3D Gaussian Splatting in Real-Time Rendering and Volumetric Rendering: A Survey

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Abstract

3D Gaussian Splatting (3DGS) is an advanced rendering technique that leverages Gaussian functions to enhance the fidelity and efficiency of scene representation in real-time and volumetric rendering. By integrating primitive-based and volumetric representations, 3DGS addresses challenges in modeling dynamic and complex environments, offering high-quality rendering and rapid scene synthesis. The extension to 4D Gaussian Splatting (4D-GS) further enhances real-time rendering capabilities for dynamic scenes. However, 3DGS faces limitations such as high memory consumption and challenges in capturing complex lighting conditions. Recent advancements, such as the Compact 3D Gaussian Representation (C3DGR) and Hierarchical GS Compression (HGSC), have focused on optimizing data structures and algorithms to enhance scalability and resource efficiency. Additionally, the integration of large models and advanced illumination modeling techniques has significantly improved scene understanding and rendering quality. The ongoing evolution of 3D Gaussian Splatting methodologies, including innovations like GScream and Motion-Aware 3D Gaussian Splatting, continues to address these challenges, ensuring that 3DGS remains a cutting-edge technology in real-time and volumetric rendering. These advancements underscore the potential of 3DGS to revolutionize scene representation and understanding, offering robust solutions for a wide range of applications in computer graphics.

1 Introduction

1.1 Overview of 3D Gaussian Splatting

3D Gaussian Splatting (3DGS) is a sophisticated rendering technique that synergizes primitive-based and volumetric representations, significantly improving the fidelity and efficiency of neural rendering. By employing mixtures of Gaussians, 3DGS adeptly models 3D scenes, effectively addressing representation challenges and ensuring high-quality rendering [1]. The use of Gaussian functions allows for remarkable rendering quality and speed, particularly in novel view synthesis [2].

A key feature of 3DGS is its capability to efficiently manage dynamic scenes. The advancement to 4D Gaussian Splatting (4D-GS) further enhances this ability, facilitating real-time rendering of dynamic environments [3]. However, 3DGS encounters limitations in capturing complex lighting conditions and view-dependent color due to its dependence on low-order spherical harmonics [4].

Additionally, 3DGS improves the physical accuracy of rendering opaque surfaces through approximations that enhance surface representation [5]. Its integration with position-based dynamics (PBD) fosters the creation of innovative effects in virtual scenes, showcasing its versatility and potential for advancements in the rendering domain [6].

Furthermore, 3DGS has been proposed as a method for reconstructing scenes from unconstrained image collections, utilizing 3D Gaussian points for flexible and precise scene appearance modeling [7]. This adaptability highlights its significance as a powerful tool for comprehensive scene understanding

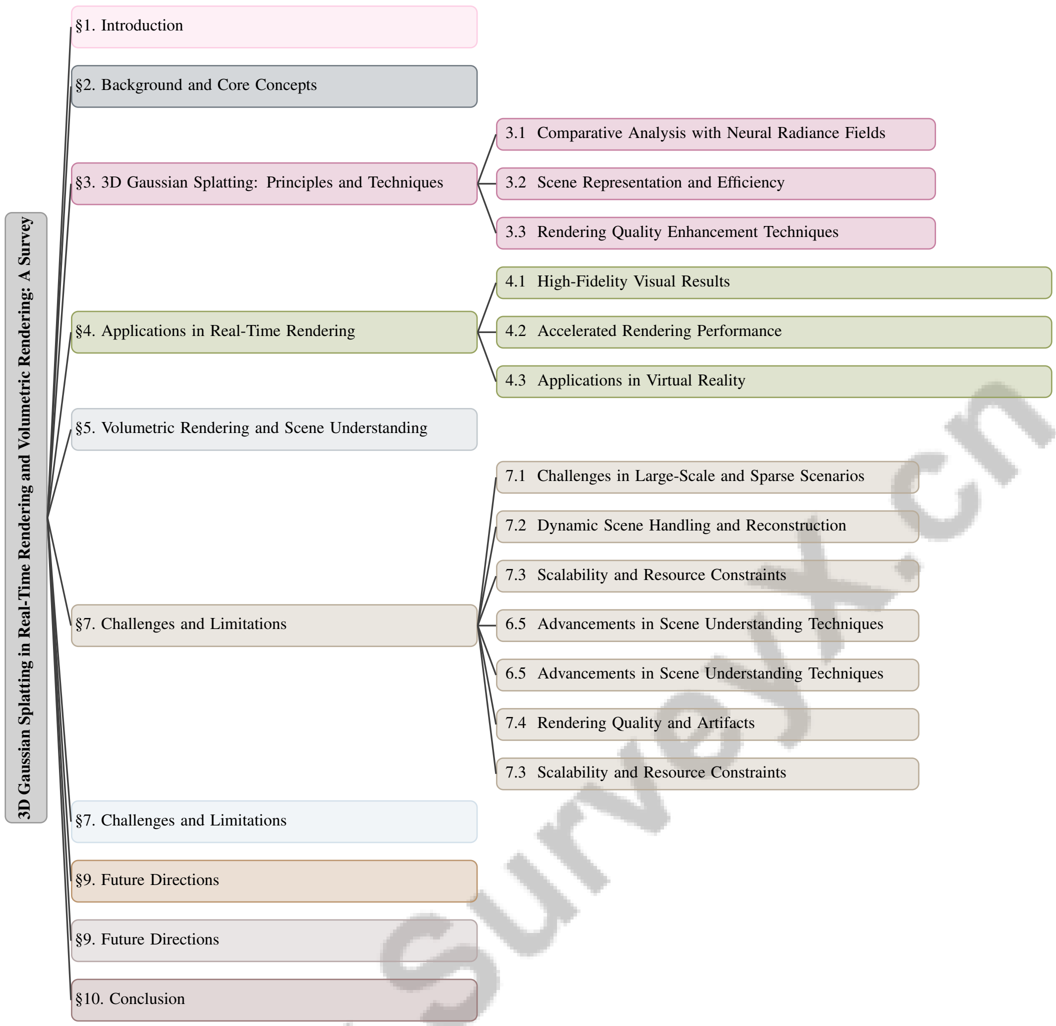

Figure 1: chapter structure

and manipulation, marking it as a vital contributor to advancements in real-time and volumetric rendering technologies.

1.2 Significance in Real-Time and Volumetric Rendering

The significance of 3D Gaussian Splatting (3DGS) in real-time and volumetric rendering is evident in its ability to enhance rendering quality and speed, especially in novel view synthesis [8]. This technique addresses the shortcomings of traditional rendering methods by delivering high-quality visual results alongside efficient rendering processes. In dynamic scenes, where achieving real-time performance while maintaining visual fidelity is challenging, 3DGS demonstrates notable robustness and adaptability [3]. The integration of Variational Bayes Gaussian Splatting (VBGS) further illustrates its suitability for real-time applications, particularly in robotics and navigation contexts [1].

Despite its advantages, the substantial data size associated with 3DGS complicates storage and transmission, necessitating effective compression strategies for practical application [2]. Ongoing optimization efforts aim to mitigate high-frequency artifacts and enhance performance under sparse viewpoint conditions, broadening its applicability across various rendering scenarios.

Collectively, these advancements underscore the pivotal role of 3D Gaussian Splatting in rendering, offering robust solutions that balance real-time performance with high-quality visual outcomes. Continuous improvements in compression and optimization techniques for 3DGS significantly enhance its capabilities, positioning it as a critical technology for real-time and volumetric rendering applications. By modeling scenes with collections of three-dimensional Gaussians and optimizing their attributes, 3DGS achieves rapid rendering and high image fidelity while addressing prior limitations related to storage and memory demands. These enhancements facilitate its adoption in diverse fields such as virtual reality, interactive media, and automated 3D content creation, solidifying 3DGS's status as a crucial component in the evolution of computer graphics technology [9, 10, 11, 12, 13].

1.3 Structure of the Survey

This survey is systematically organized to provide a comprehensive understanding of 3D Gaussian Splatting (3DGS) and its applications in real-time and volumetric rendering. The paper is divided into several key sections, each addressing distinct aspects of the topic. It begins with an introduction that establishes the importance and potential of 3DGS in contemporary rendering techniques.

