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Gaussian Splatting As A New Way Of Rendering 3D Scenes

Fiodar Yakavenka, Tariq Eldakruri, Edip Senyurek
Department Of Computer Engineering, Vistula University, Poland

Abstract:
Background: *Rendering photorealistic 3D scenes has long been a compromise between image quality and computational speed. Early splatting methods proposed the idea of projecting elements onto a 2D plane, and later approaches with neural networks, such as NeRF (around 2020), made it possible to achieve high-quality rendering of scenes at the cost of significant computational costs, which limited their use in real time. Photogrammetry and Structure-from-Motion (2023) techniques have made practical 3D reconstruction from photographs possible by providing point clouds used to initialize various representations of a scene. Based on these developments, in 2023, the 3D Gaussian Splatting method was introduced — a point representation of a scene combined with fast speed, allowing for real-time rendering without loss of visual quality.*
Results: *3D Gaussian Splatting offers a compromise between photorealistic image quality and real-time computing speed. Unlike NeRF-type approaches, the nature of Gaussian primitives and the use of differentiable rasterization make it possible to achieve high rendering performance without significant losses in visual accuracy, which makes the technology promising for various fields of application: art, medicine, design and other areas related to 3D rendering. But unfortunately, unresolved problems remain, for example, the issue of information storage, limited editability of scenes and the difficulty of integrating technology into already established processes.*
Conclusion: *Gaussian Splatting combines photorealistic rendering quality with real-time performance, paving the way for practical applications in VR/AR, photogrammetry, and video games, although issues of data volume and scene editability remain promising areas of further research.*
Key Word: *3D Reconstruction, Computer Graphics, Gaussian Splatting, Neural Rendering, Point Cloud, Real-Time Rendering*

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I. Introduction

Rendering complex 3D scenes, locations, and animations is an important part of both the entertainment world, in the form of cartoons, CGI in films, games, and in the professional world: interior and exterior design, visualization of medical CT and MR images. 3D visualizations allow doctors to see 3D scans of bones and areas of the patient's body, which makes it faster and more reliable to make a diagnosis, CAD programs allow engineers to put together details, and advertisers can implement their most unusual and creative projects. A relatively new technology, called Gaussian Splatting, aims to change our established approach to polygon-based 3D rendering and offer a new, potentially more productive and detailed option. Gaussian splatting provides the ability to render complex photorealistic 3D scenes in real time without requiring huge computing power, which could potentially change the established approach to 3D rendering.

II. Methodology

Rendering 3D scenes is a process, which contains many pitfalls, such as the difficulty of achieving a convincing and realistic-looking picture, the huge consumption of computing resources, a lot of man-hours to create a good-looking picture, as well as the attachment to polygons, small triangles, which make up any object (even round objects, which are difficult to make really round by making them of their triangles).

On April 5, 1996, Pixar Studios showed the world the cartoon "Toy Story", completely created with the help of 3D graphics. Creating the film took 800,000 machine-hours and 114,240 frames of animation, distributed across 1,561 scenes with a total runtime of over 77 minutes. Pixar could render less than 30 seconds of the film per day. The movie was a breakthrough, but a tremendous amount of effort and computing power was expended on it. Today we have many more ways and possibilities to create 3D scenes [1][2].

Photogrammetry is the process of capturing images and combining them to create a digital model of the physical world. It is a technique for making 3D scenes from 2D images taken from different angles. However, this method has drawbacks. It struggles with geometric details, cannot handle scenes with moving or deforming elements reliably, its output quality is dependent on lighting [3].

Photogrammetry needs actual images to reconstruct an object and create a 3D model, without measuring the locations of points by an organized laser ray. Therefore, a good quality product needs good quality data and measurement (photos need to be taken from different angles in the right pattern and cover every side of the object) This means good photogrammetry requires a good dataset. It's also important to take photos in the right pattern, so that every area of a site, monument or artifact is covered.

NeRF optimizes volumetric representation of a scene describing it as a vector-valued function. The system generates images using deep learning algorithms for building complex 3D scenes from source images, bypassing limitations associated with rendering details and processing deforming objects.

This algorithm uses deep neural network, that takes as input a single continuous 5D coordinate, comprising spatial position (x, y, z) and viewing direction (θ, φ), and outputs the volumetric Concentration and emitted radiance (depending on the component type) at that point. Example of NeRFs rendered scene is shown on Figure 1.

Figure 1: NeRFs scene rendering example [4]

3D Gaussian Splatting is the latest volumetric creating technique that is used to transfer real data into 3D view and visualize it in real time. The results of using this method are like those obtained using Radiance field methods (Nerf), but the method has its own advantages: it's faster to set up, faster to create, and provides the same or even better quality. It eliminates the disadvantages of NeRFs by using 3D Gaussians, using their parameters such as anisotropic covariances, positions, and opacity to effectively model complex scenes.

One of the most remarkable approaches to radiance field rendering is 3D Gaussian Splatting, which achieves state-of-the-art visual clarity and offers competitive performance while rendering. It enables real-time scene synthesis at 1080p resolution with performance exceeding 100 fps [5]. As can be seen in Figure 2 and Figure 3, Gaussian Splatting shows high quality photorealistic results.

