Rendering and Optimization of Gaussian Radiance Fields

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1 Project Area

This is a fairly new subject when it comes to research. Our main source of information comes from a recent paper, 3D Gaussian Splatting for Real-Time Radiance Field Rendering [2]. Other papers have detailed similar approaches to modeling of scenes, such as Neural Radiance Fields (NeRFs) [1], or DeepVoxels [4], but the novel approach of this paper is its use of gaussians to encapsulate scene information and its fast rasterization.

The general approach they followed is to first instantiate 3D gaussians based on sparse point clouds created with a process called structure from motion (SfM) [3]. Then, the gaussians are split and duplicated until they more densely fill the space, later on being moved, removed, or split as needed. The gaussians are optimized to fit the scene by iterations of rendering (rasterization) and gradient descent against the known images of the scene. One of the main advances of this paper in particular was their fast implementation of rasterization, which allows many more "splats" to receive gradients. This greatly speeds up training time as well as accuracy of the final scene.

2 Motivation

(Valerie, maybe you can speak to this a bit more) (Any ideas of exactly what sort of motivation we're talking about here?)

We chose this topic for our project at least partially because it appeals to the mixed strengths of our group, as well as to the desire to work on new and novel material. Valerie's main focus of interest is graphics and she had already skimmed the paper on her own. Cameron has prior experience when it comes to machine learning and gradient descent optimization (?). Andrew is relatively inexperienced when it comes to either of these fields. However, as a math major, he was interested in diving deeper into the world of gradient descent optimization, especially as a way to manipulate 3D gaussians.

3 Directions of Investigation

As discussed by the paper in section 8, one possible section of improvement would be to implement the optimization steps of the code entirely in C. They note that

"The majority (80%) of our training time is spent in Python code, since we built our solution in PyTorch to allow our method to be easily used by others. Only the rasterization routine is implemented as optimized CUDA kernels. We expect that porting the remaining optimization entirely to CUDA, as e.g., done in InstantNGP [Müller et al . 2022], could enable significant further speedup for applications where performance is essential."

4 Expected Results

References

[1] Jonathan T. Barron, Ben Mildenhall, Dor Verbin, Pratul P. Srinivasan, and Peter Hedman. Mip-nerf 360: Unbounded anti-aliased neural radiance fields, 2022.

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

[3] Jaeryun Ko and Yo-Sung Ho. Point cloud generation using structure from motion with multiple view images. 2016. URL https://api.semanticscholar.org/CorpusID:45273242.

[4] Vincent Sitzmann, Justus Thies, Felix Heide, Matthias Nießner, Gordon Wetzstein, and Michael Zollhöfer. Deepvoxels: Learning persistent 3d feature embeddings, 2019.