Following the introduction, the survey explores the background and core concepts, offering detailed explanations of the foundational principles that underpin 3DGS, including its methodology and the evolution of related technologies. This section equips readers with the necessary context to grasp the technical intricacies of 3DGS.

The subsequent section focuses on the principles and techniques of 3D Gaussian Splatting, comparing its unique methodologies with other rendering techniques such as Neural Radiance Fields (NeRFs). This comparative analysis elucidates the distinct advantages and limitations of 3DGS.

Applications in real-time rendering are examined next, illustrating how 3DGS achieves high-fidelity visual results and accelerated rendering performance. The practical benefits of this technology are showcased through specific applications in virtual reality, interactive media, and gaming, highlighting advancements such as real-time, user-friendly 3D editing and efficient content generation methods that significantly improve rendering quality and speed while reducing manual labor in digital content creation [14, 15, 16, 11, 12].

The role of 3DGS in volumetric rendering and scene understanding is explored, emphasizing its impact on enhancing scene comprehension and representation. This section discusses how large models and hierarchical techniques contribute to efficient scene understanding.

Challenges and limitations of 3D Gaussian Splatting are addressed in a dedicated section, identifying current obstacles such as scalability, resource constraints, and rendering quality issues. This discussion sets the stage for the subsequent section on future directions, suggesting potential research avenues and opportunities for integrating 3DGS with other technologies.

The survey concludes by synthesizing key insights from the analysis of 3D Gaussian Splatting (3DGS) and emphasizes its critical role in revolutionizing real-time and volumetric rendering. By leveraging explicit scene representation and differentiable rendering algorithms, 3DGS enhances rendering speed and editability while opening new avenues for applications in fields such as virtual reality, robotics, and urban mapping. The discussion identifies ongoing challenges within the domain and outlines potential directions for future research, underscoring the transformative impact of 3DGS on the future of 3D reconstruction and representation [17, 13, 18, 9]. This structured approach ensures a thorough exploration of 3DGS, providing readers with a clear and comprehensive understanding of its capabilities and future potential.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Definitions and Methodology of 3D Gaussian Splatting

3D Gaussian Splatting (3DGS) is a sophisticated rendering technique that leverages Gaussian functions for detailed scene modeling, particularly in complex environments. By integrating geometric priors such as depth and normal cues, 3DGS enhances scene representation and fidelity [19]. This high fidelity, however, often increases memory demands due to the extensive use of 3D Gaussians [20].

The methodology of 3DGS employs a multi-scale representation strategy, as seen in Multi-Scale 3D Gaussian Splatting (MS3DGS), which adapts the size and number of Gaussians according to rendering resolution to optimize performance [21]. Techniques like Analytic-Splatting further improve rendering by analytically approximating the integral of Gaussian signals within a pixel window, enhancing anti-aliasing and detail fidelity [22]. Moreover, 3DGS can integrate with position-based dynamics to simulate dynamic interactions, as demonstrated in Gaussian Splashing (GSP) frameworks [6].

Variational Bayes Gaussian Splatting (VBGS) refines Gaussian splats through variational inference, allowing efficient updates from partial observations [1]. This method effectively tackles the challenge of real-time scene updates. The 4D Gaussian Splatting method extends 3DGS to dynamic scenes by integrating 3D Gaussians with a Gaussian deformation field, enabling real-time rendering of dynamic environments [3].

Challenges in 3DGS include insufficient representation of view-dependent colors and specular reflections, limiting its effectiveness under complex lighting [4]. Over-reconstruction issues may also occur, leading to blurry images when large Gaussians fail to capture fine details [23].

3D Gaussian Splatting represents a significant advancement in rendering technology, offering a flexible and efficient framework for scene reconstruction. Its ongoing development addresses existing limitations, enhancing applicability across diverse scenarios. Innovations like Gaussian in the Wild (GS-W) further refine the approach by using 3D Gaussian points with distinct intrinsic and dynamic appearance features for effective scene modeling [7].

2.2 Evolution and Relevance of Technologies

The evolution of rendering technologies underscores the significance of 3D Gaussian Splatting (3DGS) in computer graphics. Traditional methods, such as Neural Radiance Fields (NeRFs) and pixelSplat, laid the groundwork for 3D reconstruction but often suffer from high memory costs and slow rendering speeds, limiting their scalability [24]. These methods typically require computationally intensive processes or scene-specific optimizations, complicating the efficient capture of intricate details [25].

To address these challenges, advancements in scene representation technologies have introduced Gaussian primitives, offering a more effective alternative to traditional mesh and voxel-based representations. This shift significantly enhances geometry extraction and detail preservation, crucial for high-quality rendering. Innovations like the Gaussian Opacity Field (GOF) have emerged to tackle challenges related to geometry extraction and detail preservation in existing 3D Gaussian methods [26].

Recent developments have highlighted the importance of robust initialization mechanisms and sophisticated illumination modeling. Techniques such as CSS, which improve pose estimation and rendering consistency, exemplify efforts to enhance rendering fidelity and efficiency [27]. These advancements emphasize the integration of algorithmic innovations with hardware improvements to rectify inefficiencies and improve rendering quality in dynamic scene reconstruction using NeRF-based techniques [25].

The continuous advancements in 3D Gaussian Splatting (3DGS) significantly enhance its functionalities, broadening its applicability across fields such as robotics, urban mapping, autonomous navigation, and virtual reality. This technology improves 3D representation and rendering capabilities while opening new research avenues in Extended Reality (XR), where its potential remains largely unexplored [15, 28]. This trajectory ensures that 3D Gaussian Splatting remains at the forefront of rendering technology, providing robust solutions for complex scene representation and manipulation.

3 3D Gaussian Splatting: Principles and Techniques

Exploring the principles and techniques of 3D Gaussian Splatting (3DGS) reveals foundational aspects that distinguish it from other rendering methodologies. Table 1 presents a detailed summary of the methods and techniques utilized in the study of 3D Gaussian Splatting (3DGS), emphasizing its comparative advantages over Neural Radiance Fields (NeRFs) and its contributions to scene representation efficiency and rendering quality enhancement. Additionally, Table 5 presents a detailed comparison of rendering methodologies, underscoring the unique strengths of 3D Gaussian Splatting in terms of computational efficiency and rendering quality. The following subsection

Category	Feature	Method
Comparative Analysis with Neural Radiance Fields	Rendering and Visualization	LSG[4], GSD[29], SP-GS[25], MS3DGS[21]
	Efficiency Enhancement	GS[30]
	Temporal Consistency	MA-3DGS[31]
Scene Representation and Efficiency	Efficient Geometric Representation	GSP[6], 3DGS[32], VC3DGR[5]
	Adaptive Enhancement	SLS[33]
Rendering Quality Enhancement Techniques	Geometric Enhancements	DNS[19]
	Texture and Detail Enhancement	AbsGS[23], T-GS[34]
	Shading and Anti-Aliasing	AS[22]
	Compression and Efficiency	C3DGR[20], HGSC[2]

Table 1: This table provides a comprehensive overview of various methods employed in 3D Gaussian Splatting (3DGS) research, categorized into three main areas: comparative analysis with Neural Radiance Fields (NeRFs), scene representation and efficiency, and rendering quality enhancement techniques. Each category highlights specific features and methods, showcasing the diverse approaches and innovations aimed at optimizing 3DGS for real-time rendering and high-quality visual outputs.

presents a comparative analysis with Neural Radiance Fields (NeRFs), highlighting the unique strengths and limitations of each approach in novel view synthesis. This examination underscores 3DGS's advantages, particularly in computational efficiency and real-time rendering, enhancing its applications in modern graphics.

3.1 Comparative Analysis with Neural Radiance Fields

Method Name	**Rendering Efficiency**	**Scene Representation**	**Computational Cost**
GS[30]	Rapid Training Speeds	Enhanced Gaussian Representation	Low Computational Loads
GSD[29]	Real-time Rendering	Explicit Representation	Efficient Rendering
SP-GS[25]	Real-time Rendering	Superpoints Clustering	Low Computational Burden
C3DGR[20]	Improved Rendering Speed	High-quality Scene	Reduced Storage Requirements
MS3DGS[21]	Rendering Speed	Multi-scale Representation	Low Computational Loads
VC3DGR[5]	Improved Rendering Quality	Analytical Integration	Low Computational Loads
MA-3DGS[31]	Improved Rendering Quality	Dynamic Scene Reconstruction	Reduced Redundancy
LSG[4]	High-quality Visual	Latent Neural Descriptors	Low Computational Loads

Table 2: Comparison of various 3D Gaussian Splatting (3DGS) methods in terms of rendering efficiency, scene representation, and computational cost. The table highlights the distinct features and performance metrics of each method, showcasing their contributions to enhancing real-time rendering and scene quality in novel view synthesis.

