

# A Survey on 3D Gaussian Splatting

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**Abstract**—3D Gaussian splatting (GS) has recently emerged as a transformative technique in the realm of explicit radiance field and computer graphics. This innovative approach, characterized by the utilization of millions of learnable 3D Gaussians, represents a significant departure from mainstream neural radiance field approaches, which predominantly use implicit, coordinate-based models to map spatial coordinates to pixel values. 3D GS, with its explicit scene representation and differentiable rendering algorithm, not only promises real-time rendering capability but also introduces unprecedented levels of editability. This positions 3D GS as a potential game-changer for the next generation of 3D reconstruction and representation. In the present paper, we provide the first systematic overview of the recent developments and critical contributions in the domain of 3D GS. We begin with a detailed exploration of the underlying principles and the driving forces behind the emergence of 3D GS, laying the groundwork for understanding its significance. A focal point of our discussion is the practical applicability of 3D GS. By enabling unprecedented rendering speed, 3D GS opens up a plethora of applications, ranging from virtual reality to interactive media and beyond. This is complemented by a comparative analysis of leading 3D GS models, evaluated across various benchmark tasks to highlight their performance and practical utility. The survey concludes by identifying current challenges and suggesting potential avenues for future research in this domain. Through this survey, we aim to provide a valuable resource for both newcomers and seasoned researchers, fostering further exploration and advancement in applicable and explicit radiance field representation.

**Index Terms**—3D Gaussian Splatting, Explicit Radiance Field, Real-time Rendering, Scene Understanding

## 1 INTRODUCTION

THE objective of image based 3D scene reconstruction is to convert a collection of views or videos capturing a scene into a 3D model that can be processed and understood by computers. This hard and long-standing problem is fundamental for machines to comprehend the complexity of real-world environments, facilitating a wide array of applications such as 3D modeling and animation, robot navigation, historical preservation, augmented/virtual reality, and autonomous driving.

The journey of 3D scene reconstruction began long before the surge of deep learning, with early endeavors focusing on light fields and basic scene reconstruction methods [1]–[3]. These early attempts, however, were limited by their reliance on dense sampling and structured capture, leading to significant challenges in handling complex scenes and lighting conditions. The emergence of structure-from-motion [4] and subsequent advancements in multi-view stereo [5] algorithms provided a more robust framework for 3D scene reconstruction. Despite these advancements, such methods struggled with novel-view synthesis and lacked compatibility with deep scene understanding models. NeRF represents a quantum leap in this progression. By leveraging deep neural networks, NeRF enabled the direct mapping of spatial coordinates to color and density. The success of NeRF hinged on its ability to create continuous, volumetric scene functions, producing results with unprecedented detail and realism. However, as with any burgeoning technology, this implementation came at a cost: i) Computational Intensity. NeRF based methods are computationally intensive [6]–[9], often requiring extensive training times and substantial

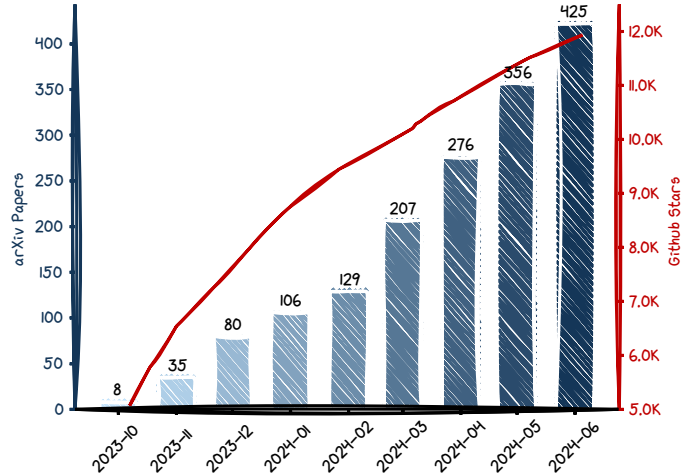


Fig. 1. The number of follow-up arXiv papers and official github stars on 3D GS is increasing every month.

resources for rendering, especially for high-resolution outputs. ii) Editability. Manipulating scenes represented implicitly is challenging, since direct modifications to the neural network’s weights are not intuitively related to changes in geometric or appearance properties of the scene.

It is in this context that 3D Gaussian splatting (GS) [10] emerges, not merely as an incremental improvement but as a paradigm-shifting approach that redefines the boundaries of scene representation and rendering. While NeRF excelled in creating photorealistic images, the need for faster, more efficient rendering methods was becoming increasingly apparent, especially for applications (e.g., virtual reality and autonomous driving) that are highly sensitive to latency. 3D GS addressed this need by introducing an advanced, explicit scene representation that models a scene using millions of learnable 3D Gaussians in space. Unlike the implicit, coordinate-based models [11], [12], 3D GS employs an

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explicit representation and highly parallelized workflows, facilitating more efficient computation and rendering. The innovation of 3D GS lies in its unique blend of the benefits of differentiable pipelines and point-based rendering techniques [13]–[17]. By representing scenes with learnable 3D Gaussians, it preserves the strong fitting capability of continuous volumetric radiance fields, essential for high-quality image synthesis, while simultaneously avoiding the computational overhead associated with NeRF based methods (*e.g.*, computationally expensive ray-marching, and unnecessary calculations in empty space).

The introduction of 3D GS is not just a technical advancement; it represents a fundamental shift in how we approach scene representation and rendering in computer vision and graphics. By enabling real-time rendering capabilities without compromising on visual quality, 3D GS opens up a plethora of possibilities for applications ranging from virtual reality and augmented reality to real-time cinematic rendering and beyond [18]–[21]. This technology holds the promise of not only enhancing existing applications but also enabling new ones that were previously unfeasible due to computational constraints. Furthermore, 3D GS's explicit scene representation offers unprecedented flexibility to control the objects and scene dynamics, a crucial factor in complex scenarios involving intricate geometries and varying lighting conditions [22]–[24]. This level of editability, combined with the efficiency of the training and rendering process, positions 3D GS as a transformative force in shaping future developments in relevant fields.

In an effort to assist readers in keeping pace with the swift evolution of 3D GS, we provide the first survey on 3D GS, which presents a systematic and timely collection of the most significant literature on the topic. Given that 3D GS is a very recent innovation (Fig. 1), this survey focuses in particular on its principles, and the diverse developments and contributions that have emerged since its introduction. The selected follow-up works are primarily sourced from top-tier conferences, to provide a thorough and up-to-date analysis of the theoretical foundations, remarkable developments, and burgeoning applications of 3D GS. Acknowledging the nascent yet rapidly evolving nature of 3D GS, this survey is inevitably a biased view, but we strive to offer a balanced perspective that reflects both the current state and the future potential of this field. Our aim is to encapsulate the primary research trends and serve as a valuable resource for both researchers and practitioners eager to understand and contribute to this rapidly evolving domain.

A summary of the structure of this article can be found in Fig. 2, which is presented as follows: Sec. 2 provides a brief background on problem formulation, terminology, and related research domains. Sec. 3 introduces the essential insights of 3D GS, encompassing the rendering process with learned 3D Gaussians and the optimization details (*i.e.*, how to learn 3D Gaussians) of 3D GS. Sec. 4 presents several fruitful directions that aim to improve the capabilities of the original 3D GS. Sec. 5 unveils the diverse application areas and tasks where 3D GS has made significant impacts, showcasing its versatility. Sec. 6 conducts performance comparison and analysis. Finally, Sec. 7 and 8 highlight the open questions for further research and conclude the survey.

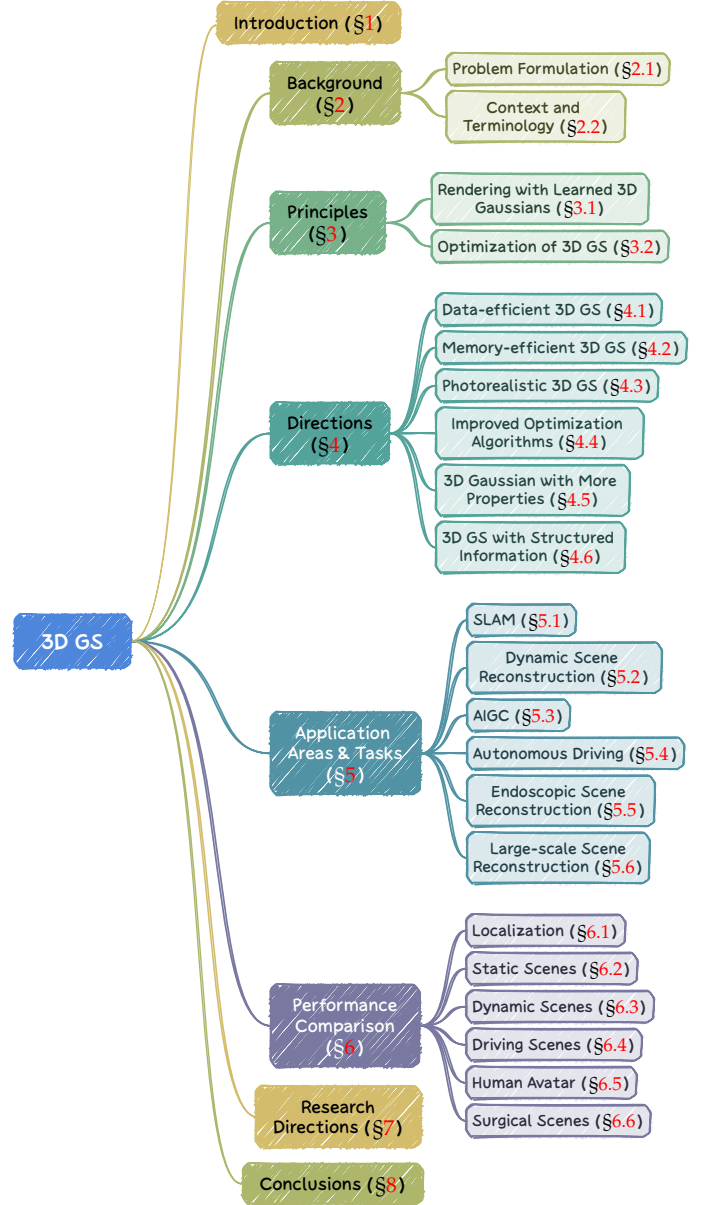


Fig. 2. Structure of the overall review.

