High-quality Approximation of Scientific Data using 3D Gaussian Splatting

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Comparison of an isosurface rendered in ParaView (left), 3D Gaussian splat rendering of a Gaussian splat model trained using a point cloud extracted from the isosurface (middle), and using a randomly initialized point cloud (right). This bonsai dataset consists of 256x256x256 elements (16 MB), courtesy of the open scientific visualization dataset repository.

Abstract

This work applies recent advancements in 3D Gaussian splatting to generate high-quality approximations of scientific data. Typically, a 3D Gaussian

splatting model is built from a structure-from-motion or randomly initialized point cloud, refined through machine learning to match ground truth images. We modified this pipeline to train Gaussian models directly from scientific data, bypassing the need for structure-from-motion. We tested exporting an isosurface as a point cloud to train a Gaussian model, with promising results. We also tried using a cinema database, but it was less effective due to poor point cloud initialization. Our findings suggest this technique could enable efficient post-hoc visualization with fewer computational resources.



Conclusions

We demonstrate the potential of new 3D Gaussian splatting techniques as a valuable tool for scientific data visualization, particularly for reconstructing and approximating the data with high-fidelity. By bypassing structure-from-motion and leveraging volumetric data directly, we have developed a method that produces high-quality 3D Gaussian models suitable for real-time visualization. Our findings emphasize the importance of a robust initial point cloud, which is critical for achieving accurate reconstructions.

Next Steps

- Expand Testing: Apply 3D Gaussian splatting to larger, more complex datasets.
- Performance Analysis: Collect performance data across different

datasets and hardware configurations to quantify the benefits of this approach.

• **Explore In Situ Training**: Investigate the feasibility of training Gaussian models in situ, or at least producing the necessary components in situ.

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