3D Gaussian Splatting (3DGS) and Neural Radiance Fields (NeRFs) are innovative approaches in novel view synthesis, each with distinct advantages and limitations. 3DGS excels in real-time rendering and high-quality outputs, leveraging Gaussian functions for rapid scene modeling and surpassing traditional rasterization techniques. The efficiency of 3DGS is enhanced by methods like GScream, which uses depth-guided training and cross-attention feature regularization for effective object removal and scene manipulation [30]. Conversely, NeRFs, known for detailed volumetric reconstructions, incur significant computational costs, limiting their real-time applicability [29]. Their reliance on dense neural networks for fine detail capture makes them resource-intensive and slow, positioning 3DGS as a practical choice for rapid rendering scenarios [25].

Recent advancements, such as the Compact 3D Gaussian Representation (C3DGR), optimize 3DGS by incorporating a learnable masking strategy to enhance 3D scene representation while reducing computational load [20]. The use of coarser Gaussians for lower resolutions and finer Gaussians for higher resolutions further improves rendering efficiency [21]. The Unified Gaussian Primitives Scene (UGPS) approach enhances rendering speed and scene representation efficiency through explicit representations [35], while Volumetrically Consistent 3D Gaussian Rasterization (VC3DGR) improves opaque surface representation accuracy by analytically integrating 3D Gaussians to compute transmittance [5]. The Motion-Aware 3D Gaussian Splatting method utilizes optical flow as a reliable motion prior, maintaining temporal consistency and reducing redundancy in Gaussian modeling [31]. Latent-SpecGS, integrating latent neural descriptors within 3D Gaussians, further showcases 3DGS's potential for high-quality rendering under complex lighting conditions [4]. Table 2 presents a comparative analysis of different 3D Gaussian Splatting methods, emphasizing their efficiency and capability in rendering and scene representation, which are crucial for advancing real-time novel view synthesis.

3.2 Scene Representation and Efficiency

Method Name	Scene Representation	Rendering Efficiency	Application Scenarios
SLS[33]	Semantic Feature Embeddings	Fewer Computational Resources	Dynamic Environments
3DGS[32]	3D Gaussians	Real-time Performance	Virtual Reality
VC3DGR[5]	Opaque Surfaces	Rasterization Framework	View Synthesis
GSP[6]	Unified Volumetric Representation	Particle-based Representations	3D Graphics Tasks

Table 3: Comparison of advanced scene representation methods in terms of their rendering efficiency and application scenarios. The table highlights the distinct approaches employed by each method, illustrating their respective advantages in dynamic environments, virtual reality, view synthesis, and 3D graphics tasks.

The application of Gaussian functions in 3DGS establishes a robust framework for representing complex geometries, enhancing light transport accuracy and overall scene quality [35]. This method optimizes scene representation and improves computational efficiency, vital for real-time rendering applications. The SpotLessSplats (SLS) method exemplifies a significant advancement, employing adaptive masking techniques based on semantic features to enhance scene representation and reconstruction efficiency [33]. This approach allows selective emphasis on relevant scene elements while disregarding distractors, thereby improving rendered output quality.

Recent studies explore the integration of 3D Gaussians for scene rendering [32], optimizing light transport and enhancing rendering quality for complex geometries. The Gaussian Opacity Field (GOF) technique ensures consistency with volume rendering during training, facilitating adaptive mesh extraction that accurately represents geometric details. Moreover, the integration of 3D Gaussian Splatting attributes through the 3D Gaussians method optimizes scene representation and rendering efficiency [32]. The Volumetrically Consistent 3D Gaussian Rasterization (VC3DGR) method exemplifies this by efficiently accumulating density along the ray, providing a superior representation of opaque objects [5].

The Gaussian Splashing Particle Representation (GSP) emphasizes particle-based representations for rendering and dynamic simulation, ensuring realistic interactions and high-quality visual outputs [6]. By leveraging the coherence of particle-based representations, GSP contributes to overall efficiency and realism in rendered scenes. These advancements underscore the transformative potential of 3DGS to significantly enhance scene representation and rendering efficiency in real-time applications. Representing 3D objects as collections of Gaussian ellipsoids accelerates rendering speeds for novel view synthesis and supports applications in robotics, urban mapping, and virtual reality. By providing an explicit and flexible representation of 3D scenes, 3DGS enables realistic visual effects and facilitates editing tasks such as dynamic reconstruction and geometry manipulation, establishing it as a leading method in the evolution of computer graphics and 3D vision [36, 18, 9]. The integration of innovative techniques like SLS, GOF, and GSP continues to advance high-fidelity rendering, offering robust solutions for diverse applications in computer graphics. Table 3 provides a comprehensive comparison of various scene representation methods, detailing their rendering efficiency and potential application scenarios in the context of real-time rendering and computer graphics.

3.3 Rendering Quality Enhancement Techniques

Method Name	Rendering Techniques	Visual Output Quality	Data Optimization
T-GS[34]	Local Taylor Expansion	High-fidelity Textures	Hierarchical Compression
AS[22]	Analytic Approximation	Detail Fidelity	Hierarchical Compression
AbsGS[23]	Gradient Collision Avoidance	Enhanced Detail Recovery	Accurate Gaussian Splitting
HGSC[2]	Octree Structure	Maintaining Rendering Quality	Hierarchical GS Compression
DNS[19]	Depth Cues	Photorealism Improvement	Mesh Extraction
C3DGR[20]	Learnable Masking Strategy	High-quality Reconstruction	Vector Quantization

Table 4: Comparison of advanced rendering techniques in 3D Gaussian Splatting (3DGS) highlighting their respective methods for rendering, visual output quality, and data optimization. The table presents a systematic overview of various state-of-the-art methods, including T-GS, AS, AbsGS, HGSC, DNS, and C3DGR, each employing unique strategies to enhance rendering quality and efficiency.

Enhancing rendering quality is crucial for the effectiveness and versatility of 3DGS in both real-time and volumetric applications. This technique utilizes explicit 3D Gaussian representations to achieve rapid rendering speeds and high-quality reconstructions from multi-view images, presenting a promising alternative to traditional neural radiance field methods. However, challenges such as needle-like artifacts and suboptimal geometries persist, necessitating ongoing advancements to fully harness the potential of 3DGS in fields like virtual reality and interactive media [36, 37, 9, 17, 13].

Innovative techniques have been developed to address the challenges of achieving high-quality visual outputs, particularly in complex scenes. The introduction of an RGB decoder function represents a significant advancement, effectively addressing color inconsistencies and enhancing the robustness of 3DGS. This improvement is critical for mitigating the impact of dynamic objects, or distractors, which can distort rendering results in static scenes. By incorporating a self-supervised approach that utilizes image residuals and a pretrained segmentation network, the RGB decoder function enables accurate identification and exclusion of these distractors, resulting in cleaner reconstructions and improved PSNR metrics [38, 39]. This method ensures color fidelity across varying lighting conditions, essential for realistic visual outputs.

The Texture-GS method further enhances rendering quality by allowing flexible editing of textures while maintaining real-time rendering capabilities, thus providing more control over texture details [34]. The Analytic-Splatting method improves pixel shading by analytically computing the Gaussian integral within the pixel window, significantly enhancing anti-aliasing and resulting in smoother, more detailed visual outputs [22].

The AbsGS method addresses over-reconstruction challenges by accurately splitting large Gaussians where fine details are needed, thus improving 3D scene representation [23]. This technique captures intricate details with high fidelity, enhancing overall rendering quality. The Hierarchical GS Compression (HGSC) technique effectively reduces data size by pruning unimportant Gaussians and employing a hierarchical compression strategy, maintaining rendering quality while optimizing storage for real-time applications [2].