## 2 BACKGROUND

In this section, we first provide a brief formulation of radiance fields (Sec. 2.1), a key concept in scene rendering. It outlines two main types of radiance field representations: implicit, like NeRF [12], which uses neural networks for a straightforward yet computationally demanding rendering; and explicit, like grid [25], which employs discrete structures for quicker access but at the cost of higher memory use. Sec. 2.2 further establishes linkages with relevant fields such as scene reconstruction and rendering. For a comprehensive overview of radiance fields, scene reconstruction and representation, and rendering methods, please see the excellent surveys [26]–[30] for more insights.

### 2.1 Problem Formulation

#### 2.1.1 Radiance Field

A radiance field is a representation of light distribution in a 3D space, which captures how light interacts with surfaces

and materials in the environment [27]. Mathematically, a radiance field can be described as a function  $L : \mathbb{R}^5 \mapsto \mathbb{R}^+$ , where  $L(x, y, z, \theta, \phi)$  maps a point in space  $(x, y, z)$ , and a direction specified by spherical coordinates  $(\theta, \phi)$ , to a non-negative radiance value. Radiance fields can be encapsulated through implicit or explicit representations, each with specific advantages for scene representation and rendering.

### 2.1.2 Implicit Radiance Field

An implicit radiance field represents light distribution in a scene without explicitly defining the geometry of the scene. In the deep learning era, it often uses neural networks to learn a continuous volumetric scene representation [31], [32]. The most prominent example is NeRF [12]. In NeRF, a neural network, typically a multi-layer perceptron (MLP), is used to map a set of spatial coordinates  $(x, y, z)$  and viewing directions  $(\theta, \phi)$  to color and density values. The radiance at any point is not stored explicitly but is computed on-the-fly by querying the MLP. Hence, the function can be written as:

$$L_{\text{implicit}}(x, y, z, \theta, \phi) = \text{MLP}(x, y, z, \theta, \phi). \quad (1)$$

This format allows for a differentiable and compact representation of complex scenes, albeit often at the cost of high computational load due to volumetric ray marching [10].

### 2.1.3 Explicit Radiance Field

In contrast, an explicit radiance field directly represents the distribution of light in a discrete spatial structure, such as a voxel grid or a set of points [25], [33]. Each element in this structure stores the radiance information for its respective location in space. This allows for more direct and often faster access to radiance data but at the cost of higher memory usage and potentially lower resolution. A generic form for an explicit radiance field representation can be written as:

$$L_{\text{explicit}}(x, y, z, \theta, \phi) = \text{DataStructure}[(x, y, z)] \cdot f(\theta, \phi), \quad (2)$$

where DataStructure could be in the format of volumes, point clouds, etc.  $f(\theta, \phi)$  is a function that modifies the radiance based on the viewing direction.

### 2.1.4 3D Gaussian Splatting: Best-of-Both Worlds

3D GS [10] is an explicit radiance field with the advantages of implicit radiance fields. Concretely, it leverages the strengths of both paradigms by utilizing learnable 3D Gaussians as a flexible and efficient representation. These Gaussians are optimized under the supervision of multi-view images to accurately represent the scene. Such a 3D Gaussian based differentiable pipeline combines the benefits of neural network-based optimization and explicit, structured data storage. This hybrid approach aims to achieve real-time, high-quality rendering and requires less training time, particularly for complex scenes and high-resolution outputs. The 3D Gaussian representation is formulated as:

$$L_{3\text{DGS}}(x, y, z, \theta, \phi) = \sum_i G(x, y, z, \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \cdot c_i(\theta, \phi), \quad (3)$$

where  $G$  is the Gaussian function with mean  $\boldsymbol{\mu}_i$  and covariance  $\boldsymbol{\Sigma}_i$ , and  $c$  represents the view-dependent color.

## 2.2 Context and Terminology

Several techniques and research disciplines possess a close relationship with 3D GS, which will be described briefly in the following sections for clarity.

### 2.2.1 Scene Reconstruction and Rendering

Roughly speaking, scene reconstruction involves creating a 3D model of a scene from a collection of images or other data. Rendering is a more specific term that focuses on transforming computer-readable information (e.g., 3D objects in the scene) to pixel-based images. Early techniques generated realistic images based on the light fields [1]–[3]. The structure-from-motion [4] and multi-view stereo [5] algorithms further advanced this field by estimating 3D structures from image sequences. These historical methods provide a solid foundation for more complex scene reconstruction and rendering techniques [34]–[37].

### 2.2.2 Neural Rendering and Radiance Fields

Neural rendering integrates deep learning with traditional graphics techniques to create photorealistic images. Early attempts utilized convolutional networks for estimating blending weights [36] or texture-space solutions [38]. As mentioned in Sec. 2.1.1, the radiance field represents a function that describes the amount of light traveling in every direction through every point in space. NeRFs [8], [9], [12] use neural networks, typically MLPs, to model the radiance fields, enabling detailed and realistic scene rendering.

### 2.2.3 Volumetric Representations and Ray-Marching

Volumetric representations model objects and scenes not just as surfaces but as volumes filled with materials or empty space. This allows for a more accurate rendering of phenomena like fog, smoke, or translucent materials. Ray-marching is a technique used with volumetric representations to render images by tracing the path of light through a volume [11]. NeRF [12] shares the same spirit of volumetric ray-marching and introduces importance sampling and positional encoding to improve the quality of synthesized images. While providing high-quality results, volumetric ray-marching is computationally expensive, motivating the search for more efficient methods like 3D GS.

### 2.2.4 Point-based Rendering

Point-based rendering is a technique for visualizing 3D scenes using points rather than traditional polygons. This method is particularly effective for rendering complex, unstructured, or sparse geometric data. Points can be augmented with additional properties like learnable neural descriptors [39], [40], and rendered efficiently [41], [42], but this approach suffers from issues like holes in the rendering or aliasing effects. 3D GS [10] extends this concept by using anisotropic Gaussians for a more continuous and cohesive representation of the scene. More implementation details will be further discussed in Sec. 3.

## 3 3D GAUSSIAN SPLATTING: PRINCIPLES

3D GS offers a breakthrough in real-time, high-resolution image rendering, without relying on deep neural networks.



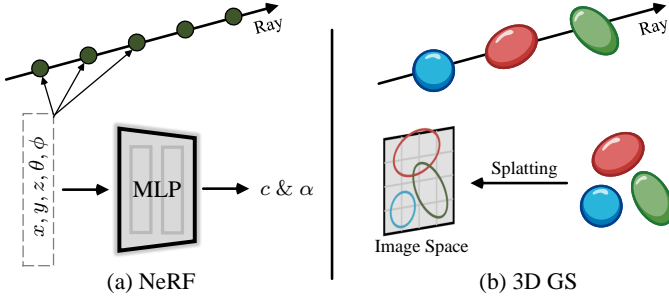


Fig. 3. NeRFs vs. 3D GS. (a) NeRF samples along the ray and then queries the MLP to obtain corresponding colors and opacities, which can be seen as a *backward* mapping (ray tracing). (b) In contrast, 3D GS projects all 3D Gaussians into the image space (*i.e.*, splatting) and then performs parallel rendering, which can be viewed as a *forward* mapping (splatting and rasterization). Best viewed in color.

This section aims to provide essential insights of 3D GS. We first elaborate on how 3D GS synthesizes an image given well-constructed 3D Gaussians in Sec. 3.1, *i.e.*, the forward process of 3D GS. Then, we introduce how to obtain well-constructed 3D Gaussians for a given scene in Sec. 3.2, *i.e.*, the optimization process of 3D GS.

### 3.1 Rendering with Learned 3D Gaussians

Consider a scene represented by (millions of) optimized 3D Gaussians. The objective is to generate an image from a specified camera pose. Recall that NeRFs approach this task through computationally demanding volumetric ray-marching, sampling 3D space points per pixel. Such a paradigm struggles with high-resolution image synthesis, failing to achieve real-time rendering, especially for platforms with limited computing resources [10]. By contrast, 3D GS begins by projecting these 3D Gaussians onto a pixel-based image plane, a process termed “splatting” (see Fig. 3b). Afterwards, 3D GS sorts these Gaussians and computes the value for each pixel. As shown in Fig. 3, the rendering of NeRFs and 3D GS can be viewed as an inverse process of each other. In what follows, we begin with the definition of a 3D Gaussian, which is the minimal element of the scene representation in 3D GS. Next, we describe how these 3D Gaussians can be used for differentiable rendering. Finally, we introduce the acceleration technique used in 3D GS, which is the key to fast rendering.

- **Properties of 3D Gaussian.** A 3D Gaussian is characterized by its center (position)  $\mu$ , opacity  $\alpha$ , 3D covariance matrix  $\Sigma$ , and color  $c$ .  $c$  is represented by spherical harmonics for view-dependent appearance. All the properties are learnable and optimized through back-propagation.

- **Frustum Culling.** Given a specified camera pose, this step determines which 3D Gaussians are outside the camera’s frustum. By doing so, 3D Gaussians outside the given view will not be involved in the subsequent computation, thus saving computational resources.

- **Splatting.** In this step, 3D Gaussians (ellipsoids) in 3D space are projected into the 2D image space (ellipses) for rendering. Given the viewing transformation  $W$  and 3D covariance matrix  $\Sigma$ , the projected 2D covariance matrix  $\Sigma'$  is computed using:

$$\Sigma' = JW\Sigma W^\top J^\top, \quad (4)$$

where  $J$  is the Jacobian of the affine approximation of the projective transformation [10], [43].

