Supplemenatary Material: Plenoptic PNG: Real-Time Neural Radiance Fields in 150 KB

We provide additional training details, quantitative and qualitative results in the appendix. We also invite the reviewers to watch our supplementary video and to play with our web demo.

1. Training Details

We follow default parameters of Instant-NGP [4] for training. Specifically we minimize the Huber Loss with 50,000 steps using Adam [3] optimizer. During training our voxelbased density grid cache has resolution of 128. For object level scenes, we use single scale voxel grid. For unbounded scenes, we use voxel grids with five scales, where higher scale covers half of each dimension (i.e, 0.5 width, 0.5 height and 0.5 depth) with the same resolution centered at (0.5, 0.5, 0.5).

2. Additional Qualitative Results

We provide additional qualitative results for all the datasets.

3. Additional Quantiative Results

Comparisons with real-time methods. We provide a quantitative comparison with real-time Web-compatible methods in Table 1. This table shows that our approach benefits from a small model size, fast training speed, minimal VRAM requirements, and real-time rendering capabilities, while maintaining comparable rendering quality.

Detailed quantitative performance per scene. We show detailed quantitative results of our PPNG model across the NeRF Synthetics, NSVF Synthetic, BlendedMVS, and Tanks and Temples datasets from Table 6. to Table 15.

Table 1. Comparison with the real-time WebGL rendered models. We use values provided from [5] for SNeRG [2], MobileNeRF [1], Re-Rend [5], and author provided values for PlenOctree [6]

Model Name	PSNR	Size	GPU Usage	Training Time
SNeRG [2]	30.4	87 MB	3627 MB	15 hrs
PlenOctree [6]	30.9 31.7	126 MB 1976 MB	570 MB 1690 MB	20 hrs 50 hrs
Re-Rend [5]	29.0	199 MB	532 MB	60 hrs
PPNG-1	28.8	151 KB	47 MB	13.1 min
PPNG-2	31.0	2.49 MB	47 MB	9.8 min
PPNG-3	31.5	32.8 MB	47 MB	4.9 min

Table 2. PSNR evaluation for for Tanks and Temples dataset.

Table 5. PSNR evaluation for for BlendedMVS dataset.

	Barn	Caterpillar	Family	Ignatius	Truck		Character	Fountain	Jade	Statues
PPNG-1	24.52	22.78	29.97	26.71	24.42	PPNG-1	25.4	24.14	24.87	24.67
PPNG-2	25.71	24.32	32.50	27.16	26.46	PPNG-2	28.88	26.07	25.14	26.04
PPNG-3	26.42	24.88	33.28	27.51	27.05	PPNG-3	29.65	26.52	24.91	26.48

Table 3. SSIM evaluation for for Tanks and Temples dataset.

dataset.

Table 6. SSIM evaluation for for BlendedMVS dataset.

Fountain

0.823

0.881

0.901

Jade

0.849

0.861

0.870

Statues

0.838

0.879

0.900

Character

0.911

0.956

0.965

PPNG-1

PPNG-2

PPNG-3

	Barn	Caterpillar	Family	Ignatius	Truck	
PPNG-1	0.827	0.882	0.937	0.937	0.881	
PPNG-2	0.848	0.900	0.958	0.943	0.910	
PPNG-3	0.869	0.915	0.968	0.951	0.923	

Table 4. LPIPS (AlexNet) evaluation for for Tanks and Temples

Table 7. LPIPS ((AlexNet) eva	aluation for	for BlendedM	IVS datas	set
Table 7. LPIPS ((AlexNet) eva	aluation for	for BlendedM	IVS datas	;e

	Barn	Caterpillar	Family	Ignatius	Truck		Character	Fountain	Jade	Statues
PPNG-1	0.327	0.200	0.085	0.086	0.197	PPNG-1	0.076	0.18	0.128	0.152
PPNG-2	0.274	0.152	0.046	0.077	0.132	PPNG-2	0.029	0.095	0.102	0.092
PPNG-3	0.208	0.131	0.036	0.072	0.112	PPNG-3	0.023	0.078	0.096	0.073