The DNSplatter method introduces depth and normal priors that significantly improve scene representation fidelity by incorporating geometric cues to enhance detail accuracy [19]. This method proves particularly effective in complex scenarios where maintaining high-quality rendering is crucial. The development of C3DGR sets a new benchmark in 3D scene representation, demonstrating improved rendering speed and reduced storage requirements while maintaining high-quality reconstruction [20]. This advancement is pivotal for expanding the applicability of 3DGS in resource-constrained environments.

Table 4 provides a comprehensive comparison of contemporary techniques aimed at enhancing rendering quality in 3D Gaussian Splatting, detailing their approaches in rendering, visual output quality, and data optimization.

In recent years, the advancements in rendering technologies have significantly transformed the landscape of visual media. One notable technique that has emerged is 3D Gaussian Splatting (3DGS), which offers remarkable benefits in various applications. Figure 2 illustrates the hierarchical categorization of applications of 3D Gaussian Splatting in real-time rendering, highlighting its contributions to high-fidelity visual results, accelerated rendering performance, and versatility in virtual reality, interactive media, and gaming. This categorization not only underscores the effectiveness of 3DGS but also serves as a foundation for understanding its broader implications in the field of computer graphics.

Feature	3D Gaussian Splatting	Neural Radiance Fields	Compact 3D Gaussian Representation
Rendering Efficiency	Real-time Rendering	Resource-intensive	Reduced Computational Load
Scene Representation	Rapid Scene Modeling	Volumetric Reconstructions	Learnable Masking Strategy
Rendering Quality	High-quality Outputs	Fine Detail Capture	Improved Rendering Speed

Table 5: This table provides a comparative analysis of three rendering methods: 3D Gaussian Splatting, Neural Radiance Fields, and Compact 3D Gaussian Representation. It highlights key features such as rendering efficiency, scene representation, and rendering quality, emphasizing the distinct advantages and computational benefits of each approach in the context of novel view synthesis.

4 Applications in Real-Time Rendering

4.1 High-Fidelity Visual Results

3D Gaussian Splatting (3DGS) is instrumental in achieving high-fidelity visual results in real-time rendering, surpassing traditional methods by utilizing Gaussian functions for smooth and detailed scene representations [32]. This technique excels in rendering complex geometries and dynamic scenes where traditional rasterization fails. The Latent-SpecGS method enhances specular reflections and view-dependent color synthesis, setting a benchmark in novel view synthesis tasks [4]. DN-Splatter adds depth and normal priors to 3DGS, improving 3D reconstructions' fidelity, especially indoors [19]. Volumetrically Consistent 3D Gaussian Rasterization (VC3DGR) enhances opaque surface representation by analytically integrating 3D Gaussians to compute transmittance, optimizing rendering efficiency [5]. Motion-Aware 3D Gaussian Splatting uses optical flow as a motion prior to maintain fidelity in dynamic scenes [31], while GS-W effectively models scenes under complex lighting conditions [7].

4.2 Accelerated Rendering Performance

3D Gaussian Splatting (3DGS) significantly enhances real-time rendering speed while maintaining visual quality. Multi-Scale 3D Gaussian Splatting (MS3DGS) adjusts Gaussian splats dynamically based on resolution, optimizing performance [21]. The GS-LRM model demonstrates accelerated rendering through large-scale reconstruction techniques [40], while CF3DGS processes frames sequentially without pre-computed camera poses, boosting inference speed [24]. SplatFields employs neural Gaussian splats for real-time rendering, enhancing computational efficiency [41]. The GSS method uses a multi-resolution hash grid and a tiny MLP for real-time stylization, emphasizing efficient data processing [42]. These advancements position 3DGS at the forefront of rendering technology, providing efficient, high-quality solutions for diverse applications.

4.3 Applications in Virtual Reality, Interactive Media, and Gaming

3D Gaussian Splatting (3DGS) is versatile in virtual reality (VR), interactive media, and gaming, delivering high-fidelity visual experiences with real-time performance. By employing Gaussian functions, 3DGS enhances realism and interactivity in fields such as robotics, urban mapping, and virtual/augmented reality [43, 44, 16, 18]. In VR, methods like SCGS enable effective editing and segmentation of large environments [18]. Interactive media and gaming benefit from 3DGS's ability to render complex scenes quickly with high detail [9]. GScream facilitates seamless object removal and manipulation through depth-guided training [30]. In AR, 3DGS's efficiency is leveraged for immersive experiences requiring precise scene understanding. Compact 3D Gaussian Representation (C3DGR) optimizes scene representation for resource-efficient AR applications [20], while the Gaussian Opacity Field (GOF) enhances geometry extraction [26]. GaussStudio exemplifies 3DGS's potential for flexible 3D scene editing, offering dynamic and engaging experiences in interactive media and gaming [45].

5 Volumetric Rendering and Scene Understanding

5.1 Enhancing Scene Understanding with Large Models

The integration of large models within 3D Gaussian Splatting (3DGS) has substantially advanced scene understanding in dynamic, complex environments. The Scale-Aware Robust Optimization Gaussian Splatting (SaRO-GS) method addresses the challenge of accurately representing temporal dynamics in video-based scene reconstruction. By employing a 4D Gaussian primitive-based representation, SaRO-GS facilitates real-time rendering and manages complexities such as significant motion and appearance changes through a Scale-aware Residual Field and Adaptive Optimization Schedule. These innovations enhance dynamic scene reconstruction efficiency and precision [46, 47, 9, 48, 49].

DynaSurfGS represents a breakthrough in dynamic surface reconstruction, crucial for applications in robotics and interactive media, by preserving intricate details in real-time outputs. Utilizing planar-based Gaussian splatting and 4D spatial-temporal representations, it achieves photorealistic rendering and improves dynamic scene analysis [50, 49, 14, 51]. In applications like SLAM and medical XR, large models in 3DGS enhance spatial comprehension and visualization [15].

The GScream method exemplifies the potential of large models by employing depth-guided training and cross-attention feature regularization for object removal and scene manipulation, enhancing understanding of complex scenes [30]. 3D Convex Splatting (3DCS) efficiently represents complex geometries with fewer primitives, reducing memory usage and rendering times, while the Gaussian Opacity Field (GOF) ensures accurate 3D reconstructions [26].

The Motion-Aware 3D Gaussian Splatting approach, incorporating optical flow as a motion prior, enhances dynamic scene reconstruction by leveraging rich motion information, improving rendering quality and efficiency [31, 52, 18, 9]. This method maintains temporal consistency and reduces redundancy in Gaussian modeling, essential for effective scene understanding. The GScream method further advances scene geometry learning and manipulation [30]. Techniques like CSS contribute to digital heritage preservation by reconstructing historically significant scenes from crowdsourced imagery [27].

5.2 Hierarchical and Efficient Scene Representation

3D Gaussian Splatting (3DGS) enhances scene representation efficiency through hierarchical techniques, allowing scalable representation of complex scenes while optimizing computational resources and rendering quality [21]. The Multi-Scale 3D Gaussian Splatting (MS3DGS) method dynamically adjusts Gaussian splats' granularity based on rendering resolution, using coarser Gaussians for distant objects and finer ones for intricate details [21].

The Hierarchical Gaussian Splatting Compression (HGSC) technique reduces data size without compromising rendering quality via a multi-level compression strategy that prunes less significant Gaussians. This approach ensures high-quality rendered output while optimizing storage and transmission efficiency, critical for real-time applications [2]. The integration of the Gaussian Opacity Field (GOF) technique improves volume rendering consistency during training, enabling adaptive mesh extraction that enhances geometric detail representation [35].

The SpotLessSplats (SLS) method further evolves hierarchical scene representation by employing adaptive masking based on semantic features, enhancing accuracy and efficiency in scene representation, especially in environments with numerous distractors [33].

5.3 Advancements in Scene Understanding Techniques

Recent advancements in scene understanding techniques have significantly enhanced 3D Gaussian Splatting (3DGS) capabilities, particularly in dynamic and complex environments. Large models leveraging extensive datasets improve scene reconstruction accuracy and detail [15]. Methods like Scale-Aware Robust Optimization Gaussian Splatting (SaRO-GS) advance scene understanding through scale-aware optimization, capturing intricate temporal dynamics and managing significant motion and object appearance variations [53, 49, 12, 48].