Figure 2: Gaussian splatting scene rendering example [5]

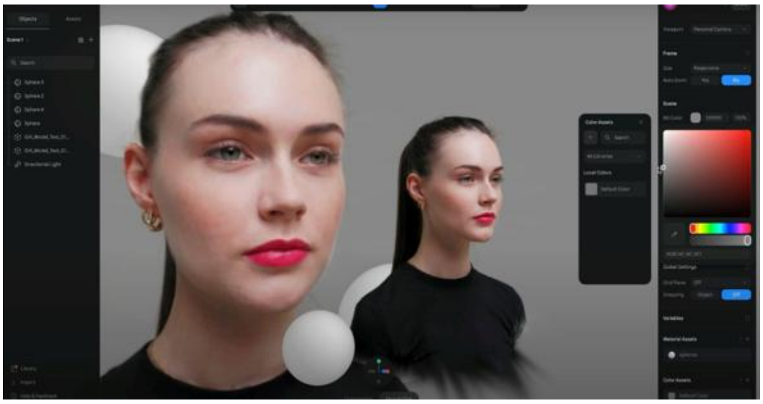

Figure 3: UI of Gaussian Splatting rendering application [6]

Gaussian splatting characterizes the world as a collection of millions of 3D points. And there every single point is described with four main parameters: location (x, y, z), opacity, color and covariance matrix. For modeling dynamic scenes Gaussians are moved and rotated over time Gaussians, but they keep the same size, opacity, and color. Rendering process using Gaussian Splatting can be seen in Figure 4.

Figure 4: Gaussian splatting rendering in progress [7]

Requirements for 3D Gaussian Splatting hardware requirements are CUDA-ready GPU with Compute Capability 7.0+, 24 GB VRAM. However, for smaller renders it is possible to have less video memory (~8GB), which is still big by today's standards. Rendering software is usually built with Python language using PyTorch.

III. Usage

Medical usage: when necessary, changes are made to the pipeline, Gaussian Splatting can be used in medicine to assemble 3D scenes, for example, X-ray images by binding splats to visualize X-ray absorption. Y. Li was able to use gaussians to reconstruct the MRI image, which could potentially help reduce the radiation exposure of patients during this procedure [8].

Media/entertainment usage: recent work effectively utilizes 3D Gaussian Splatting in combination with domains such as generative models, avatars, and scene editing. For example, DreamGaussian accelerates the creation of realistic 3D scenes from single view images using an algorithm: first a generative Gaussian Splatting process based on diffusion, second and process for selection the grid from the 3D Gaussians with querying of local density, and last stage is a UV-space improvement for more texture details.

Simultaneous Localization and Mapping (SLAM): SLAM is a fundamental task in the field of robotics and autonomous systems. Simultaneous Localization and Mapping enable devices to understand their coordinates in an unfamiliar environment and at the same time map it to it. SLAM is necessary for different applications, self-driven cars, robotics and augmented reality. 3D Gaussian Splatting is used as an innovative view to scene representation in SLAM (3D Gaussian Splatting uses anisotropic Gaussians instead of point/surface clouds or voxel meshes to display the surroundings).

Autonomous driving usage: the purpose of autonomous driving systems is to provide navigation and control of vehicles without human intervention. Vehicles using such systems are usually equipped with cameras, LIDAR sensors, these are sensors that can read the range to an object, as well as various radar systems. Such hardware specifications, coupled with modern algorithms, including machine learning, allow you to create a visual representation of the environment for real-time decision-making on the road. Real-time reconstruction of the environment is indispensable for safe navigation of unmanned vehicles but is challenging due to computational complexity and rapidly changing environments. 3D Gaussian Splatting can be used to reproduce the surrounding environment by fusing point clouds (e.g. from LIDAR sensors) into a continuous cast of everything surrounding the vehicle.

IV. Advantages And Disadvantages

Gaussian Splatting provides multiple times faster rendering and training time. During testing, the approximate data showed an increase in the speed of rendering scenes by about 50 times compared to NeRFs for a similar scene, which is an extremely strong leap in the development of technology. Potentially, with more detailed and complex scenes, the increase may be even more significant. In their work Chen, G. & Wang, W. noticed that 3D Gaussians based systems generally outperform the three dense SLAM (Simultaneous localization and mapping) competitors. For example, Gaussian-SLAM establishes new SOTA and outperforms previous methods by a large margin. Compared to Point-SLAM, GSSLAM is about 578 times faster in achieving very competitive accuracy [9].

While the overall effect is great and the rendering performance is impressive, it also has a downside. A fundamental principle is the diverse regularization strategies for protecting the scene representation from degrading the Gaussians. On the other hand, Yurkova mentioned that Gaussian splatting is not free from some well-known artifacts present in NeRFs which they both inherit from the shared image formation model: lower quality in less seen or unseen regions, floaters close to an image plane, etc. [7].

V. Conclusion

Despite the problems, such as the large amount of video memory required for training, the lack of interaction and the ability to change the environment within a scene, it is a very promising technology. We can imagine VR games with graphics indistinguishable from reality, or interactive movies where you can watch characters and events from anywhere within the scene. Theoretical possibility to create interactive maps where you don't just move between 360-degree photos but can move smoothly and see objects up close. It is a promising technology that just needs some time to get ready and potentially become a mainstream option of rendering complex and photorealistic 3D scenes.

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