- **Rendering by Pixels.** Before delving into the final version of 3D GS which utilizes several techniques to boost parallel computation, we first elaborate on its simpler form to offer insights into its basic working mechanism. Given the position of a pixel  $x$ , its distance to all overlapping Gaussians, *i.e.*, the depths of these Gaussians, can be computed through the viewing transformation  $W$ , forming a sorted list of Gaussians  $\mathcal{N}$ . Then, alpha compositing is adopted to compute the final color of this pixel:

$$C = \sum_{n=1}^{|\mathcal{N}|} c_n \alpha'_n \prod_{j=1}^{n-1} (1 - \alpha'_j), \quad (5)$$

where  $c_n$  is the learned color. The final opacity  $\alpha'_n$  is the multiplication result of the learned opacity  $\alpha_n$  and the Gaussian, defined as follows:

$$\alpha'_n = \alpha_n \times \exp\left(-\frac{1}{2}(\mathbf{x}' - \mu'_n)^\top \Sigma_n'^{-1}(\mathbf{x}' - \mu'_n)\right), \quad (6)$$

where  $\mathbf{x}'$  and  $\mu'_n$  are coordinates in the projected space. It is a reasonable concern that the rendering process described could be slower compared to NeRFs, given that generating the required sorted list is hard to parallelize. Indeed, this concern is justified; rendering speeds can be significantly impacted when utilizing such a simplistic, pixel-by-pixel approach. To achieve real-time rendering, 3D GS makes several concessions to accommodate parallel computation.

- **Tiles (Patches).** To avoid the cost computation of deriving Gaussians for each pixel, 3D GS shifts the precision from pixel-level to patch-level detail. Concretely, 3D GS initially divides the image into multiple non-overlapping patches (called “tiles” in the original paper [10]). Fig. 4b provides an illustration of tiles. Each tile comprises  $16 \times 16$  pixels as suggested in [10]. 3D GS further determines which tiles intersect with these projected Gaussians. Given that a projected Gaussian may cover several tiles, a logical method involves replicating the Gaussian, assigning each copy an identifier (*i.e.*, a tile ID) for the relevant tile.

- **Parallel Rendering.** After replication, 3D GS combines the respective tile ID with the depth value obtained from the view transformation for each Gaussian. This results in an unsorted list of bytes where the upper bits represent the tile ID and the lower bits signify depth. By doing so, the sorted list can be directly utilized for rendering (*i.e.*, alpha compositing). Fig. 4c and Fig. 4d provide the visual demonstration of such concepts. It’s worth highlighting that rendering each tile and pixel occurs **independently**, making this process highly suitable for parallel computations. An additional benefit is that each tile’s pixels can access a common **shared memory** and maintain an **uniform read sequence** (Fig. 5), enabling parallel execution of alpha compositing with increased efficiency. In the official implementation of the original paper [10], the framework regards the processing of tiles and pixels as analogous to the blocks and threads, respectively, in CUDA programming architecture.

In a nutshell, 3D GS introduces several approximations during rendering to enhance computational efficiency while maintaining a high standard of image synthesis quality.

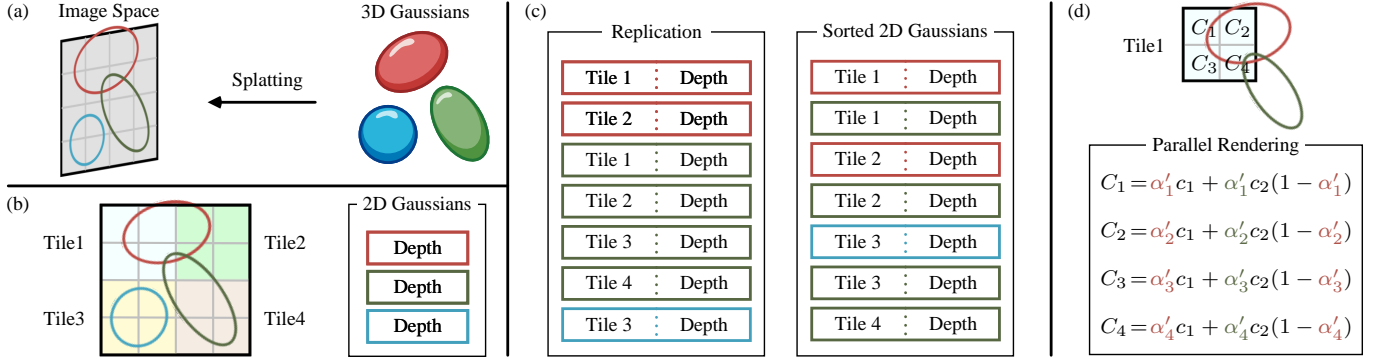


Fig. 4. An illustration of the forward process of 3D GS (see Sec. 3.1). (a) The splatting step projects 3D Gaussians into image space. (b) 3D GS divides the image into multiple non-overlapping patches, *i.e.*, tiles. (c) 3D GS replicates the Gaussians which cover several tiles, assigning each copy an identifier, *i.e.*, a tile ID. (d) By rendering the sorted Gaussians, we can obtain all pixels within the tile. Note that the computational workflows for pixels and tiles are independent and can be done in parallel. Best viewed in color.

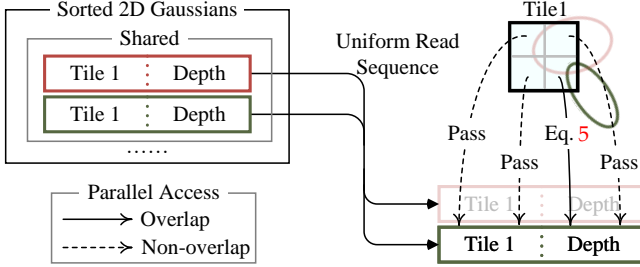


Fig. 5. An illustration of the tile based parallel (at the pixel-level) rendering. All the pixels within a tile (Tile1 here) access the same ordered Gaussian list stored in a shared memory for rendering. As the system processes each Gaussian sequentially, every pixel in the tile evaluates the Gaussian’s contribution according to the distance (*i.e.*, the  $\exp$  term in Eq. 6). Therefore, the rendering for a tile can be completed by iterating through the list of Gaussians just once. The computation for the red Gaussian follows a similar way and is omitted here for simplicity.

### 3.2 Optimization of 3D Gaussian Splatting

At the heart of 3D GS lies an optimization procedure devised to construct a copious collection of 3D Gaussians that accurately captures the scene’s essence, thereby facilitating free-viewpoint rendering. On the one hand, the properties of 3D Gaussians should be optimized via differentiable rendering to fit the textures of a given scene. On the other hand, the number of 3D Gaussians that can represent a given scene well is unknown in advance. One promising avenue is to let the neural network automatically learn the density of 3D Gaussians. We will introduce how to optimize the properties of each Gaussian in Sec. 3.2.1 and how to control the density of the Gaussians in Sec. 3.2.2. The two procedures are interleaved within the optimization workflow. Since there are many manually set hyperparameters in the optimization process, we omit the notations of most hyperparameters for clarity.

#### 3.2.1 Parameter Optimization

• **Loss Function.** Once the synthesis of the image is completed, the difference between the rendered image and ground truth can be measured. All the learnable parameters are optimized by stochastic gradient descent using the  $\ell_1$  and D-SSIM loss functions:

$$\mathcal{L} = (1 - \lambda)\mathcal{L}_1 + \lambda\mathcal{L}_{\text{D-SSIM}}, \quad (7)$$

where  $\lambda \in [0, 1]$  is a weighting factor. The loss function of 3D GS is slightly different from that of NeRFs. NeRFs typically

calculate the loss at the pixel level rather than the image level because of the costly ray-marching.

• **Parameter Update.** Most properties of a 3D Gaussian can be optimized directly through back-propagation. It is essential to note that directly optimizing the covariance matrix  $\Sigma$  can result in a non-positive semi-definite matrix, which would not adhere to the physical interpretation typically associated with covariance matrices. To circumvent this issue, 3D GS chooses to optimize a quaternion  $q$  and a 3D vector  $s$ .  $q$  and  $s$  represent rotation and scale, respectively. This approach allows the covariance matrix  $\Sigma$  to be reconstructed as follows:

$$\Sigma = RSS^T R^T, \quad (8)$$

where  $R$  and  $S$  denote the rotation and scaling matrix derived from  $q$  and  $s$ , respectively. There is a complex computational graph to obtain the opacity  $\alpha$ , *i.e.*,  $q$  and  $s \mapsto \Sigma$ ,  $\Sigma \mapsto \Sigma'$ , and  $\Sigma' \mapsto \alpha$ . To avoid the cost of automatic differentiation, 3D GS derives the gradients for  $q$  and  $s$  so as to compute them directly during optimization.

#### 3.2.2 Density Control

• **Initialization.** 3D GS starts with the initial set of sparse points from SfM or random initialization. Note that a good initialization is essential to convergence and reconstruction quality [44]. Afterwards, point densification and pruning are adopted to control the density of 3D Gaussians.

• **Point Densification.** In the point densification phase, 3D GS adaptively increases the density of Gaussians to better capture the details of a scene. This process focuses on areas with missing geometric features or regions where Gaussians are too spread out. The densification procedure will be performed at regular intervals (*i.e.*, after a certain number of training iterations), focusing on those Gaussians with large view-space positional gradients (*i.e.*, above a specific threshold). It involves either cloning small Gaussians in under-reconstructed areas or splitting large Gaussians in over-reconstructed regions. For cloning, a copy of the Gaussian is created and moved towards the positional gradient. For splitting, a large Gaussian is replaced with two smaller ones, reducing their scale by a specific factor. This step seeks an optimal distribution and representation of Gaussians in 3D space, enhancing the overall quality of the reconstruction.

• **Point Pruning.** The point pruning stage involves the removal of superfluous or less impactful Gaussians, which

can be viewed as a regularization process. It is executed by eliminating Gaussians that are virtually transparent (with  $\alpha$  below a specified threshold) and those that are excessively large in either world-space or view-space. In addition, to prevent unjustified increases in Gaussian density near input cameras, the alpha value of the Gaussians is set close to zero after a certain number of iterations. This allows for a controlled increase in the density of necessary Gaussians while enabling the culling of redundant ones. The process not only helps in conserving computational resources but also ensures that the Gaussians in the model remain precise and effective for the representation of the scene.

## 4 3D GAUSSIAN SPLATTING: DIRECTIONS

Though 3D GS has achieved impressive milestones, significant room for improvement remains, *e.g.*, data and hardware requirement, rendering and optimization algorithm, and applications in downstream tasks. In the subsequent sections, we seek to elaborate on select extended versions of 3D GS. These are: i) Data-efficient 3D GS [45]–[55] (Sec. 4.1), ii) Memory-efficient 3D GS [56]–[64] (Sec. 4.2), iii) Photorealistic 3D GS [65]–[80] (Sec. 4.3), iv) Improved Optimization Algorithms [22], [77], [81]–[86] (Sec. 4.4), v) 3D Gaussian with More Properties [87]–[93] (Sec. 4.5), and vi) 3D GS with Structured Information [94]–[96] (Sec. 4.6).