The DNSplatter method integrates depth and normal priors to enhance scene representation fidelity, crucial for high-quality 3D reconstructions in challenging indoor environments [19]. Motion-Aware 3D Gaussian Splatting further advances scene understanding by using optical flow as a motion prior, enhancing temporal consistency and reducing redundancy in Gaussian modeling [31].

Advanced illumination modeling techniques, such as the Latent-SpecGS method, enhance rendered scene quality by incorporating latent neural descriptors within 3D Gaussians, improving specular reflections and view-dependent color synthesis [4]. The continuous evolution of scene understanding techniques, exemplified by SaRO-GS, DNSplatter, and Latent-SpecGS, highlights the potential of 3D Gaussian Splatting to revolutionize real-time and volumetric rendering, offering robust solutions across computer graphics applications.

6 Challenges and Limitations

In exploring the challenges and limitations associated with 3D Gaussian Splatting (3DGS), it is essential to recognize the multifaceted nature of these obstacles as they pertain to various rendering scenarios. The following subsection delves into the specific challenges encountered in large-scale and sparse environments, highlighting the intricacies of memory consumption, algorithmic efficiency, and the need for robust scene representation techniques. By addressing these issues, we can better understand the implications for the overall effectiveness and applicability of 3DGS in real-world applications.

6.1 Challenges in Large-Scale and Sparse Scenarios

3D Gaussian Splatting (3DGS), while offering significant advancements in rendering technology, faces several challenges when applied to large-scale and sparse scenarios. One of the primary challenges is the substantial memory consumption resulting from the extensive use of 3D Gaussian splats. This high memory requirement can impede the scalability of 3DGS, particularly when dealing with large-scale environments where the number of Gaussians needed for accurate scene representation can become prohibitively large [20].

Moreover, the 4D Gaussian Splatting (4D-GS) method, an extension of 3DGS designed for dynamic scenes, encounters difficulties in handling large motions and complex scene changes. This limitation underscores the need for further advancements in the algorithm to enhance its adaptability and performance in dynamic environments [3].

Another significant challenge is the reliance on precise camera calibration for accurate feature extraction, as observed in methods such as Gaussian in the Wild (GS-W). This method assumes known camera poses, which may not always be available or accurate in real-world scenarios, potentially impacting the quality of the rendered outputs [7].

Additionally, the extensive use of 3D Gaussian splats in 3DGS can lead to substantial memory consumption, which poses a barrier to scalability, particularly in large-scale environments [20]. This challenge necessitates the development of effective compression and optimization strategies to facilitate the practical application of 3DGS in large-scale rendering tasks.

The Unified Gaussian Primitives Scene (UGPS) approach, while addressing certain aspects of scene representation, also highlights the challenges faced by 3DGS in efficiently handling extremely sparse conditions and highly complex scenes with limited data availability [54]. These challenges necessitate ongoing research to enhance the efficiency and applicability of 3DGS across diverse rendering scenarios.

6.2 Dynamic Scene Handling and Reconstruction

The application of 3D Gaussian Splatting (3DGS) in dynamic scene handling and reconstruction has gained considerable traction due to its ability to transform multi-view images into explicit 3D Gaussian representations, enabling efficient real-time rendering of novel views. This technique not only accelerates rendering speeds compared to traditional methods but also supports advanced editing tasks such as dynamic reconstruction, geometry editing, and physical simulation, thereby offering high-quality visual outputs while addressing the challenges of real-time performance. [36, 9]. However, several challenges and limitations persist in this domain, particularly related to computational overhead and the accuracy of motion representation.

One of the primary challenges in dynamic scene handling with 3DGS is the increased computational overhead associated with the K-means clustering algorithm used during training. This process, while essential for optimizing Gaussian splats, can lead to increased computational demands, which may hinder the real-time capabilities of 3DGS [55]. This challenge underscores the need for more efficient algorithms that can reduce computational overhead without compromising the quality of the rendered output.

Another significant challenge in dynamic scene handling is the reliance on optical flow predictions, as observed in the Motion-Aware 3D Gaussian Splatting method. While optical flow serves as a valuable motion prior, it can introduce noise into the rendering process, potentially affecting the temporal consistency and overall quality of the rendered scenes [31]. Addressing this limitation requires the development of more robust motion estimation techniques that can operate efficiently in real-time scenarios.

AI-generated, for reference only.

The use of K-means clustering during the training phase of 3DGS also contributes to computational overhead, which can hinder the method's applicability in real-time settings [55]. While this approach is effective in optimizing the distribution of Gaussian splats, it necessitates significant computational resources, highlighting the importance of developing more efficient training algorithms that can reduce the time and resource requirements.

Moreover, the dependency on external tools for generating reference images, as seen in methods like the CompGS framework, presents another limitation in dynamic scene handling. The reliance on external tools for generating reference images can introduce variability in the quality of the rendered output, necessitating more integrated solutions [31].

The need for improved motion handling capabilities in 3DGS is further emphasized by the development of the Motion-Aware 3D Gaussian Splatting method. This approach utilizes optical flow as a motion prior to enhance temporal consistency and reduce redundancy in Gaussian modeling, addressing the challenges of dynamic scene reconstruction [31].

6.3 Scalability and Resource Constraints

3D Gaussian Splatting (3DGS) presents notable advantages in rendering efficiency and quality, yet it faces significant challenges in terms of scalability and resource constraints, particularly when applied to large-scale environments. As the complexity and size of scenes increase, the demand for computational resources and memory can become prohibitively high, which negatively impacts the overall effectiveness and applicability of rendering methods in real-time scenarios. For instance, 3D Gaussian Splatting, while capable of producing excellent visual quality and fast training times, faces significant challenges due to its substantial memory requirements for storing and transmitting scene data. Recent advancements, such as the introduction of efficient primitive pruning, adaptive coefficient adjustment for directional radiance, and codebook-based quantization, have demonstrated a 27

One of the primary challenges with scaling 3DGS lies in the computational demands of the K-means clustering algorithm, which is integral to the optimization of Gaussian splats during the training process . This process can be resource-intensive, leading to increased memory consumption and computational time, which may limit the practical application of 3DGS in large-scale rendering tasks [20].

To address these scalability challenges, recent advancements have focused on optimizing the data structures and algorithms used in 3DGS. The development of the Compact 3D Gaussian Representation (C3DGR) exemplifies these efforts, as it utilizes a learnable masking strategy to enhance 3D scene representation while reducing computational load [20]. This method allows for more efficient processing and storage of large-scale scenes, addressing one of the primary limitations of 3DGS in resource-constrained environments.

Furthermore, the integration of advanced techniques, such as the Multi-Scale 3D Gaussian Splatting (MS3DGS) method, has significantly improved the scalability of 3DGS. By dynamically adjusting the size and number of Gaussian splats based on the rendering resolution, MS3DGS optimizes resource utilization, making it suitable for large-scale applications [21].

The ongoing evolution of 3D Gaussian Splatting methodologies continues to address the challenges associated with scalability and resource constraints, ensuring its applicability in a wide range of rendering scenarios. The development of techniques such as the Compact 3D Gaussian Representation (C3DGR) [20] and the Gaussian Opacity Field (GOF) [26] further enhances the efficiency and applicability of 3DGS in complex and resource-intensive environments.

By utilizing large models and sophisticated algorithmic techniques, 3D Gaussian Splatting (3DGS) has shown significant promise in addressing scalability and resource limitations, thereby facilitating its integration into a wide range of applications including virtual reality, interactive media, and gaming. This method leverages efficient training to convert multi-view images into explicit 3D Gaussian representations, enabling real-time rendering and high-quality textured mesh generation. Notably, 3DGS can produce detailed 3D content rapidly—achieving up to ten times the speed of traditional methods—while also reducing the reliance on manual labor in 3D asset creation, thus empowering both professional and non-professional users across various domains such as digital games, advertising, and the Metaverse. [28, 9, 10, 11, 12]. These advancements ensure that 3D

Gaussian Splatting remains a cutting-edge technology, capable of delivering high-quality visual results with optimized performance and resource utilization.

