



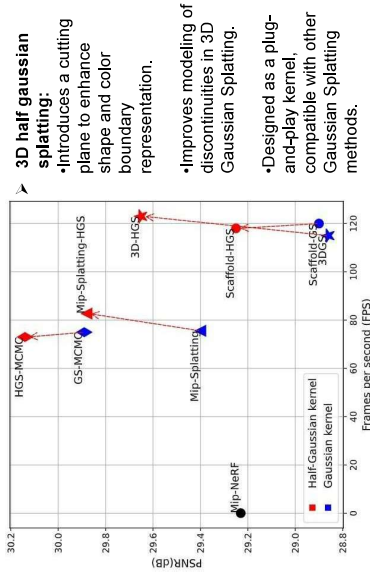
3D-HGS: 3D half gaussian splatting

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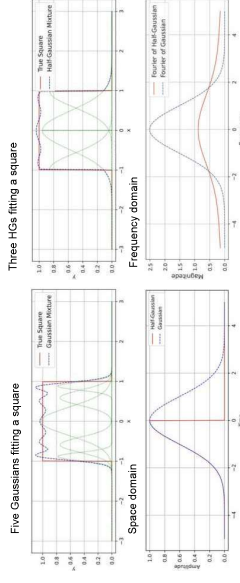


Motivation



- **3D half gaussian splatting:**
 - Introduces a cutting plane to enhance shape and color boundary representation.
- Improves modeling of discontinuities in 3D Gaussian Splatting.
- Designed as a plug-and-play kernel compatible with other Gaussian Splatting methods.

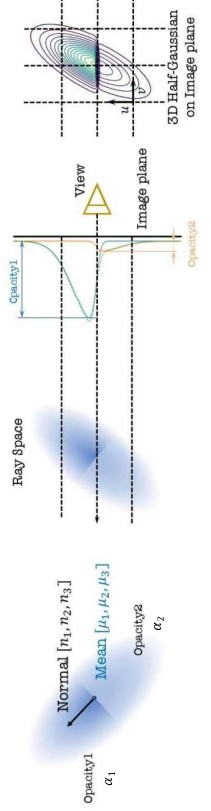
Comparison of Half-Gaussian and Gaussian Kernels



Time Domain: Half-Gaussians better approximate sharp edges with fewer kernels and lower error.

Frequency Domain: Preserve more high-frequency components, improving edge fidelity.

Our Method: 3D-HGS



Parameters	3D-GS	3D-HGS
$\mu \in R^{1+3}, \Sigma \in R^{3+3}, n \in R^{1+3}$		
Kernel	$G_2(x-\mu) = \pi e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$	$HG_2(x-\mu) = \frac{1}{2} [2\alpha_2 + (\alpha_1 - \alpha_2)(x, y)] \delta_2(x - \mu)$
Projection to 2D	$G_2(x-\mu) = e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$	$HG_2(x-\mu) = \begin{cases} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)} & n^T(x-\mu) \geq 0 \\ 0 & n^T(x-\mu) \leq 0 \end{cases}$

Qualitative Results



Quantitative Results

Dataset	Method	Mip-NeRF360		Tanks&Temples		Deep Blending	
		PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
Mip-NeRF [1]	Mip-NeRF [1]	29.23	0.844	22.22	0.759	29.40	0.901
	2D-GS [8]	28.98	0.867	23.43	0.845	29.70	0.902
	Fre-GS [30]	27.85	0.826	23.96	0.841	29.93	0.904
	GES [6]	28.69	0.857	23.35	0.836	29.68	0.901
3D-GS [9]	3D-GS [9]	28.88	0.870	23.60	0.847	29.41	0.903
	3D-HGS (Ours)	29.66	0.878	24.45	0.885	29.76	0.905
	Scaffold-GS [15]	28.95	0.848	23.96	0.853	30.21	0.906
	Scaffold-HGS(Ours)	29.25	0.867	24.42	0.865	30.36	0.910
Mip-Splatting [29]	Mip-Splatting [29]	29.39	0.880	23.75	0.857	29.46	0.901
	Mip-Splatting-HGS(Ours)	29.88	0.881	24.53	0.878	29.61	0.903
GS-MCMC [10]	GS-MCMC [10]	29.89	0.900	24.29	0.860	29.67	0.890
	HGS-MCMC(Ours)	30.13	0.886	25.08	0.877	29.80	0.898