Edge Case/Sparse View Analysis on 3D Gaussian Splatting

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Motivation

- 3D Gaussian splatting (GSplats) is a technique used in novel view synthesis that involves projecting and blending 3D scene information onto a new viewpoint using Gaussian distributions, providing a realistic representation of the synthesized view. It has shown to be 50 times faster than SOTA NeRF models, while keeping high-quality renders.
- Instant NGP (Neural Graphic Primitives) is a method that employs neural networks to predict and render 3D graphic primitives directly in the image space, enabling high-speed and high-quality generation of novel views with improved realism. It has proven to be one of the fastest NeRF models, which makes it suitable for comparison to GSplats.
- The (gaussian splatting) models' ability to produce novel views haven't been explored for uncommon situations such as: transparent objects, reflective surfaces and sparse (incomplete) image sets.

Figure 1: Transparent Water glass

Figure 2: Reflective Water bottle

- **Goal:** Compare 3D gaussian splatting and Instant Neural Graphic Primitives methods to reconstruct 3D novel views for 2 datasets pertaining to unique edge cases: transparent objects, reflective surfaces and sparse view inputs.

Related Work

Neural Radiance Fields (NeRFs)
- Optimizes a Neural Network to represent a 5D scene representation.
- Training process is time consuming, requiring a substantial quantity of images.[1]

Instant NGP (Neural Graphic Primitives)
- Model uses a multiresolution structure for making an architecture that is trivial to parallelize on modern GPUs.
- The slow computational performance from COLMAP to training of neural networks can lead to long experiment times.[2]

3D Gaussian Splatting
- Anisotropic 3D Gaussians are introduced as a high-quality unstructured representation of radiance fields.
- A fast differentiable rendering approach for the GPU is used which allows anisotropic splatting and fast back-propagation to achieve high quality novel view synthesis.
- The memory consumption is significantly higher than NeRF-based solutions. [3]

References

[1] Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis, 2020.

[2] Thomas Müller, Alex Evans, Christoph Schied, and Alexander Keller. Instant neural graphics primitives with a multiresolution hash encoding. ACM Trans. Graph., 41(4):102:1–102:15, July 2022.

[3] Bernhard Kerbl, Georgios Kopanas, Thomas Leimkühler, and George Drettakis. 3d gaussian splatting for real-time radiance field rendering, 2023.