### 4.1 Data-efficient 3D GS

A notable issue of 3D GS is the emergence of artifacts in areas with insufficient observational data. This challenge is a prevalent limitation in radiance field rendering, where sparse data often leads to inaccuracies in reconstruction. From a practical perspective, reconstructing scenes from limited viewpoints is of significant interest, particularly for the potential to enhance functionality with minimal input.

Two primary strategies are used for data-efficient 3D GS. i) Regularization based methods introduce additional constraints such as depth information to enhance the detail and global consistency [46], [49], [51], [55]. For example, DNGaussian [49] introduced a depth-regularized approach to address the challenge of geometry degradation in sparse input views. FSGS [46] devised a Gaussian Unpooling process for initialization and also introduced depth regularization. MVSplat [51] proposed a cost volume representation so as to provide geometry cues. Unfortunately, when dealing with a limited number of views, or even just one, the efficacy of regularization techniques tends to diminish, which leads to ii) generalizability based methods that focus specially on learning priors [47], [48], [53]. One typical implementation is to generate 3D Gaussians that can be used for rendering directly without optimization, by using deep neural networks. This paradigm typically requires multiple views for training but can reconstruct the 3D scene with only one input image. For instance, PixelSplat [47] proposed to sample Gaussians from dense probability distributions. It incorporated a multi-view epipolar transformer and a reparameterization trick to avoid local minima and maintain gradient flow. Splatter Image [48] applied GS in a monocular setting through a learning-based approach, utilizing a 2D image-to-image network that maps an input image to a

3D Gaussian per pixel. Note that this paradigm is mainly focused on the reconstruction of objects, and its generalizability leaves a lot of room for improvement.

### 4.2 Memory-efficient 3D GS

While 3D GS demonstrates remarkable capabilities, its scalability poses significant challenges, particularly when juxtaposed with NeRF-based methods. The latter benefits from the simplicity of storing merely the parameters of a learned MLP. This scalability issue becomes increasingly acute in the context of large-scale scene management, where the computational and memory demands escalate substantially. Consequently, there is an urgent need to optimize memory usage in both model training and storage.

There are two main directions to reduce memory usage. i) The first involves reducing the number of 3D Gaussians [58], [62], [63], *i.e.*, pruning insignificant 3D Gaussians. For example, Papantonakis *et al.* [63] proposed a resolution-aware pruning method to prune Gaussians, reducing the Gaussian count by half. Lee *et al.* [58] introduced a new volume-based masking strategy that efficiently reduces the quantity of Gaussians without compromising performance. ii) The second category focuses on compressing the memory usage of 3D Gaussian properties [58], [61], [62]. For instance, Niedermayr *et al.* [61] compressed color and Gaussian parameters into compact codebooks, using sensitivity measures for effective quantization and fine-tuning. HAC [62] predicted the probability of each quantized attribute using Gaussian distributions and then devise an adaptive quantization module. Although current methods achieve compression ratios of several to dozens of times for storage (after training), there remains considerable potential for reducing memory usage during the training phase.

### 4.3 Photorealistic 3D GS

The current rendering pipeline of 3D GS (Sec. 3.1) is straightforward and involves several drawbacks. For instance, the simple visibility algorithm may lead to a drastic switch in the depth/blending order of Gaussians [10]. The realness of rendered images, including aspects such as aliasing, reflections, and artifacts, can be further optimized.

Here we list several key points for enhancing realness. i) Varying Resolutions [67], [78]. Due to the discrete sampling paradigm (viewing each pixel as a single point instead of an area), 3D GS is susceptible to aliasing when dealing with varying resolutions, which leads to blurring or jagged edges. Yan *et al.* [67] argued that this is mainly because traditional rendering methods cannot effectively manage the disparity between the sampling frequency of pixels and the high-frequency details of the scene, leading to visual artifacts and performance issues. Hence, they introduced multi-scale 3D GS, where the scene is represented using Gaussians of varying sizes. Analytic-Splatting [78] adopted an analytic approximation of the Gaussian integral within the pixel area, leveraging a conditioned logistic function for the cumulative distribution function to better capture the intensity response of pixels. ii) Reflections [68], [97], [98]. Achieving realistic rendering of reflective materials is a hard and long-standing problem in 3D scene reconstruction. GaussianShader [68] enhanced neural rendering for scenes



with reflective surfaces by integrating a simplified shading function with 3D Gaussians. **iii) Geometry.** One limitation of 3D GS is the neglect of underlying scene geometry and structure, particularly in complex scenes and under varying view and lighting conditions. This sparks research on geometry-aware reconstruction [22], [44], [99]–[102]. For example, GeoGaussian [77] focused on preserving the geometry of non-textured regions like walls and furniture, which tend to degrade over time.

#### 4.4 Improved Optimization Algorithms

The anisotropic Gaussians, while beneficial for representing complex geometries, can create undesirable visual artifacts. For example, those large 3D Gaussians, especially in regions with view-dependent appearance, can cause popping artifacts, where visual elements abruptly appear or disappear, breaking the immersion. Further, incorporating additional regularization (e.g., geometry [77], [83] and frequency [84]) and improving the optimization process of 3D GS (Sec. 3.2) may accelerate convergence, smooth visual noise, and improve quality of rendered images.

Three main directions stand out for improving the optimization of 3D GS. **i) Introducing Additional Regularization** [22], [84]. 3D GS often faces challenges with over-reconstruction, where sparse, large 3D Gaussians cause blur and artifacts due to poor representation in high-variance regions. To address this, FreGS [84] introduced a progressive frequency regularization method, which refines Gaussian densification from a frequency perspective. Another notable branch is geometry-aware reconstruction, as introduced in Sec. 4.3. This line of work focuses in particular on how to preserve scene’s structure. For instance, Scaffold-GS [22] introduced a sparse grid of anchor points to organize local 3D Gaussians, which are dynamically adjusted for attributes like opacity and color based on the viewer’s perspective and distance. **ii) Improving Optimization Procedure** [44], [77]. In addressing the challenges of dense initialization for texture-less surfaces, especially in large-scale scenes, GaussianPro [44] devised an advanced Gaussian densification (S3.2.2) strategy using the priors of reconstructed geometries and patch matching techniques. **iii) Relaxing Constraints in Optimization** [81], [82]. Reliance on external tools/algorithms for can introduce errors and cap the system’s performance potential. For instance, SfM, commonly used in the initialization process, is error-prone and struggle with complex scenes. Yang *et al.* [81] proposed COLMAP-Free 3D GS, which introduces video stream continuity and an explicit point cloud representation so as to eliminate the need for SfM preprocessing. Though impressive, existing methods primarily concentrate on optimizing Gaussians to accurately reconstruct scenes from scratch, neglecting a challenging yet promising paradigm which reconstructs scenes in a few-shot manner through established “meta representations”. See “learning physical priors from large-scale data” in Sec. 7 for further insights.

#### 4.5 3D Gaussian with More Properties

Despite impressive, the properties of 3D Gaussian (Sec. 3.1) are designed to be used for novel-view synthesis only. By augmenting 3D Gaussian with additional properties, such as

linguistic [87]–[89], semantic/instance [90]–[92], and spatial-temporal [93] properties, 3D GS demonstrates its considerable potential to revolutionize various domains.

Here we list several interesting applications using 3D Gaussians with specially designed properties. **i) Language Embedded Scene Representation** [87]–[89]. Due to the high computational and memory demands of current language-embedded scene representations, Shi *et al.* [87] proposed a quantization scheme that augments 3D Gaussian with streamlined language embeddings instead of the original high-dimensional embeddings. This method also mitigated semantic ambiguity and enhanced the precision of open-vocabulary querying by smoothing out semantic features across different views, guided by uncertainty values. **ii) Scene Understanding and Editing** [90]–[92]. Feature 3DGS [90] integrated 3D GS with feature field distillation from 2D foundation models. By learning a lower-dimensional feature field and applying a lightweight convolutional decoder for upsampling, Feature 3DGS achieved faster training and rendering speeds while enabling high-quality feature field distillation, supporting applications like semantic segmentation and language-guided editing. **iii) Spatiotemporal Modeling** [93], [103]. To capture the complex spatial and temporal dynamics of 3D scenes, Yang *et al.* [93] conceptualized spacetime as a unified entity and approximates the spatiotemporal volume of dynamic scenes using a collection of 4D Gaussians. The proposed 4D Gaussian representation and corresponding rendering pipeline are capable of modeling arbitrary rotations in space and time and allow for end-to-end training.

#### 4.6 3D GS with Structured Information

Rather than augmenting 3D Gaussian with additional properties, another promising avenue of adapting to downstream tasks is to introduce structured information (e.g., spatial MLPs and grids) tailored for specific applications.