6.4 Advancements in Scene Understanding Techniques

The field of 3D Gaussian Splatting (3DGS) has witnessed significant advancements in scene understanding techniques, driven by the integration of large models and innovative methodologies. Recent advancements in 3D Gaussian Splatting (3DGS) have significantly improved its ability to generate detailed and accurate scene reconstructions, particularly in complex and dynamic environments. By leveraging techniques such as Gaussian Splatting and progressive optimization strategies, including geometry optimization and appearance refinement, these developments enable the integration of 3D priors, resulting in high-fidelity representations that effectively capture intricate details and textures. Additionally, the novel approach addresses issues like over-reconstruction, enhancing the rendering quality while maintaining efficient memory usage. [12, 39]

One of the key developments in this area is the integration of the GScream method, which employs depth-guided training and cross-attention feature regularization to enhance scene understanding and manipulation [30]. This approach enables the effective removal and manipulation of objects within a scene, significantly improving the accuracy and detail of scene representations.

The DNSplatter method further contributes to scene understanding by incorporating depth and normal priors, which enhance the fidelity of scene representation by providing additional geometric cues for rendering [19]. This method is particularly effective in complex scenarios where maintaining high-quality reconstruction is challenging.

The introduction of the Motion-Aware 3D Gaussian Splatting method marks a significant advancement in scene understanding techniques, as it enhances the capabilities of 3D Gaussian Splatting (3D-GS) by enabling efficient real-time rendering and manipulation of dynamic scenes. This method leverages explicit scene representation through Gaussian ellipsoids, facilitating applications in diverse fields such as robotics, urban mapping, and virtual reality, while also addressing the limitations of traditional rendering methods and improving the overall efficiency of novel view synthesis. [36, 44, 18, 9]. By incorporating optical flow as a reliable motion prior, this method enhances temporal consistency and reduces redundancy in Gaussian modeling, which is essential for effective scene understanding in dynamic environments .

The integration of large models within the 3D Gaussian Splatting framework has further enhanced scene understanding, particularly in dynamic and complex environments. This integration ensures that intricate details are accurately captured, providing a deeper understanding of dynamic scenes [15].

Moreover, the development of the 3D Convex Splatting (3DCS) technique has improved the efficiency of scene representation by utilizing fewer primitives while maintaining high-quality rendering . This approach is especially advantageous in resource-constrained environments, where optimizing scene representation is essential for enabling real-time applications, as demonstrated by advancements in Gaussian Splatting techniques that enhance rendering efficiency and maintain high fidelity even in large-scale, high-resolution scenarios. [56, 49, 57]

6.5 Advancements in Scene Understanding Techniques

Recent advancements in scene understanding techniques have significantly bolstered the capabilities of 3D Gaussian Splatting (3DGS), enhancing its application in various domains. One of the critical developments in this area is the integration of depth and normal priors, as demonstrated by the DNSplatter method. By incorporating geometric cues such as depth and normal information, this technique significantly improves the fidelity of scene representation, allowing for more accurate and detailed reconstructions [19].

The introduction of the Gaussian Opacity Field (GOF) method significantly enhances scene representation by aligning the training process with volume rendering techniques, thereby enabling more accurate geometry extraction from 3D Gaussian representations. This approach not only facilitates efficient and high-quality surface reconstruction in unbounded scenes but also improves consistency in rendering, ultimately leading to superior performance in novel view synthesis compared to existing methods. [12, 58, 26, 45]. This technique allows for adaptive mesh extraction, which better represents the geometric details of the scene, resulting in higher-quality visual outputs .

Moreover, the development of the Compact 3D Gaussian Representation (C3DGR) method has set a new standard in 3D scene representation by demonstrating improved rendering speed and reduced storage requirements while maintaining high-quality reconstruction [20]. This advancement is crucial in expanding the applicability of 3DGS in resource-constrained environments.

The DNSplatter method, which incorporates depth and normal priors, has significantly improved the fidelity of scene representation by enhancing detail accuracy [19]. This method is particularly effective in complex scenarios where maintaining high-quality reconstruction is challenging.

Moreover, the integration of large models within 3DGS, as demonstrated by the GScream method, has shown significant potential in enhancing scene understanding through efficient scene representation and manipulation [30]. This method employs depth-guided training and cross-attention feature regularization, enabling the effective removal of objects and enhancing overall scene comprehension.

Additionally, the development of the 3D Convex Splatting (3DCS) technique represents a significant advancement in scene representation, allowing for the efficient handling of complex geometries with fewer primitives and improved rendering efficiency . This method, along with the Gaussian Opacity Field (GOF) technique, ensures consistency with volume rendering during training, which facilitates adaptive mesh extraction and enhances the representation of geometric details [26].

6.6 Rendering Quality and Artifacts

Benchmark	Size	Domain	Task Format	Metric

Table 6: This table presents a comprehensive overview of representative benchmarks used in the evaluation of 3D Gaussian Splatting techniques. It details the size, domain, task format, and metric associated with each benchmark, providing a clear framework for assessing the rendering quality and artifact management in 3DGS applications.

3D Gaussian Splatting (3DGS) has emerged as a powerful technique in the realm of real-time and volumetric rendering, offering significant improvements in rendering speed and quality. Despite its advancements, this technology encounters specific challenges and limitations that can significantly impact the quality of the rendered output, especially when dealing with complex scenes. For instance, issues such as inaccurate geometry and the time-consuming nature of generating detailed 3D models can arise due to difficulties in integrating 3D priors into implicit representations. Additionally, the efficiency of rendering can be hindered by the need for the renderer to access the entire retained model, which complicates the mapping to specialized hardware and affects spatial coherence [12, 32]. Table 7 provides a detailed overview of the benchmarks employed to evaluate the rendering quality and artifact management in 3D Gaussian Splatting techniques.

One of the primary challenges associated with 3DGS is the occurrence of rendering artifacts, which can arise due to various factors such as inadequate sampling rates and complex lighting conditions. Techniques like Analytic-Splatting have been developed to tackle these issues by analytically computing the Gaussian integral within the pixel window, thus enhancing anti-aliasing and detail fidelity [22]. This method ensures that the rendered images are smooth and free of jagged edges, which are common artifacts in traditional rendering methods.

Another challenge in 3DGS is the representation of view-dependent colors and specular reflections, which can significantly impact the quality of rendered images. The Latent-SpecGS method addresses this issue by integrating latent neural descriptors within 3D Gaussians, allowing for high-quality rendering under complex lighting conditions [4]. This approach ensures that the rendered images maintain their visual fidelity, even in challenging lighting scenarios.

The Compact 3D Gaussian Representation (C3DGR) method has also made significant strides in enhancing rendering quality by reducing memory consumption while maintaining high-quality scene reconstructions [20]. This optimization is crucial for enabling 3DGS to be effectively deployed in resource-constrained environments, where efficient use of resources is paramount.

Moreover, the Hierarchical GS Compression (HGSC) technique has been developed to address the challenge of data size reduction while maintaining the quality of rendered outputs. By pruning unimportant Gaussians and employing a hierarchical compression strategy, HGSC effectively reduces data size without compromising rendering quality [2].

6.7 Scalability and Resource Constraints

The scalability and resource constraints associated with 3D Gaussian Splatting (3DGS) present significant challenges that must be addressed to fully realize the potential of this rendering technique in large-scale and dynamic environments. One of the primary challenges is the substantial memory consumption resulting from the extensive use of 3D Gaussian splats, which can impede the scalability of 3DGS, particularly in large-scale environments [20].

To address this challenge, recent advancements have focused on optimizing data structures and algorithms to enhance the scalability and performance of 3DGS. The introduction of the Compact 3D Gaussian Representation (C3DGR) method has been instrumental in reducing memory consumption while maintaining high-quality scene representation [20]. This method employs a learnable masking strategy that optimizes 3D scene representation, significantly reducing computational load without compromising rendering quality.

Another significant advancement is the development of the Hierarchical GS Compression (HGSC) technique, which effectively reduces data size by pruning unimportant Gaussians and utilizing a hierarchical compression strategy. This approach ensures that the quality of the rendered output is maintained while optimizing storage and transmission efficiency, which is crucial for real-time applications [2].

The Motion-Aware 3D Gaussian Splatting method addresses the challenge of dynamic scene handling by utilizing optical flow as a reliable motion prior. This approach enhances temporal consistency and reduces redundancy in Gaussian modeling, ensuring efficient rendering of dynamic scenes [31].