Method for Edge Case/Sparse View Reconstruction

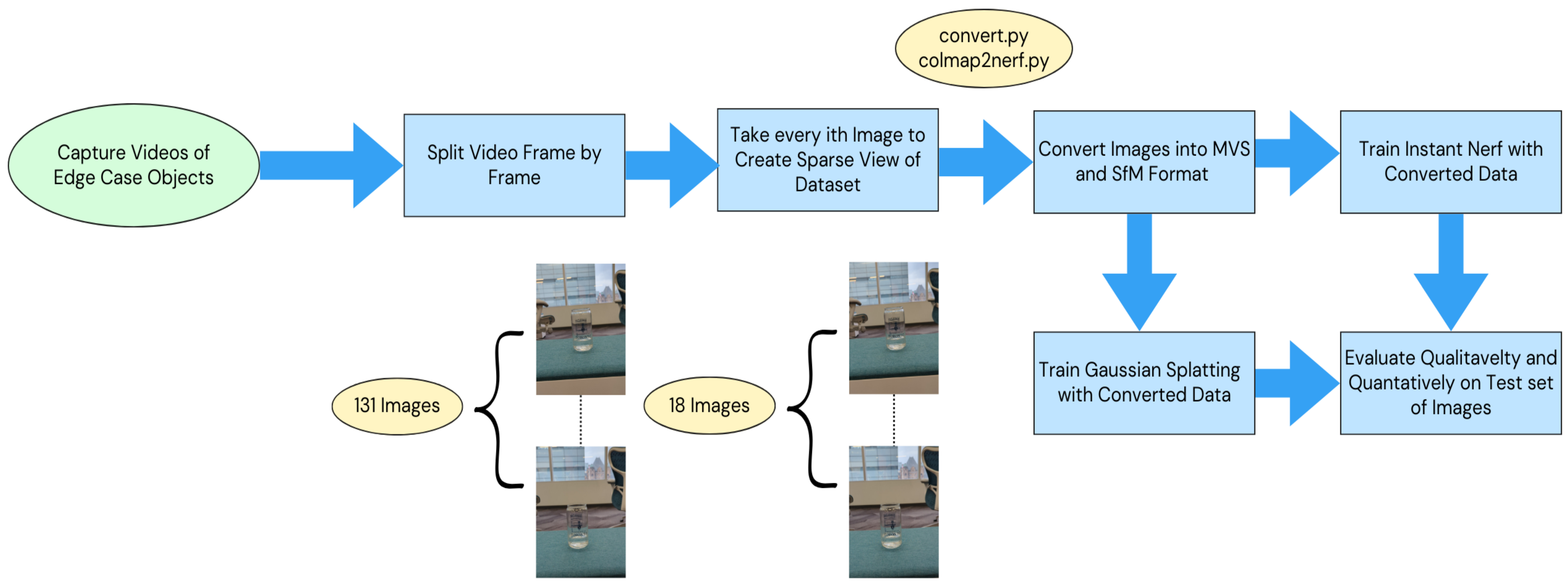

Figure 3: Reconstruction Workflow

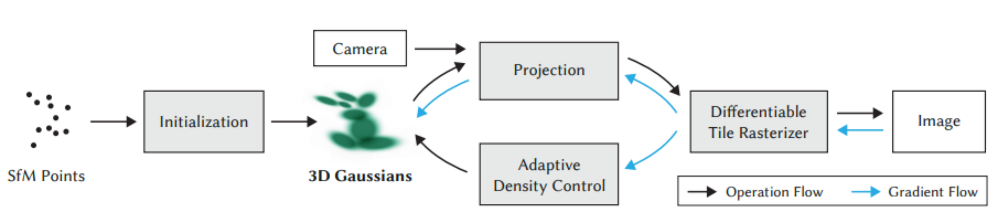

Figure 4: Overview of 3D Gaussian Splatting Algorithm

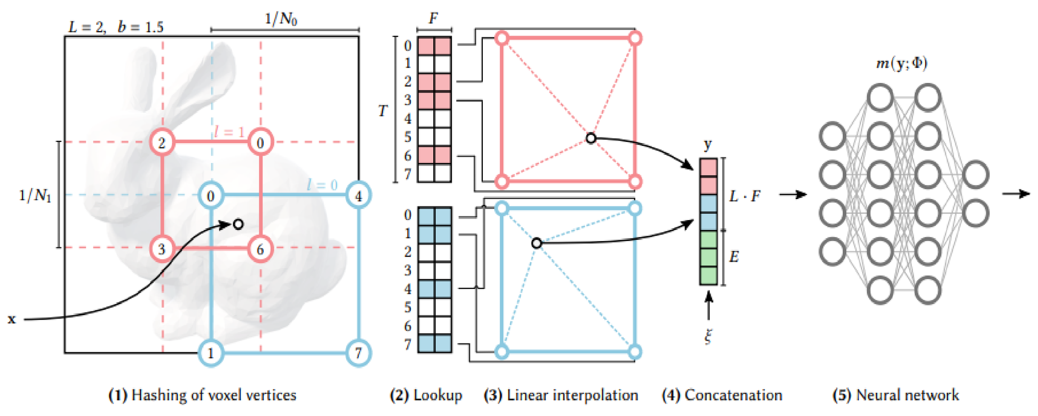

Figure 5: Overview of Instant NGP Algorithm

Experimental Results

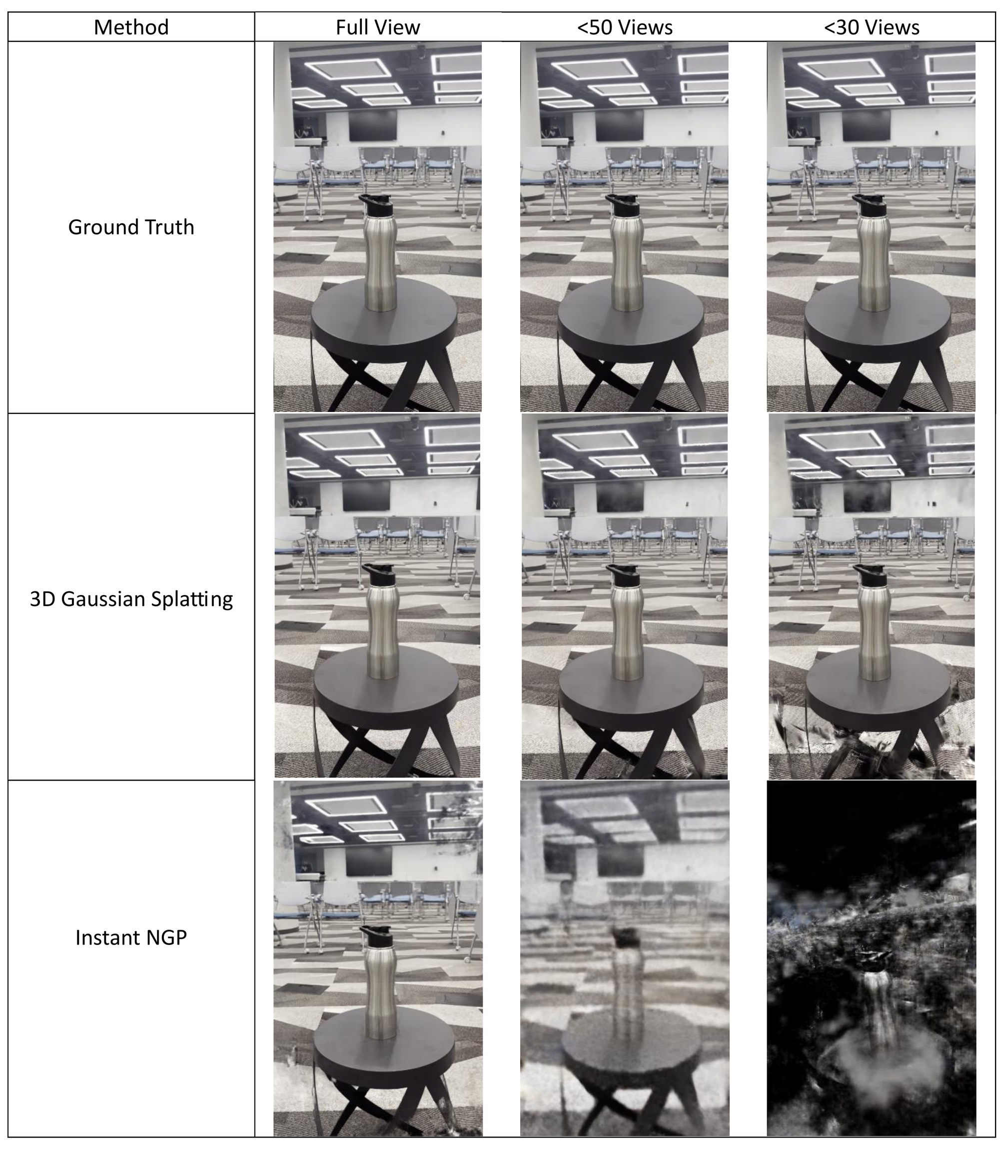

Figure 6: Qualitative Analysis w/ Reflective Dataset