Next we showcase various fascinating uses of 3D GS with specially devised structured information. **i) Facial Expression Modeling.** Considering the challenge of creating high-fidelity 3D head avatars under sparse view conditions, Gaussian Head Avatar [96] introduced controllable 3D Gaussians and an MLP-based deformation field. Concretely, it captured detailed facial expressions and dynamics by optimizing neutral 3D Gaussians alongside the deformation field, thus ensuring both detail fidelity and expression accuracy. **ii) Spatiotemporal Modeling.** Yang *et al.* [94] proposed to reconstruct dynamic scenes with deformable 3D Gaussians. The deformable 3D Gaussians are learned in a canonical space, coupled with a deformation field (i.e., a spatial MLP) that models the spatial-temporal dynamics. The proposed method also incorporated an annealing smoothing training mechanism to enhance temporal smoothness without additional computational costs. **iii) Style Transfer.** Saroha *et al.* [153] proposed GS in style, an advanced approach for real-time neural scene stylization. To maintain a cohesive stylized appearance across multiple views without compromising on rendering speed, they used pre-trained 3D Gaussians coupled with a multi-resolution hash grid and a small MLP to produce stylized views. In a nutshell, incorporating structured information can serve as a complementary


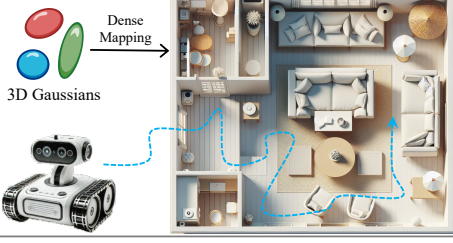

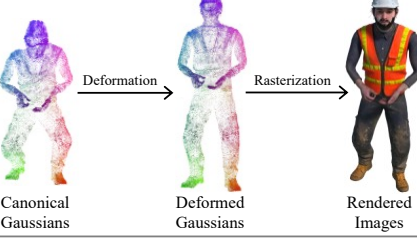

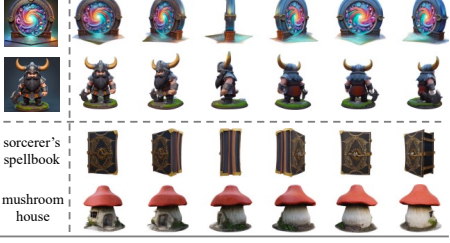

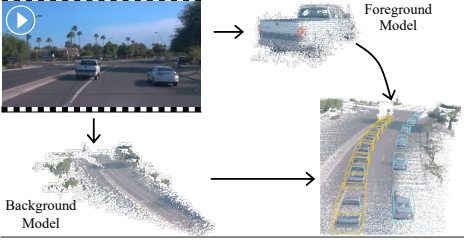

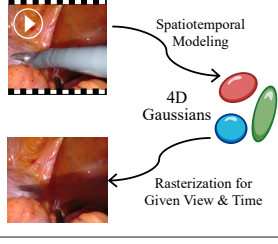

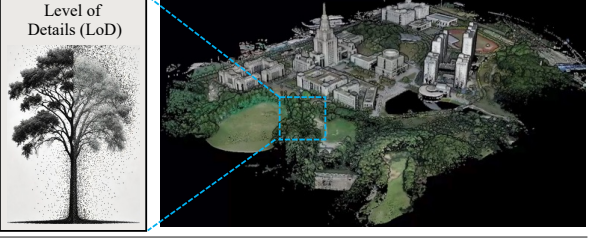
 <p>Simultaneous Localization and Mapping</p>  <p>[104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117]</p>	 <p>Dynamic Scene Reconstruction</p>  <p>[118], [94], [95], [93], [119], [120], [121], [122], [103], [123], [124], [125]</p>	 <p>AI-Generated Content</p>  <p>[126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [90], [136]</p>
 <p>Autonomous Driving</p>  <p>[137], [138], [139]</p>	 <p>Endoscopic Scene Reconstruction</p>  <p>[140], [141], [142], [143], [116], [144]</p>	 <p>Large-scale Scene Reconstruction</p>  <p>[44], [145], [146], [147], [148], [149], [150], [151], [152]</p>

Fig. 6. Typical applications that have been benefited from GS (Sec. 5). Some images are borrowed from [125], [128], [138], [142], [151] and redrawn.

part for adapting to tasks that are incompatible with the sparsity and disorder of 3D Gaussians.

## 5 APPLICATION AREAS AND TASKS

Building on the rapid advancements in 3D GS, a wide range of innovative applications has emerged across multiple domains (Fig. 6) such as robotics (Sec. 5.1), dynamic scene reconstruction and representation (Sec. 5.2), AI-generated content (Sec. 5.3), autonomous driving (Sec. 5.4), medical systems (Sec. 5.5), large-scale scene reconstruction (Sec. 5.6), and even other scientific disciplines [24], [154]–[156]. Here, we highlight key examples that underscore the transformative impact and potential of 3D GS.

### 5.1 Simultaneous Localization and Mapping (SLAM)

SLAM is a computational problem central to robotics and autonomous systems. It involves the challenge of a robot/device understanding its position in an unknown environment while simultaneously mapping the environment's layout. SLAM is critical in various applications such as autonomous vehicles and robotic navigation. The core of SLAM is to create a map of an unknown environment and determine the device's location on this map in real-time. As a result, SLAM poses great challenges for computationally intensive scene representation techniques, yet serves as a good testbed for 3D GS [157].

3D GS enters the SLAM domain as an innovative approach for scene representation. Traditional SLAM systems often use point/surfel clouds or voxel grids to represent environments [158]–[165]. In contrast, 3D GS uti-

lizes anisotropic Gaussians to better represent environments. Recent innovative studies have employed 3D GS in SLAM [104]–[108], [110], [113], [166], showcasing the potential and versatility of this paradigm. An intuitive way is to use 3D Gaussian as the basic representation of the dense map and optimize the tracking process. For instance, GS-SLAM [104] adopted an adaptive strategy to add or remove 3D Gaussians so as to optimize scene geometry reconstruction and improve the mapping of previously observed areas. Similarly, Sun *et al.* [113] proposed additional regularization terms during the online mapping to avoid overfitting to the latest frame. SplaTAM [105] integrated a straightforward online tracking and mapping method that leverages a silhouette mask for capturing the presence of scene density, facilitating dense optimization and structured map expansion. On the other hand, designing advanced scene representations is worth exploring. For example, Photo-SLAM [108] proposed a hybrid Gaussian map, which combines explicit geometric features for precise localization with implicit photometric features for texture mapping. In addition, one interesting problem is how the Gaussian based map representations can help robotics tasks, and some early attempts in navigation have been made [167]–[169]. Though impressive, existing GS based SLAM systems still face persistent challenges such as dynamic elements, sensor noise, non-Lambertian objects, and depth ambiguities that require further exploration.

### 5.2 Dynamic Scene Reconstruction

Dynamic scene reconstruction refers to the process of capturing and representing the three-dimensional structure and



appearance of a scene that changes over time [170]–[173]. This involves creating a digital model that accurately reflects the geometry, motion, and visual aspects of the objects in the scene as they evolve. Dynamic scene reconstruction is crucial in various applications, *e.g.*, virtual and augmented reality, 3D animation, and computer vision.

To extend the concept of 3D GS to dynamic scenes, a straightforward approach is to incorporate the temporal dimension, allowing for the representation of scenes that change over time. 3D GS based methods [93]–[95], [103], [118]–[123], [174]–[178] for dynamic scene reconstruction can generally be divided into two main categories. The first category utilizes additional structured information like spatial MLPs or grids (Sec. 4.6). For example, Yang *et al.* [94] first proposed deformable 3D Gaussians tailored for dynamic scenes. These 3D Gaussians are learned in a canonical space and can be used to model spatial-temporal deformation with an implicit deformation field (implemented as an MLP). GaGS [125] involves the voxelization of a set of Gaussian distributions, followed by the use of sparse convolutions to extract geometry-aware features, which are then utilized for deformation learning. On the other hand, the second category is based on the idea that scene changes can be encoded into the 3D Gaussian representation with a specially designed rendering process (Sec. 4.5). For instance, Luiten *et al.* [118] introduced dynamic 3D Gaussians to model dynamic scenes by keeping the properties of 3D Gaussians unchanged over time while allowing their positions and orientations to change. Yang *et al.* [93] designed a 4D Gaussian representation, where additional properties are used to represent 4D rotations and spherical harmonics, to approximate the spatial-temporal volume of scenes. While significant progress has been made in modeling dynamics and deformation at the Gaussian level, there is a compelling need to explore motion modeling at the object level, which might offer solutions to prevalent challenges like artifact reduction and the precise capture of fine-grained movements across long temporal sequences.

### 5.3 AI-Generated Content (AIGC)

AIGC refers to the digital content that is autonomously created or significantly altered by artificial intelligence systems, particularly in the fields of computer vision, natural language processing, and machine learning. AIGC is characterized by its ability to simulate, extend, or augment human-generated content, enabling applications that range from realistic image synthesis to dynamic narrative creation. The significance of AIGC lies in its transformative potential across various sectors, including entertainment, education, and technology development [179]–[182]. It's a pivotal element in the evolving landscape of digital content creation, offering scalable, customizable, and often more efficient alternatives to traditional methods.

This explicit nature of 3D GS facilitates real-time rendering capabilities and unprecedented levels of control and editability, making it highly relevant for and AIGC applications. The explicit scene representations and differentiable rendering algorithms of 3D GS align perfectly with the requirements of AIGC for generating high-fidelity, real-time, and editable content, crucial for applications in virtual

reality, interactive media, and beyond. Recent works have effectively utilized 3D GS in conjunction with fields like generative models [126]–[129], [183]–[207], avatars [23], [130]–[133], [208]–[229], and scene editing [90]–[92], [102], [119]–[121], [134]–[136], [230]–[239]. For instance, DreamGaussian [126] accelerated the generation of photorealistic 3D assets from single-view image through a three-step process: a diffusion based generative GS process, followed by an efficient algorithm for mesh extraction from 3D Gaussians based on local density querying, and finally a UV-space refinement stage to improve texture details. By combining 3D GS with a parametric morphable face model, GaussianAvatars [214] offered enhanced fidelity and flexibility in avatar animation, significantly improving upon current methods in novel-view rendering and expression reenactment. To improve the efficacy of text instruction based editing, Chen *et al.* [134] devised a semantic tracker to track the editing target during training while Fang *et al.* [135] proposed to extract the region of interest corresponding to the instruction. These advancements hold promise for numerous industrial applications, including digital assetization (with mesh extraction), the generation of long-form videos (*e.g.*, Sora), *etc.*

### 5.4 Autonomous Driving

Autonomous driving aims to allow vehicles to navigate and operate without human intervention. These vehicles are equipped with a suite of sensors, including cameras, light detection and ranging (LiDAR), and radar, combined with advanced algorithms, machine learning models, and significant computational power [240]–[243]. The central aim is to perceive the environment, make informed decisions, and execute maneuvers safely and efficiently [244]–[247].