Table 8. PSNR evaluation for NeRF synthetic dataset.

	chair	drums	ficus	hotdog	lego	materials	mic	ship
PPNG-1	29.69	23.14	28.2	33.82	30.39	26.89	32.08	26.9
PPNG-2	32.5	25.07	31.04	35.22	33.37	27.5	34.11	29.13
PPNG-3	33.54	25.41	31.6	36.17	34.54	28.53	35.18	30.27

Table 9. SSIM evaluation for for NeRF synthetic dataset.

	chair	drums	ficus	hotdog	lego	materials	mic	ship
PPNG-1	0.94	0.904	0.937	0.966	0.937	0.918	0.969	0.84
PPNG-2	0.968	0.919	0.96	0.975	0.967	0.915	0.978	0.869
PPNG-3	0.973	0.915	0.964	0.978	0.974	0.926	0.979	0.884

Table 10. LPIPS (AlexNet) evaluation for for NeRF synthetic dataset.

	chair	drums	ficus	hotdog	lego	materials	mic	ship
PPNG-1	0.056	0.116	0.046	0.041	0.04	0.09	0.044	0.207
PPNG-2	0.022	0.077	0.034	0.028	0.018	0.094	0.027	0.135
PPNG-3	0.015	0.075	0.031	0.022	0.014	0.072	0.021	0.1

Table 11. PSNR evaluation for Synthetic NSVF dataset.

	Bike	Lifestyle	Palace	Robot	Spaceship	Steamtrain	Toad	Wineholder
PPNG-1	26.42	28.07	31.85	30.87	29.89	30.89	25.99	26.42
PPNG-2	34.71	30.74	34.42	34.61	30.54	33.21	32.65	28.83
PPNG-3	35.64	31.43	36.27	35.5	31.0	33.92	34.15	29.7

Table 12. SSIM evaluation for for Synthetic NSVF dataset.

	Bike	Lifestyle	Palace	Robot	Spaceship	Steamtrain	Toad	Wineholder
PPNG-1	0.955	0.927	0.934	0.973	0.966	0.971	0.89	0.927
PPNG-2	0.984	0.946	0.962	0.987	0.966	0.98	0.966	0.951
PPNG-3	0.987	0.954	0.975	0.989	0.967	0.984	0.977	0.96

Table 13. LPIPS (AlexNet) evaluation for for Synthetic NSVF dataset.

Bike	Lifestyle	Palace	Robot	Spaceship	Steamtrain	Toad	Wineholder
0.028	0.072	0.044	0.023	0.037	0.027	0.09	0.063
0.008	0.046	0.02	0.009	0.038	0.017	0.025	0.035
0.006	0.038	0.012	0.008	0.037	0.015	0.015	0.027
	Bike 0.028 0.008 0.006	BikeLifestyle0.0280.0720.0080.0460.0060.038	BikeLifestylePalace0.0280.0720.0440.0080.0460.020.0060.0380.012	BikeLifestylePalaceRobot0.0280.0720.0440.0230.0080.0460.020.0090.0060.0380.0120.008	BikeLifestylePalaceRobotSpaceship0.0280.0720.0440.0230.0370.0080.0460.020.0090.0380.0060.0380.0120.0080.037	BikeLifestylePalaceRobotSpaceshipSteamtrain0.0280.0720.0440.0230.0370.0270.0080.0460.020.0090.0380.0170.0060.0380.0120.0080.0370.015	BikeLifestylePalaceRobotSpaceshipSteamtrainToad0.0280.0720.0440.0230.0370.0270.090.0080.0460.020.0090.0380.0170.0250.0060.0380.0120.0080.0370.0150.015



Figure 1. Qualitative results for Blended MVS dataset.



Figure 2. Qualitative results for Synthetic NSVF dataset



PPNG-1

PPNG-2

PPNG-3

Figure 3. Qualitative results for Tanks and Temples dataset



PPNG-1

PPNG-2

PPNG-3

Figure 4. Qualitative results for unboudned 360° dataset.

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