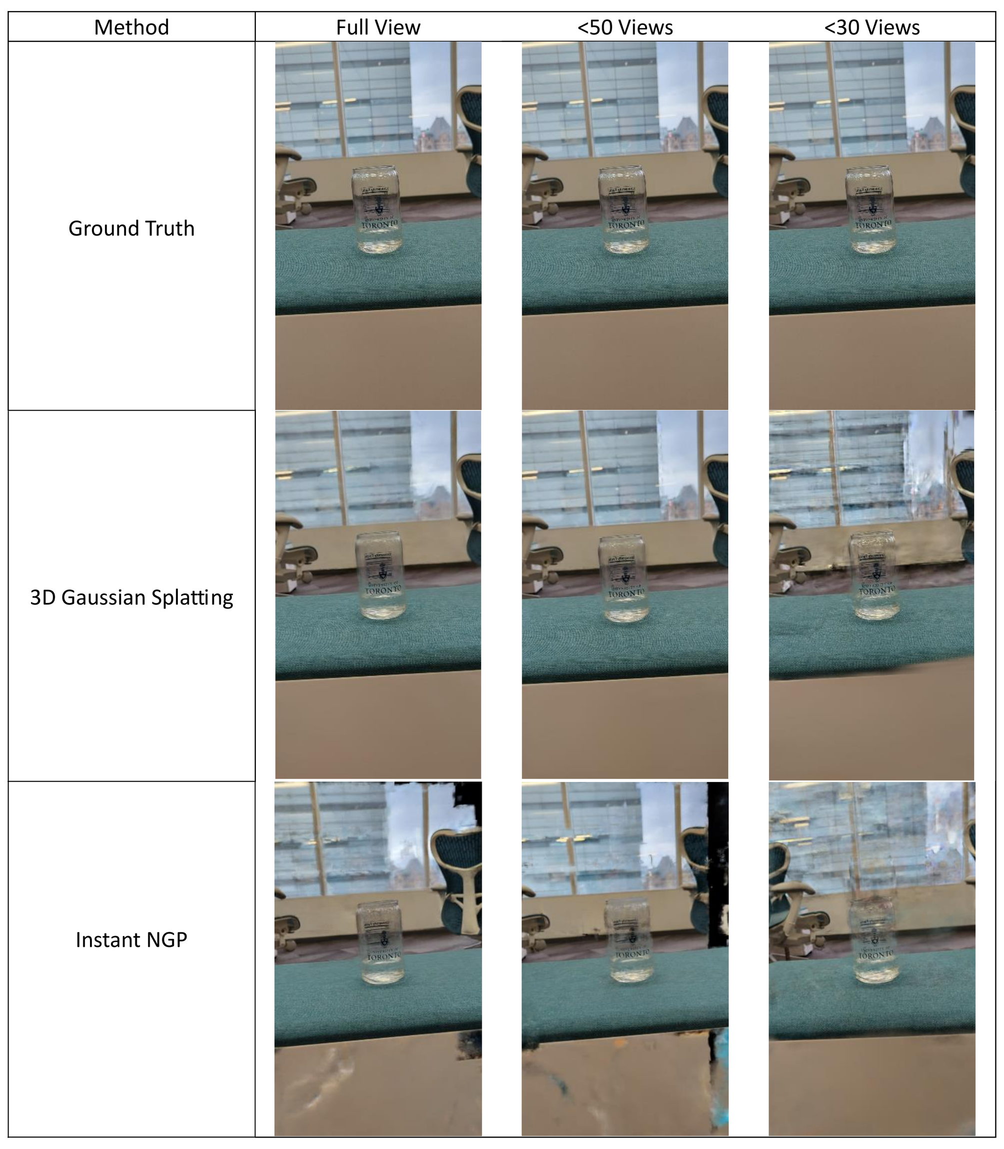

Figure 7: Qualitative Analysis w/ Transparent Dataset

Method	Views	PSNR	LPIPS	SSIM	Training Time (h:m:s)	Training Iterations
3D Gaussian Splatting	Full	31.23	0.086	0.959	0:29:47	10000
	<50	25.86	0.149	0.907	0:28:08	10000
	<30	19.06	0.259	0.805	0:16:03	10000
Instant NGP	Full	16.53	0.342	0.672	0:30:39	30000
	<50	13.68	0.518	0.599	0:27:09	30000
	<30	8.98	0.629	0.310	0:26:37	30000

Figure 8: Quantitative Analysis w/ Reflective Dataset

Method	Views	PSNR	LPIPS	SSIM	Training Time (h:m:s)	Training Iterations
3D Gaussian Splatting	Full	28.32	0.247	0.886	1:01:21	10000
	<50	26.56	0.271	0.850	0:54:01	10000
	<30	22.88	0.323	0.801	0:52:39	10000
Instant NGP	Full	15.35	0.428	0.522	0:48:21	50000
	<50	14.42	0.489	0.463	0:47:02	50000
	<30	15.01	0.474	0.512	0:44:22	50000

Figure 9: Quantitative Analysis w/ Transparent Dataset