Autonomous vehicles need to perceive and interpret their surroundings to navigate safely. This involves reconstructing the driving scene in real-time, accurately identifying static and dynamic objects, and understanding their spatial relationships and movements [248]–[250]. In dynamic driving scenes, the environment is continuously changing due to moving objects like other vehicles, pedestrians, or animals [251]. Accurately reconstructing these scenes in real-time is crucial for safe navigation but is challenging due to the complexity and variability of the elements involved. In autonomous driving, 3D GS can be utilized to reconstruct a scene by blending data points (such as those obtained from sensors like LiDAR) into a cohesive and continuous representation. This is particularly useful for handling the varying densities of data points and ensuring a smooth and accurate reconstruction of both the static background and dynamic objects in a scene. To reconstruct complex 3D scenes from sparse sensor data, especially at high speeds and with moving objects, mainstream frameworks separated the urban/street scene into static and dynamic elements, where the dynamic elements are modeled using a composite dynamic Gaussian graph [137], point clouds combined with semantic logits [138], or physically constrained models [139]. By delving deeper into physics- and semantics-aware 3D GS (see “physics- and semantics-aware scene representation” in Sec. 7), one can expect that 3D GS could ideally serve as the cornerstone for environment perception in autonomous driving.

## 5.5 Endoscopic Scene Reconstruction

Surgical 3D reconstruction represents a fundamental task in robot-assisted minimally invasive surgery, aimed at enhancing intraoperative navigation, preoperative planning, and educational simulations through precise modeling of dynamic surgical scenes. Pioneering the integration of cutting-edge dynamic radiance fields into this domain, recent advancements have focused on surmounting the inherent challenges of single-viewpoint video reconstructions – such as occlusions by surgical instruments and sparse viewpoint diversity within the confined spaces of endoscopic exploration [252]–[254]. Despite the progress, the call for high fidelity in tissue deformability and topological variance remains, coupled with the pressing demand for faster rendering to bridge the utility in applications sensitive to latency [140]–[142]. This synthesis of immediacy and precision in reconstructing deformable tissues from endoscopic videos is essential in propelling robotic surgery towards reduced patient trauma and AR/VR applications, ultimately fostering a more intuitive surgical environment and nurturing the future of surgical automation and robotic proficiency.

Compared to typical dynamic scene reconstruction, endoscopic scene reconstruction faces unique challenges, *e.g.*, sparse training data, due to constrained camera movement in confined space, unobserved regions due to tool occlusion, and pronounced non-rigid deformation of tissues. Existing approaches mainly used additional depth guidance to infer the geometry of tissues [140]–[142]. For instance, EndoGS [142] integrated depth-guided supervision with spatial-temporal weight masks and surface-aligned regularization terms to enhance the quality and speed of 3D tissue rendering while addressing tool occlusion. Endo-Gaussian [141] introduced two new strategies: holistic Gaussian initialization for dense initialization and spatiotemporal Gaussian tracking for modeling surface dynamics. Zhao *et al.* [143] argued that these methods suffer from under-reconstruction and proposed to alleviate this problem from frequency perspectives. In addition, EndoGSLAM [116] and Gaussian Pancake [144] devised SLAM systems for endoscopic scenes and showed significant speed advantages. Note that present efforts are mainly directed towards reconstructing from a single viewpoint, which continues to face obstacles in surgical applications.

## 5.6 Large-scale Scene Reconstruction

Large-scale scene reconstruction is a critical component in fields such as autonomous driving, aerial surveying, and AR/VR, demanding both photorealistic visual quality and real-time rendering capabilities. Before the emergence of 3D GS, the task has been approached using NeRF based methods, which, while effective for smaller scenes, often fall short in detail and rendering speed when scaled to larger areas (*e.g.*, over  $1.5 \text{ km}^2$ ). Though 3D GS has demonstrated considerable advantages over NeRFs, the direct application of 3D GS to large-scale environments introduces significant challenges. 3D GS requires an immense number of Gaussians to maintain visual quality over extensive areas, leading to prohibitive GPU memory demands and considerable computational burdens during rendering. For instance, a scene spanning  $2.7 \text{ km}^2$  may require over 20 million

Gaussians, pushing the limits of even the most advanced hardware (*e.g.*, NVIDIA A100 with 40GB memory) [146].

To address the highlighted challenges, researchers have made significant strides in two key areas: **i)** For training, a divide-and-conquer strategy [145]–[148] has been adopted, which segments a large scene into multiple, independent cells. This facilitates parallel optimization for expansive environments. With the same spirit, Zhao *et al.* [152] proposed a distributed implementation of 3D GS training. An additional challenge lies in maintaining visual quality, as large-scale scenes often feature texture-less surfaces that can hamper the effectiveness of optimization such as Gaussian initialization and density control (Sec. 3.2). Enhancing the optimization algorithm presents a viable solution to mitigate this issue [44], [147]. **ii)** Regarding rendering, the adoption of the Level of Details (LoD) technique from computer graphics has proven instrumental. LoD adjusts the complexity of 3D scenes to balance visual quality with computational efficiency. Current implementations involve feeding only the essential Gaussians to the rasterizer [147], or designing explicit LoD structures like the Octree [148] and hierarchy [145]. Furthermore, integrating extra input modalities like LiDAR can further enhanced the reconstruction process [149]–[151]. One prominent challenge in large-scale scene reconstruction is limited capture, which could be alleviated by utilizing good priors (see “learning physical priors from large-scale data.” in Sec. 7).

## 6 PERFORMANCE COMPARISON

In this section, we provide more empirical evidence by presenting the performance of several 3D GS algorithms that we previously discussed. The diverse applications of 3D GS across numerous tasks, coupled with the custom-tailored algorithmic designs for each task, render a uniform comparison of all 3D GS algorithms across a single task or dataset impracticable. Therefore, drawing from our analysis in Sec. 5, we have chosen several representative tasks within the 3D GS domain for an in-depth performance evaluation. The performance scores are primarily sourced from the original papers, except where indicated otherwise.

### 6.1 Performance Benchmarking: Localization

The localization task in SLAM involves determining the precise position and orientation of a robot or device within an environment, typically using sensor data.

- **Dataset:** Replica [255] dataset is a collection of 18 highly detailed 3D indoor scenes. These scenes are not only visually realistic but also offer comprehensive data including dense meshes, high-quality HDR textures, and detailed semantic information for each element. Following [256], three sequences about rooms and five sequences about offices are used for the evaluation.

- **Benchmarking Algorithms:** For performance comparison, we involve five recent 3D GS based algorithms [104]–[107], [113] and six typical SLAM methods [256]–[261]

- **Evaluation Metric:** The root mean square error (RMSE) of the absolute trajectory error (ATE) is a commonly used metric in evaluating SLAM systems [262], which measures the root mean square of the Euclidean distances between the estimated and true positions over the entire trajectory.

TABLE 1

**Quantitative localization results (§6.1)** on Replica [255], in terms of absolute trajectory error (ATE, cm). (The three best scores are marked in **red**, **blue**, and **green**, respectively. These notes also apply to the other tables.)

Method	GS	Room0	Room1	Room2	Office0	Office1	Office2	Office3	Office4	Avarage
iMAP [256] [ICCV21]		3.12	2.54	2.31	1.69	1.03	3.99	4.05	1.93	2.58
Vox-Fusion [257] [ISMAR22]		1.37	4.70	1.47	8.48	2.04	2.58	1.11	2.94	3.09
NICE-SLAM [258] [CVPR22]		0.97	1.31	1.07	0.88	1.00	1.06	1.10	1.13	1.06
ESLAM [259] [CVPR23]		0.71	0.70	0.52	0.57	0.55	0.58	0.72	<b>0.63</b>	0.63
Point-SLAM [260] [ICCV23]		0.61	<b>0.41</b>	0.37	<b>0.38</b>	0.48	0.54	0.69	0.72	0.52
Co-SLAM [261] [CVPR23]		0.70	0.95	1.35	0.59	0.55	2.03	1.56	0.72	1.00
Gaussian-SLAM [107] [arXiv]	✓	3.35	8.74	3.13	1.11	0.81	0.78	1.08	7.21	3.27
GSSLAM [106] [CVPR24]	✓	<b>0.47</b>	0.43	<b>0.31</b>	0.70	0.57	<b>0.31</b>	<b>0.31</b>	3.20	0.79
GS-SLAM [104] [CVPR24]	✓	0.48	0.53	0.33	0.52	<b>0.41</b>	0.59	0.46	0.70	<b>0.50</b>
SplaTAM [105] [CVPR24]	✓	<b>0.31</b>	<b>0.40</b>	<b>0.29</b>	<b>0.47</b>	<b>0.27</b>	<b>0.29</b>	<b>0.32</b>	<b>0.55</b>	<b>0.36</b>
HFSLAM [113] [IJROS24]	✓	<b>0.19</b>	<b>0.34</b>	<b>0.16</b>	<b>0.21</b>	<b>0.26</b>	<b>0.23</b>	<b>0.21</b>	<b>0.38</b>	<b>0.25</b>

TABLE 2

**Quantitative rendering results (§6.2)** on Replica [255], in terms of PSNR, SSIM, and LPIPS. The numbers of FPS are taken from [106].