Moreover, the integration of large models within the 3DGS framework has significantly improved its scalability and performance. Large models, such as those used in the GS-W method, leverage extensive datasets to enhance the accuracy and detail of scene reconstructions, thereby expanding the applicability of 3DGS across various domains [7].

The development of the Compact 3D Gaussian Representation (C3DGR) method further contributes to scalability by optimizing the representation of 3D scenes. This method reduces memory consumption and computational load, making it a practical solution for large-scale rendering tasks [20]. Additionally, the hierarchical GS Compression (HGSC) technique effectively reduces data size by pruning unimportant Gaussians and employing a multi-level compression strategy, ensuring that the quality of the rendered output is maintained while optimizing storage requirements [2].

Moreover, the integration of the Gaussian Opacity Field (GOF) technique has enhanced the accuracy and efficiency of scene representation by ensuring consistency with volume rendering during training, allowing for adaptive mesh extraction that better represents the scene's geometric details . This method effectively tackles the challenge of efficiently representing intricate geometries within large-scale environments by optimizing the 3D Gaussian Splatting (3DGS) technique, significantly enhancing its scalability. Specifically, through innovations such as selective Gaussian densification and a pruning mechanism for redundant Gaussians, the approach enables high-resolution scene representation while reducing computational demands and storage requirements. As a result, this advancement not only streamlines the training and rendering processes but also maintains high fidelity in visual outputs, positioning 3DGS as a viable solution for real-time rendering in expansive settings. [57, 9]

The ongoing advancements in optimization techniques, particularly the introduction of the Gradient-Driven 3D Segmentation (GD3DS) method, have significantly improved the scalability and performance of 3D Gaussian Splatting (3DGS) by enabling faster convergence and enhanced detail refinement in 3D content generation, thereby facilitating the creation of high-quality textured meshes from single-view images in a fraction of the time compared to traditional methods. [37, 12, 11, 9]. By introducing a gradient-driven approach to 3D segmentation, this method significantly reduces computational load while maintaining high-quality scene representation, making it a valuable tool for real-time rendering applications .

The continuous evolution of 3DGS methodologies, such as the development of the Multi-Scale 3D Gaussian Splatting (MS3DGS) method [21], the Gaussian Opacity Field (GOF) [26], and the Compact 3D Gaussian Representation (C3DGR) [20], underscores the commitment to advancing the scalability and efficiency of 3DGS. These innovations ensure that 3DGS remains a cutting-edge technology in the realm of real-time and volumetric rendering, offering robust solutions for complex scene representation and manipulation.

7 Challenges and Limitations

7.1 Challenges in Large-Scale and Sparse Scenarios

Implementing 3D Gaussian Splatting (3DGS) in large-scale and sparse environments faces substantial challenges, primarily due to high memory demands from extensive use of 3D Gaussian splats, which can hinder scalability in scenarios requiring numerous Gaussians for precise scene representation [20]. The 4D Gaussian Splatting (4D-GS) method, adapted for dynamic scenes, encounters difficulties with large motions and complex transformations, necessitating algorithmic advancements for improved adaptability [3]. Additionally, methods like Gaussian in the Wild (GS-W) require precise camera calibration, where inaccuracies can degrade rendering quality [7]. The Unified Gaussian Primitives Scene (UGPS) approach also underscores challenges in managing sparse conditions and complex scenes efficiently, highlighting the need for continued research to enhance 3DGS applicability across diverse scenarios [35].

7.2 Dynamic Scene Handling and Reconstruction

3D Gaussian Splatting (3DGS) is recognized for its potential in dynamic scene handling and reconstruction, offering real-time performance with high-quality visual outputs. However, computational overhead and motion representation accuracy remain significant hurdles. Errors from local affine approximations can impair photo-realistic rendering, while physics-grounded motion synthesis shows promise in creating realistic object behaviors but presents complexities in optimizing motion within dynamic scenes [15, 9, 52, 59, 14]. The computational demands of the K-means clustering algorithm, crucial for optimizing Gaussian splats, challenge real-time capabilities [55]. Moreover, reliance on optical flow predictions in methods like Motion-Aware 3D Gaussian Splatting can introduce noise affecting temporal consistency [31], and dependency on external tools for reference image generation, as seen in the CompGS framework, can lead to variability in rendering quality, necessitating more integrated approaches [31].

7.3 Scalability and Resource Constraints

Despite the rendering efficiency and visual quality offered by 3D Gaussian Splatting (3DGS), its application in large-scale environments is challenged by high computational demands. Innovations like the 'EfficientGS' approach aim to address Gaussian over-proliferation and enhance representational efficiency by limiting Gaussian growth and employing pruning mechanisms, thereby reducing resource requirements without compromising rendering fidelity [57, 9]. The K-means clustering algorithm's computational demands contribute to increased memory consumption and processing time, limiting large-scale rendering applications [20]. The Compact 3D Gaussian Representation (C3DGR) addresses these issues by using a learnable masking strategy to enhance scene representation while reducing computational load [20]. Additionally, the Multi-Scale 3D Gaussian Splatting (MS3DGS) method dynamically adjusts Gaussian splat size and number based on rendering resolution, optimizing resource utilization for large-scale applications [21]. Techniques such as C3DGR [20] and the Gaussian Opacity Field (GOF) [26] further enhance 3DGS efficiency in complex environments. Leveraging large models and advanced algorithms, 3DGS overcomes scalability challenges, supporting applications in virtual reality, interactive media, and gaming. Recent advancements have cemented its status as a leading technology in computer graphics, enabling rapid rendering of high-quality visual content through innovative Gaussian ellipsoids for scene modeling, accelerating novel view synthesis compared to traditional methods like Neural Radiance Fields (NeRF) [36, 37, 18, 9, 44].

Benchmark	Size	Domain	Task Format	Metric

Table 7: This table presents a comprehensive overview of representative benchmarks used in the evaluation of 3D Gaussian Splatting techniques. It details the size, domain, task format, and metric associated with each benchmark, providing a clear framework for assessing the rendering quality and artifact management in 3DGS applications.

7.4 Rendering Quality and Artifacts

8 Future Directions

The trajectory of 3D Gaussian Splatting (3DGS) is poised for transformative advancements in rendering technology through the integration of innovative methodologies and frameworks. This integration is pivotal for enhancing scene representation and rendering quality, thereby expanding 3DGS's performance and applicability across diverse contexts.

8.1 Integration with Other Technologies

The fusion of 3DGS with advanced technologies offers substantial prospects for augmenting its capabilities, particularly in rendering and scene comprehension. Future research should target the incorporation of sophisticated 3D priors and explicit geometry supervision to elevate scene representation and accuracy in intricate environments [15].

Emerging appearance modeling techniques, such as Latent-SpecGS, which embed latent neural descriptors within 3D Gaussians, highlight 3DGS's potential for superior rendering under complex lighting scenarios [4]. Techniques like DNSplatter, which utilize depth and normal priors, have markedly enhanced scene fidelity by capitalizing on geometric cues [19]. Further exploration in this domain could yield more resilient scene reconstructions, especially in challenging scenarios.

The Compact 3D Gaussian Representation (C3DGR) method exemplifies efforts to refine data structures and algorithms, minimizing memory consumption while preserving high-quality scene representation [20]. This progress is crucial for broadening 3DGS's applicability in environments with limited resources.

Integrating large models within the 3DGS framework has demonstrated potential in enhancing scene comprehension, particularly in dynamic settings, by facilitating detailed extraction from extensive datasets [15]. Moreover, the 3D Convex Splatting (3DCS) technique boosts efficiency by deploying fewer primitives while maintaining high-quality rendering, advantageous for real-time applications in resource-constrained environments [56, 51, 49, 12, 57].

The evolution of 3DGS methodologies, underscored by innovations such as SaRO-GS, DNSplatter [19], and C3DGR [20], continues to enhance its capabilities, offering robust solutions for complex scene representation and manipulation. These advancements signify the potential of 3DGS to revolutionize real-time and volumetric rendering, yielding high-quality visual results with optimized performance and resource utilization.

