Under non-uniform lighting conditions, our proposed method achieves optimal Structural Similarity Index Measure (SSIM) and Learned Perceptual Image Patch Similarity (LPIPS) across all 6 scenes, while securing the best Peak Signal-to-Noise Ratio (PSNR) in 4 scenes—with GS-W outperforming it only in the "bike" and "buu" scenarios. This demonstrates the method's robust capability in handling illumination variations. Despite being tailored for non-uniform lighting scenarios, the proposed method still delivers State-of-the-Art (SOTA) performance under uniform lighting: it ranks first in SSIM across all scenes and in PSNR in 5 scenes, with only marginal LPIPS gaps compared to the Luminance-GS method in individual cases. This verifies its strong generalizability without incurring performance trade-offs.

1.2 Qualitative comparison under normal and non-uniform illumination conditions

While objective quantitative metrics reflect overall method performance, qualitative visual comparisons more intuitively demonstrate the detail and perceptual quality of reconstructed images. We present visual comparisons of our method and baselines under uniform and non-uniform lighting to further validate our method's superiority.

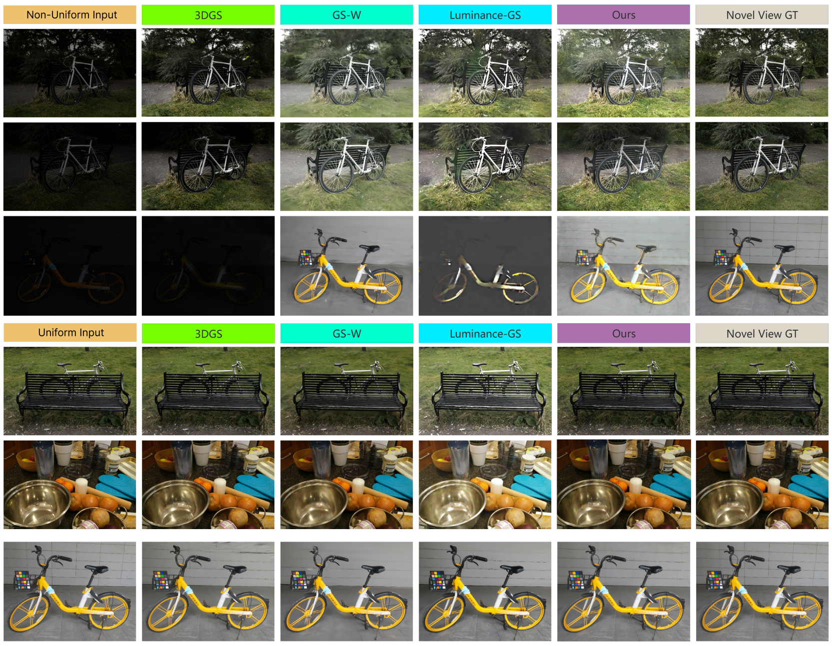

Figure 1: Rendered Results of Our Method vs. Test Images Under Uniform/Non-uniform Illumination

Taken together, the qualitative comparison results clearly demonstrate the superiority of our method under varying illumination conditions. Specifically, in non-uniform lighting scenarios, our results exhibit more natural color reproduction and richer, more complete object details and textures compared with other baseline methods. In uniform lighting scenarios, our method still delivers outstanding performance: for instance, the wall texture in the upper-right corner of the bike scene is rendered with finer details and higher fidelity to the real-world counterpart than that of the baseline methods. This indicates that our method can generate high-quality reconstruction results that are more consistent with real scenes, regardless of whether the environment is under complex or standard illumination.