Method	GS	Metric	Room0	Room1	Room2	Office0	Office1	Office2	Office3	Office4	Avarage	FPS
NICE-SLAM [258] [CVPR22]		PSNR↑	22.12	22.47	24.52	29.07	30.34	19.66	22.23	24.94	24.42	0.54
		SSIM↑	0.69	0.76	0.81	0.87	0.89	0.80	0.80	0.86	0.81	
		LPIPS↓	0.33	0.27	0.21	0.23	0.18	0.23	0.21	0.20	0.23	
Vox-Fusion [257] [ISMAR22]		PSNR↑	22.39	22.36	23.92	27.79	29.83	20.33	23.47	25.21	24.41	2.17
		SSIM↑	0.68	0.75	0.80	0.86	0.88	0.79	0.80	0.85	0.80	
		LPIPS↓	0.30	0.27	0.23	0.24	0.18	0.24	0.21	0.20	0.24	
Point-SLAM [260] [ICCV23]		PSNR↑	32.40	<b>34.08</b>	<b>35.50</b>	38.26	39.16	<b>33.99</b>	<b>33.48</b>	<b>33.49</b>	<b>35.17</b>	1.33
		SSIM↑	<b>0.97</b>	<b>0.98</b>	<b>0.98</b>	<b>0.98</b>	<b>0.99</b>	0.96	0.96	<b>0.98</b>	<b>0.97</b>	
		LPIPS↓	0.11	0.12	0.11	0.10	0.12	0.16	0.13	0.14	0.12	
SplaTAM [105] [CVPR24]	✓	PSNR↑	<b>32.86</b>	33.89	35.25	38.26	39.17	31.97	29.70	31.81	34.11	-
		SSIM↑	<b>0.98</b>	0.97	<b>0.98</b>	0.98	0.98	<b>0.97</b>	0.95	0.95	0.97	
		LPIPS↓	<b>0.07</b>	0.10	<b>0.08</b>	0.09	0.09	0.10	0.12	0.15	0.10	
GS-SLAM [104] [CVPR24]	✓	PSNR↑	31.56	32.86	32.59	<b>38.70</b>	<b>41.17</b>	32.36	32.03	32.92	34.27	-
		SSIM↑	0.97	<b>0.97</b>	0.97	<b>0.99</b>	<b>0.99</b>	<b>0.98</b>	<b>0.97</b>	<b>0.97</b>	<b>0.97</b>	
		LPIPS↓	0.09	<b>0.07</b>	0.09	<b>0.05</b>	<b>0.03</b>	<b>0.09</b>	<b>0.11</b>	<b>0.11</b>	<b>0.08</b>	
GSSLAM [106] [CVPR24]	✓	PSNR↑	<b>34.83</b>	<b>36.43</b>	<b>37.49</b>	<b>39.95</b>	<b>42.09</b>	<b>36.24</b>	<b>36.70</b>	<b>36.07</b>	<b>37.50</b>	769
		SSIM↑	0.95	0.96	0.96	0.97	0.98	0.96	<b>0.96</b>	0.96	0.96	
		LPIPS↓	<b>0.07</b>	<b>0.08</b>	<b>0.07</b>	<b>0.07</b>	<b>0.06</b>	<b>0.08</b>	<b>0.07</b>	<b>0.10</b>	<b>0.07</b>	
Gaussian-SLAM [107] [arXiv]	✓	PSNR↑	<b>34.31</b>	<b>37.28</b>	<b>38.18</b>	<b>43.97</b>	<b>43.56</b>	<b>37.39</b>	<b>36.48</b>	<b>40.19</b>	<b>38.90</b>	-
		SSIM↑	<b>0.99</b>	<b>0.99</b>	<b>0.99</b>	<b>1.00</b>	<b>0.99</b>	<b>0.99</b>	<b>0.99</b>	<b>1.00</b>	<b>0.99</b>	
		LPIPS↓	<b>0.08</b>	<b>0.07</b>	<b>0.07</b>	<b>0.04</b>	<b>0.07</b>	<b>0.08</b>	<b>0.08</b>	<b>0.07</b>	<b>0.07</b>	

• **Result:** As shown in Table 1, the recent 3D Gaussians based localization algorithms have a clear advantage over existing NeRF based dense visual SLAM. For example, HFSLAM [113] achieves a trajectory error improvement of ~50%, decreasing it from 0.52cm to **0.25cm** compared to the previous state-of-the-art (SOTA) [260]. We attribute this to the dense and accurate 3D Gaussians reconstructed for scenes, which can handle the noise of real sensors. This reveals that effective scene representations can improve the accuracy of localization tasks.

## 6.2 Performance Benchmarking: Static Scenes

Rendering focuses on transforming computer-readable information (e.g., 3D objects in the scene) to pixel-based images. This section focuses on evaluating the quality of rendering results in static scenes.

• **Dataset:** The same dataset as in Sec. 6.1, i.e., Replica [255], is used for performance comparison.

• **Benchmarking Algorithms:** For performance comparison, we involve four recent papers which introduce 3D Gaussians into their systems [104]–[107], as well as three dense SLAM methods [257], [258], [260].

• **Evaluation Metric:** Peak signal-to-noise ratio (PSNR), structural similarity (SSIM) [263], and learned perceptual image patch similarity (LPIPS) [264] are used for measuring RGB rendering performance.

• **Result:** Table 2 shows that 3D Gaussians based systems generally outperform the three dense SLAM competitors. For example, Gaussian-SLAM [107] establishes new SOTA and outperforms previous methods by a large margin. Compared to Point-SLAM [260], GSSLAM [106] is about 578 times faster in achieving very competitive accuracy. In contrast to previous method [260] that relies on depth information, such as depth-guided ray sampling, for synthesizing novel views, 3D GS based system eliminates this need, allowing for high-fidelity rendering for any views.

## 6.3 Performance Benchmarking: Dynamic Scenes

This section focuses on evaluating the rendering quality in dynamic scenes.

• **Dataset:** D-NeRF [170] dataset includes videos with 50 to 200 frames each, captured from unique viewpoints. It features synthetic, animated objects in complex scenes, with non-Lambertian materials. The dataset provides 50 to 200 training images and 20 test images per scene, designed for evaluating models in the monocular setting.

• **Benchmarking Algorithms:** For performance comparison, we involve four recent papers that model dynamic scenes with 3D GS [93], [95], [119], [176], as well as six NeRF based approaches [33], [170], [173], [265]–[267].

• **Evaluation Metric:** The same metrics as in Sec. 6.2, i.e., PSNR, SSIM [263], and LPIPS [264], are used for evaluation.



TABLE 3

**Quantitative rendering results (§6.3)** on D-NeRF [170], in terms of PSNR, SSIM, and LPIPS. \* denotes numbers taken from [95].

Method	GS	PSNR↑	SSIM↑	LPIPS↓
D-NeRF [170] [CVPR21]		30.50	0.95	0.07
TiNeuVox-B [265] [SGA22]		32.67	0.97	0.04
KPlanes [33] [CVPR23]		31.61	0.97	-
HexPlane-Slim [266] [CVPR23]		32.68	0.97	0.02
FFDNeRF [173] [ICCV23]		32.68	0.97	0.02
MSTH [267] [NeurIPS23]		31.34	0.98	0.02
3D GS* [10] [TOG23]	✓	23.19	0.93	0.08
4DGS [93] [ICLR24]	✓	34.09	0.98	-
4D-GS [95] [CVPR24]	✓	34.05	0.98	0.02
GaGS [125] [CVPR24]	✓	37.36	0.99	0.01
CoGS [119] [CVPR24]	✓	37.90	0.98	0.02
D-3DGS [94] [CVPR24]	✓	39.51	0.99	0.01

TABLE 4

**Quantitative rendering results (§6.4)** on nuScenes [243], in terms of PSNR, SSIM, and LPIPS. \* denotes numbers taken from [137].

Method	GS	PSNR↑	SSIM↑	LPIPS↓
Mip-NeRF [268] [ICCV21]		18.08	0.57	0.55
Mip-NeRF 360 [8] [CVPR22]		22.61	0.69	0.40
Instant-NGP [9] [TOG22]		16.78	0.52	0.57
Urban-NeRF [269] [CVPR22]		20.75	0.63	0.48
S-NeRF [270] [ICLR23]		25.43	0.73	0.30
SUDS [271] [CVPR23]		21.26	0.60	0.47
3D GS* [10] [TOG23]	✓	26.08	0.72	0.30
DrivingGaussian-L [137] [CVPR24]	✓	28.74	0.86	0.24

• **Result:** From Table 3 we can observe that 3D GS based methods outperform existing SOTAs by a clear margin. The static version of 3D GS [10] fails to reconstruct dynamic scenes, resulting in a sharp drop in performance. By modeling the dynamics, D-3DGS [94] outperforms the SOTA method, FFDNeRF [173], by 6.83dB in terms of PSNR. These results indicate the effectiveness of introducing additional properties or structured information to model the deformation of Gaussians so as to model the scene dynamics.

#### 6.4 Performance Benchmarking: Driving Scenes

This section focuses on evaluating the rendering quality in driving scenes, which is essential for autonomous driving.

• **Dataset:** nuScenes [243] dataset is a comprehensive collection for autonomous driving, featuring 1000 driving scenes captured using an array of sensors including six cameras, one LiDAR, five RADARs, GPS, and IMU. It provides detailed annotations for 23 object classes with 3D bounding boxes. Six challenging scenes are used for evaluation [137].

• **Benchmarking Algorithms:** For performance comparison, we involve one 3D GS based approach [137], as well as six NeRF based methods [8], [9], [268]–[271].

• **Evaluation Metric:** PSNR, SSIM [263], and LPIPS [264] are used for evaluation.

• **Result:** The results in Table 4 demonstrate that the 3D GS based methods significantly surpass the NeRF based methods across all evaluated metrics. For instance, DrivingGaussian-L [137] outperforms S-NeRF [270] by 3.31dB in terms of PSNR. This suggests that 3D Gaussians can benefit from multi-sensor information to capture dynamic objects in driving scenes, especially fast-moving ones.

#### 6.5 Performance Benchmarking: Human Avatar

Human avatar modeling aims to create the model of human avatars from a given multi-view video.

TABLE 5

**Quantitative avatar modeling results (§6.5)** on ZJU-MoCap [272], in terms of PSNR, SSIM, and LPIPS\*. The numbers of non-GS methods and FPS are taken from [210] and [224], respectively. † denotes the average of the values reported in the original paper.

Method	GS	PSNR↑	SSIM↑	LPIPS*↓	FPS
NeuralBody [272] [CVPR21]		29.03	0.96	42.47	3.5
AnimNeRF [274] [ICCV21]		29.77	0.96	46.89	2.1
PixelNeRF [275] [ICCV21]		24.71	0.89	121.86	-
NHP [276] [NeurIPS21]		28.25	0.95	64.77	-
HumanNeRF [273] [CVPR22]		30.66	0.97	33.38	0.4
Instant-NVR [277] [CVPR23]		31.01	0.97	38.45	1.5
Human101 [224] [arXiv]	✓	31.79	0.96	35.75	104.0
HUGS† [212] [CVPR24]	✓	30.98	0.97	26.67	-
3DGS-Avatar† [221] [CVPR24]	✓	30.61	0.97	29.58	-
GART [210] [CVPR24]	✓	32.22	0.98	29.21	-

• **Dataset:** ZJU-MoCap [272] dataset is a prevalent benchmark in human modeling from videos, captured with 23 synchronized cameras at a 1024×1024 resolution. Following [273], six subjects (*i.e.*, 377, 386, 387, 392, 393, and 394) are used for evaluation.

• **Benchmarking Algorithms:** For performance comparison, we involve four recent papers which model human avatar with 3D GS [210], [212], [221], [224], as well as six human rendering approaches [272]–[277].

