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TRIPS: Trilinear Point Splatting for Real-Time Radiance Field Rendering
Supplemental Material

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Abstract

Point-based radiance field rendering has demonstrated impressive results for novel view synthesis, offering a compelling blend of rendering quality and computational efficiency. However, also latest approaches in this domain are not without their shortcomings. 3D Gaussian Splatting [KKLD23] struggles when tasked with rendering highly detailed scenes, due to blurring and cloudy artifacts. On the other hand, ADOP [RFS22] can accommodate crisper images, but the neural reconstruction network decreases performance, it grapples with temporal instability and it is unable to effectively address large gaps in the point cloud.

In this paper, we present TRIPS (Trilinear Point Splatting), an approach that combines ideas from both Gaussian Splatting and ADOP. The fundamental concept behind our novel technique involves rasterizing points into a screen-space image pyramid, with the selection of the pyramid layer determined by the projected point size. This approach allows rendering arbitrarily large points using a single trilinear write. A lightweight neural network is then used to reconstruct a hole-free image including detail beyond splat resolution. Importantly, our render pipeline is entirely differentiable, allowing for automatic optimization of both point sizes and positions.

Our evaluation demonstrate that TRIPS surpasses existing state-of-the-art methods in terms of rendering quality while maintaining a real-time frame rate of 60 frames per second on readily available hardware. This performance extends to challenging scenarios, such as scenes featuring intricate geometry, expansive landscapes, and auto-exposed footage.

The project page is located at:

https://lfranke.github.io/trips

1. Individual Tabs: MipNeRF-360 (MipNeRF-360 resolutions)

Table 1: *$LPIPS_{VGG}$ scores for Mip-NeRF360 scenes. † copied from original paper [BMV*22]. ‡ copied from Kerbl and Kopanas et al. [KKLD23]. Image resolutions as in MipNerf-360: half resolution for indoor, quarter resolution for outdoor. Average ours: 0.176*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP‡	0.446	0.441	0.257	0.421	0.450	0.261	0.306	0.195	0.205
Mip-NeRF 360†	0.301	0.344	0.170	0.261	0.339	0.211	0.204	0.127	0.176
Mip-NeRF 360‡	0.305	0.346	0.171	0.265	0.347	0.213	0.207	0.128	0.179
Gaussian Spl.‡	0.205	0.336	0.103	0.210	0.317	0.220	0.204	0.129	0.205
TRIPS(ours)	0.194	0.297	0.159	0.268	0.266	0.147	0.158	0.127	0.111

Table 2: *Normalized $LPIPS_{VGG}$ scores: based on the original paper [ZIE*18], images should be normalized between -1 and 1 (as is in every table except Supplemental Tab. 1). Scored of ours with this normalization. Average ours: 0.213*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
TRIPS(ours)	0.223	0.318	0.183	0.309	0.308	0.197	0.206	0.154	0.153

Table 3: *PSNR scores for Mip-NeRF360 scenes. † copied from original paper [BMV*22]. ‡ copied from Kerbl and Kopanas et al. [KKLD23]. Image resolutions as in MipNerf-360: half resolution for indoor, quarter resolution for outdoor. Average ours: 25.94*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP‡	22.171	20.652	25.069	23.466	22.373	29.690	26.691	29.479	30.685
Mip-NeRF 360†	24.37	21.73	26.98	26.40	22.87	31.63	29.55	32.23	33.46
Mip-NeRF 360‡	24.305	21.649	26.875	26.175	22.929	31.467	29.447	31.989	33.397
Gaussian Spl.‡	25.246	21.520	27.410	26.550	22.490	30.632	28.700	30.317	31.980
TRIPS(ours)	23.466	19.439	25.384	24.174	22.044	29.066	27.002	27.662	28.710

Table 4: *SSIM scores for Mip-NeRF360 scenes. † copied from original paper [BMV*22]. ‡ copied from Kerbl and Kopanas et al. [KKLD23]. Image resolutions as in MipNerf-360: half resolution for indoor, quarter resolution for outdoor. Average ours: 0.778*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP‡	0.512	0.486	0.701	0.594	0.542	0.871	0.817	0.858	0.906
Mip-NeRF 360†	0.685	0.583	0.813	0.744	0.632	0.913	0.894	0.920	0.941
Mip-NeRF 360‡	0.685	0.584	0.809	0.745	0.631	0.910	0.892	0.917	0.938
Gaussian Spl.‡	0.771	0.605	0.868	0.775	0.638	0.914	0.905	0.922	0.938
TRIPS(ours)	0.704	0.502	0.773	0.681	0.591	0.883	0.845	0.850	0.899