• **Evaluation Metric:** PSNR, SSIM [263], and LPIPS\* [264] are used for measuring RGB rendering performance. Here LPIPS\* equals to  $LPIPS \times 1000$ .

• **Result:** Table 5 presents the numerical results of top-leading solutions in human avatar modeling. We observe that introducing 3D GS into the framework leads to consistent performance improvements in both rendering quality and speed. For instance, GART [210] outperforms current SOTA, Instant-NVR [277], by 1.21dB in terms of PSNR. Note that Human101 [224] is about 68 times faster in achieving very competitive accuracy compared to Instant-NVR [277]. Considering the enhanced fidelity, inference speed and editability, 3D GS based avatar modeling may revolutionize the field of 3D animation, interactive gaming, *etc.*

#### 6.6 Performance Benchmarking: Surgical Scenes

3D reconstruction from endoscopic video is critical to robotic-assisted minimally invasive surgery, enabling pre-operative planning, training through AR/VR simulations, and intraoperative guidance.

• **Dataset:** EndoNeRF [252] dataset presents a specialized collection of stereo camera captures, comprising two samples of in-vivo prostatectomy. It is tailored to represent real-world surgical complexities, including challenging scenes with tool occlusion and pronounced non-rigid deformation.

• **Benchmarking Algorithms:** For performance comparison, we involve three recent papers which reconstruct dynamic 3D endoscopic scenes with GS [140]–[142], as well as three NeRF-based surgical reconstruction approaches [252]–[254].

• **Evaluation Metric:** PSNR, SSIM [263], and LPIPS [264] are adopted for evaluation. In addition, the requirement for GPU memory is also reported.

• **Result:** Table 6 shows that introducing the explicit representation of 3D Gaussians leads to several significant improvements. For instance, EndoGaussian [141] outperforms a strong baseline, LerPlane-32k [253], among all metrics. In

TABLE 6

**Quantitative surgical 3D reconstruction results (§6.6)** on EndoNeRF [252], in terms of PSNR, SSIM, and LPIPS. The numbers of non-GS methods, FPS, and GPU usage (Mem.) are taken from [141]. \* denotes numbers taken from [137]. † denotes the average of the values reported in the original paper.

Method	GS	PSNR↑	SSIM↑	LPIPS↓	FPS↑	Mem.↓
EndoNeRF [252] <sup>[MICCAI22]</sup>		36.06	0.93	0.09	0.04	19GB
EndoSurf [254] <sup>[MICCAI23]</sup>		36.53	0.95	0.07	0.04	17GB
LerPlane-9k [253] <sup>[MICCAI23]</sup>		35.00	0.93	0.08	0.91	20GB
LerPlane-32k [253] <sup>[MICCAI23]</sup>		37.38	0.95	0.05	0.87	20GB
EndoGS* [142] <sup>[arXiv]</sup>	✓	36.84	0.96	0.04	-	-
Endo-4DGS† [140] <sup>[MICCAI24]</sup>	✓	37.00	0.96	0.05	-	4GB
EndoGaussian [141] <sup>[arXiv]</sup>	✓	37.85	0.96	0.05	195.09	2GB
HFGS [143] <sup>[arXiv]</sup>	✓	38.14	0.97	0.03	-	-

particular, EndoGaussian demonstrates an approximate 224-fold increase in speed while consumes just 10% of the GPU resources. These impressive results attest to the efficiency of GS-based methods, which not only expedite processing but also minimize GPU load, thus easing the demands on hardware. Such attributes are vitally significant for real-world surgical application deployment, where optimized resource usage can be a key determinant of practical utility.

## 7 FUTURE RESEARCH DIRECTIONS

As impressive as those follow-up works on 3D GS are, and as much as those fields have been or might be revolutionized by 3D GS, there is a general agreement that 3D GS still has considerable room for improvement.

- **Physics- and Semantics-aware Scene Representation.** As a new, explicit scene representation technique, 3D Gaussian offers transformative potential beyond merely enhancing novel-view synthesis. It has the potential to pave the way for simultaneous advancements in scene reconstruction and understanding by devising physics- and semantics-aware 3D GS systems. This is poised to revolutionize a range of fields and downstream applications. For instance, incorporating prior knowledge such as the general shape of objects can reduce the need for extensive training viewpoints [47], [48] while improving geometry/surface reconstruction [77], [100]. A critical metric for assessing scene representation is the realism of its generated scenes, which encompasses challenges in geometry, texture, and lighting fidelity [66], [121], [134]. By merging physical principles and semantic information within the 3D GS framework, one can expect that the realism will be enhanced, thereby facilitating dynamics modeling [21], [278], editing [90], [92], generation [126], [127], and beyond. In a nutshell, pursuing this advanced and versatile scene representation opens up new possibilities for innovation in computational creativity and practical applications across diverse domains.

- **Learning Physical Priors from Large-scale Data.** As we explore the potential of physics- and semantics-aware scene representations, leveraging large-scale datasets to learn physical priors emerges as a promising direction. The goal is to model the inherent physical properties and dynamics embedded within real-world data, transforming them into actionable insights that can be applied across various domains such as robotics and visual effects. Establishing a learning framework for extracting these physical priors enables the application of these insights to specific tasks in a few-shot manner. For instance, it allows for rapid adaptation

to new objects and environments with minimal data input. Furthermore, integrating physical priors can enhance not only the accuracy and realism of generated scenes but also their interactive and dynamic qualities. This is particularly valuable in AR/VR environments, where users interact with virtual objects that behave in ways consistent with their real-world counterparts. However, the existing body of work on capturing and distilling physics-based knowledge from extensive 2D and 3D datasets remains sparse. Notable efforts in related area include the Spring-Mass 3D Gaussians for elastic object modeling [279], and the generalizable Gaussian representation based on multi-view stereo [280]. Further exploration on real2sim and sim2real might offer viable routes for advancements in this field.

- **3D GS for Robotics.** In the world of robotics, especially when it comes to robots performing tasks that involve handling objects in ways similar to humans, there is a growing need for these machines to be able to navigate and manipulate their environment in a more intuitive and dynamic manner. This necessity stems from the desire to deploy intelligent robots in real-world settings, where they are often faced with new and unfamiliar tasks. Traditional approaches to robotic manipulation have relied heavily on understanding the environment through semantic representation, which means identifying objects and their attributes. However, these methods often overlook the importance of how things move and interact over time, which is crucial for completing tasks in the way humans intend. Imagine a robot trying to stack blocks based on a verbal command. Using only semantic representation, the robot might recognize the blocks but fail to stack them if it does not understand how the blocks should be positioned and moved relative to each other over time. This gap in understanding can lead to failure in executing tasks that require interaction with multiple objects or navigating dynamic environments. Due to its explicit nature, 3D GS can be used beyond mere semantic and structural analysis of environments; it also encompasses the dynamic aspect, providing a comprehensive understanding of how scenes evolve and objects interact over time. This is essential for robots tasked with navigating and manipulating their surroundings. Although initial GS based efforts on world models [281], [282] and reinforcement learning [283], [284] are promising, they represent only the beginning of what is possible. Further research in this area is anticipated to enhance the capabilities of robots in performing tasks that require an understanding of both the physical space and the temporal changes within it.

- **Modeling Internal Structures of Objects with 3D GS.** Despite the ability of 3D GS to produce highly realistic renderings, modeling internal structures of objects (*e.g.*, for a scanned object in computed tomography) within the current GS framework presents a notable challenge. Due to the splatting and density control process, the current representation of 3D Gaussian is unorganized and cannot align well with the object's actual internal structures. Moreover, there is a strong preference in various applications to depict objects as volumes (*e.g.*, computed tomography). However, the disordered nature of 3D GS makes volume modeling particularly difficult. Li *et al.* [285] used 3D Gaussians with density control as the basis for the volumetric representation and did not involve the splatting process. X-Gaussian [286]

involves the splatting process for fast training and inference but cannot generate volumetric representation. Using 3D GS to model the internal structures of objects remains unanswered and deserves further exploration.

• **3D GS for Simulation in Autonomous Driving.** Collecting real-world datasets for autonomous driving is both expensive and logistically challenging, yet crucial for training effective image-based perception systems. To mitigate these issues, simulation emerges as a cost-effective alternative, enabling the generation of synthetic datasets across diverse environments. However, the development of simulators capable of producing realistic and diverse synthetic data is fraught with challenges. These include achieving a high level of realism, accommodating various control methods, and accurately simulating a range of lighting conditions. While early efforts [137]–[139] in reconstructing urban/street scenes with 3D GS have been encouraging, they are just the tip of the iceberg in terms of the full capabilities. There remain numerous critical aspects to be explored, such as the integration of user-defined object models, the modeling of physics-aware scene changes (e.g., the rotation of vehicle wheels), and the enhancement of controllability and realism (e.g., in varying lighting conditions).

• **Empowering 3D GS with More Possibilities.** Despite the significant potential of 3D GS, the full scope of applications for 3D GS remains largely untapped. A promising avenue for exploration involves augmenting 3D Gaussians with additional attributes (e.g., linguistic and spatiotemporal properties as mentioned in Sec. 4.5) and introducing structured information (e.g., spatial MLPs and grids as mentioned in Sec. 4.6), tailored for specific applications. Moreover, recent studies have begun to unveil the capability of 3D GS in several domains, e.g., point cloud registration [287], image representation and compression [60], and fluid synthesis [288]. These findings highlight a significant opportunity for interdisciplinary scholars to explore 3D GS further.

## 8 CONCLUSIONS

To the best of our knowledge, this survey presents the first comprehensive overview of 3D GS, a groundbreaking technique revolutionizing explicit radiance fields, computer graphics, and computer vision. It delineates the paradigm shift from traditional NeRF based methods, spotlighting the advantages of 3D GS in real-time rendering and enhanced editability. Our in-depth analysis and extensive quantitative studies demonstrate the superiority of 3D GS in practical applications, particularly those highly sensitive to latency. We offer insights into principles, prospective research directions, and the unresolved challenges within this domain. Overall, 3D GS stands as a transformative technology, poised to significantly influence future advancements in 3D reconstruction and representation. This survey is intended to serve as a foundational resource, propelling further exploration and progress in this rapidly evolving field.

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