2. Individual Tabs: Tanks and Temples

Table 5: *$LPIPS_{VGG}$ scores for Tanks and Temples scenes (intermediate set).*

	playground	lighthouse	francis	m60	train	panther	family	horse
InstantNGP	0.581	0.477	0.472	0.414	0.527	0.410	0.456	0.437
Mip-NeRF 360	0.350	0.346	0.343	0.313	0.486	0.285	0.277	0.244
Gaussian Spl.	0.322	0.296	0.345	0.273	0.344	0.267	0.262	0.244
ADOP	0.233	0.210	0.241	0.226	0.239	0.232	0.225	0.216
TRIPS(ours)	0.229	0.208	0.221	0.208	0.223	0.207	0.202	0.194

Table 6: *PSNR scores for Tanks and Temples scenes (intermediate set).*

	playground	lighthouse	francis	m60	train	panther	family	horse
InstantNGP	18.224	20.783	23.148	24.115	18.753	26.312	21.453	19.719
Mip-NeRF 360	25.200	22.379	28.266	24.743	18.674	27.428	25.326	25.659
Gaussian Spl.	24.611	21.592	25.993	26.972	20.990	27.823	24.491	23.880
ADOP	24.856	23.057	22.036	24.707	22.335	25.666	24.013	23.261
TRIPS(ours)	25.116	23.382	24.818	25.832	22.974	26.841	23.532	23.174

Table 7: *SSIM scores for Tanks and Temples scenes (intermediate set).*

	playground	lighthouse	francis	m60	train	panther	family	horse
InstantNGP	0.493	0.713	0.764	0.766	0.596	0.808	0.681	0.721
Mip-NeRF 360	0.741	0.771	0.847	0.837	0.619	0.863	0.815	0.858
Gaussian Spl.	0.766	0.790	0.847	0.868	0.734	0.880	0.820	0.853
ADOP	0.753	0.796	0.827	0.843	0.755	0.844	0.775	0.817
TRIPS(ours)	0.746	0.787	0.848	0.849	0.764	0.851	0.791	0.825

3. Individual Tabs: MipNeRF-360 (our resolutions)

Table 8: *$LPIPS_{VGG}$ scores for MipNeRF-360 scenes with our resolutions (half indoor and outdoor).*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP	0.600	0.587	0.516	0.591	0.606	0.354	0.393	0.286	0.266
Mip-NeRF 360	0.423	0.458	0.310	0.385	0.460	0.223	0.238	0.162	0.169
Gaussian Spl	0.363	0.448	0.245	0.359	0.460	0.234	0.231	0.158	0.215
ADOP	0.319	0.409	0.259	0.376	0.422	0.241	0.264	0.221	0.223
TRIPS(ours)	0.284	0.383	0.219	0.327	0.358	0.197	0.206	0.154	0.153

Table 9: *PSNR scores for MipNeRF-360 scenes with our resolutions (half indoor and outdoor).*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP	21.479	19.880	23.556	22.791	21.828	29.347	26.618	28.528	30.904
Mip-NeRF 360	23.541	21.082	25.887	26.219	22.525	31.711	29.425	31.351	33.222
Gaussian Spl.	24.286	20.732	25.690	26.123	22.274	30.423	28.987	30.446	27.225
ADOP	21.910	19.432	23.711	23.700	20.312	25.975	23.088	23.614	24.330
TRIPS(ours)	22.961	19.668	25.385	24.964	21.725	29.066	27.002	27.662	28.710

Table 10: *SSIM scores for MipNeRF-360 scenes with our resolutions (half indoor and outdoor).*

	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
InstantNGP	0.486	0.422	0.545	0.568	0.524	0.853	0.789	0.811	0.895
Mip-NeRF 360	0.635	0.522	0.730	0.727	0.611	0.909	0.882	0.901	0.940
Gaussian Spl.	0.693	0.530	0.764	0.748	0.600	0.896	0.892	0.899	0.853
ADOP	0.610	0.475	0.674	0.652	0.546	0.839	0.769	0.737	0.818
TRIPS(ours)	0.668	0.482	0.751	0.707	0.587	0.883	0.845	0.850	0.899

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