8.2 Scalability and Performance Optimization

The ongoing evolution of 3DGS has unveiled multiple strategies for enhancing scalability and performance, pivotal for its deployment in real-time and large-scale rendering applications. By leveraging explicit representations of 3D scenes through millions of learnable Gaussian ellipsoids, 3DGS facilitates rapid rendering and advanced editing capabilities, including dynamic reconstruction and geometry manipulation. Addressing challenges and exploring new technological avenues is essential for harnessing 3DGS's full potential in applications ranging from virtual reality to interactive media [36, 17, 13, 9].

Scalability and performance in 3DGS can be enhanced through the development of efficient data structures and algorithms. The C3DGR method employs a learnable masking strategy to optimize scene representation while significantly reducing computational load and memory consumption [20], crucial for resource-constrained environments.

The Multi-Scale 3D Gaussian Splatting (MS3DGS) method optimizes resource utilization by dynamically adjusting the size and number of Gaussian splats based on rendering resolution, making it suitable for large-scale applications [21]. Additionally, the Hierarchical Gaussian Splatting Compression (HGSC) technique effectively reduces data size by pruning unimportant Gaussians and employing a hierarchical compression strategy, crucial for efficient storage and transmission in real-time applications [2].

The Gradient-Driven 3D Segmentation (GD3DS) method enhances scalability and performance by introducing a gradient-driven approach to 3D segmentation, significantly reducing computational load while maintaining high-quality scene representation. This advancement is essential for generating high-quality 3D content in fields such as digital gaming, advertising, and the Metaverse, where rapid and cost-effective asset creation is vital [37, 12, 11, 9].

Furthermore, the Motion-Aware 3D Gaussian Splatting method demonstrates 3DGS's capability for high-quality rendering under complex lighting conditions while ensuring temporal consistency and reducing redundancy in Gaussian modeling [31]. Utilizing optical flow as a reliable motion prior, this method addresses critical challenges in dynamic scene reconstruction.

The continuous evolution of 3DGS methodologies, exemplified by innovations such as C3DGR [20], HGSC [2], and the Motion-Aware 3D Gaussian Splatting method [31], underscores the commitment to advancing scalability and efficiency. These advancements ensure that 3D Gaussian Splatting remains at the forefront of rendering technology, providing robust solutions for complex scene representation and manipulation across various applications in computer graphics.

9 Future Directions

9.1 Integration with Other Technologies

Integrating 3D Gaussian Splatting (3DGS) with emerging technologies offers significant advancements in rendering and scene understanding. Combining 3DGS with neural network-based approaches like Neural Radiance Fields (NeRFs) can produce high-quality visuals while reducing computational overhead, enhancing image fidelity, and addressing storage limitations, making it suitable for real-time and resource-constrained environments [60, 10, 9]. Advanced illumination modeling techniques, such as Latent-SpecGS, which incorporate latent neural descriptors within 3D Gaussians, further improve rendering quality under complex lighting conditions by enhancing view-dependent colors and specular reflections [4].

Large model integration within the 3DGS framework enhances scene understanding and representation in dynamic environments, crucial for robotics, virtual reality, and augmented reality, where precise scene comprehension is essential [15]. Techniques like the Compact 3D Gaussian Representation (C3DGR) optimize data structures and algorithms, reducing memory consumption while maintaining high-quality scene representation, vital for resource-constrained settings [20]. The Multi-Scale 3D Gaussian Splatting (MS3DGS) method improves scalability and performance by dynamically adjusting Gaussian splats based on rendering resolution, optimizing resource utilization for large-scale applications [21].

9.2 Applications in Diverse Fields

3D Gaussian Splatting (3DGS) holds potential for expansion into fields requiring high-fidelity scene representation and real-time processing, such as robotics, urban mapping, autonomous navigation, and extended reality (XR). Its versatility facilitates real-time rendering and explicit scene representation without neural networks, enhancing 3D content creation [15, 28, 18, 9, 11]. In robotics, 3DGS improves Simultaneous Localization and Mapping (SLAM) systems' accuracy and efficiency, benefiting real-time scene understanding and navigation [15].

In urban mapping, 3DGS manages large-scale environments and intricate geometries with high fidelity, crucial for capturing and representing urban landscapes. Innovations like HO-Gaussian integrate grid-based volumes and neural warping, enhancing rendering quality across multiple views and eliminating dependencies on initial Structure-from-Motion points, enabling real-time, photorealistic rendering in complex urban settings [61, 62, 63]. The Gaussian Opacity Field (GOF) ensures consistency with volume rendering, allowing adaptive mesh extraction for better geometric detail representation, essential for urban planning and infrastructure development.

In extended reality (XR), 3DGS models complex 3D scenes with Gaussian functions, seamlessly integrating virtual elements with real-world environments, enhancing realism and interactivity in XR applications [15]. The integration of large models within the 3DGS framework enhances capabilities across domains, establishing 3DGS as a leading-edge technology in computer graphics for dynamic reconstruction, geometry editing, and physical simulation [36, 44, 18, 9].

9.3 Scalability and Performance Optimization

The evolution of 3D Gaussian Splatting (3DGS) techniques enhances scalability and performance optimization, crucial for large-scale and resource-constrained applications. A primary challenge is the significant memory consumption of extensive 3D Gaussian splats, hindering scalability [20]. Recent advancements focus on optimizing data structures and algorithms to improve 3DGS scalability and performance.

The Compact 3D Gaussian Representation (C3DGR) method exemplifies these efforts, utilizing a learnable masking strategy to enhance scene representation while reducing computational load [20]. This method allows efficient processing and storage of large-scale scenes, addressing 3DGS's limitations in resource-constrained environments. The Multi-Scale 3D Gaussian Splatting (MS3DGS) method further improves scalability by dynamically adjusting Gaussian splats based on rendering resolution, optimizing resource utilization for large-scale applications [21].

Continuous development of 3DGS methodologies addresses scalability and resource constraints, ensuring broad applicability in various rendering scenarios. Techniques like C3DGR and the Gaussian Opacity Field (GOF) enhance 3DGS efficiency and applicability in complex, resource-intensive environments [20, 26]. By leveraging large models and advanced algorithms, 3DGS effectively tackles scalability and resource limitations, facilitating applications in robotics, urban mapping, and extended reality. This innovative approach allows rapid transformation of multi-view images into explicit 3D representations for real-time rendering, significantly enhancing 3D content creation efficiency, as evidenced by frameworks like DreamGaussian, producing high-quality textured meshes in minutes [28, 11, 9]. These advancements ensure 3D Gaussian Splatting remains at the forefront of rendering technology, providing robust solutions for complex scene representation and manipulation across various computer graphics applications.

10 Conclusion

This survey has delved into the transformative domain of 3D Gaussian Splatting (3DGS), highlighting its pivotal role in advancing real-time and volumetric rendering. By leveraging Gaussian functions, 3DGS enhances scene representation and rendering efficiency, surpassing traditional methods in quality and speed. Its comparative advantages over Neural Radiance Fields (NeRFs) are evident, particularly in dynamic and large-scale environments, where techniques like GScream and Motion-Aware 3D Gaussian Splatting demonstrate robust handling of dynamic scenes and complex geometries.

In optimizing scene representation and efficiency, 3DGS excels through innovations such as SpotLessSplats (SLS) and the Gaussian Opacity Field (GOF), which significantly improve light transport and rendering quality. These advancements position 3DGS as a revolutionary force in real-time rendering, offering effective solutions across diverse computer graphics applications.

Further enhancements in rendering quality, through methods like the RGB decoder function, Texture-GS, and Analytic-Splatting, address persistent challenges such as color inconsistencies and over-reconstruction, ensuring consistent delivery of high-fidelity visual results. The versatility of 3DGS is particularly notable in virtual reality, interactive media, and gaming, where innovations like SCGS, GScream, and GaussStudio facilitate the creation of immersive digital environments.

The integration of large models within the 3DGS framework has markedly improved scene understanding, particularly in dynamic and complex settings, ensuring accurate representation of intricate details. Despite these achievements, challenges in scalability, resource constraints, and rendering quality persist. Continued innovation in techniques like advanced clustering algorithms, illumination modeling, and hierarchical compression strategies will be crucial for enhancing the efficiency and robustness of 3DGS, solidifying its status as a cornerstone of modern computer graphics.

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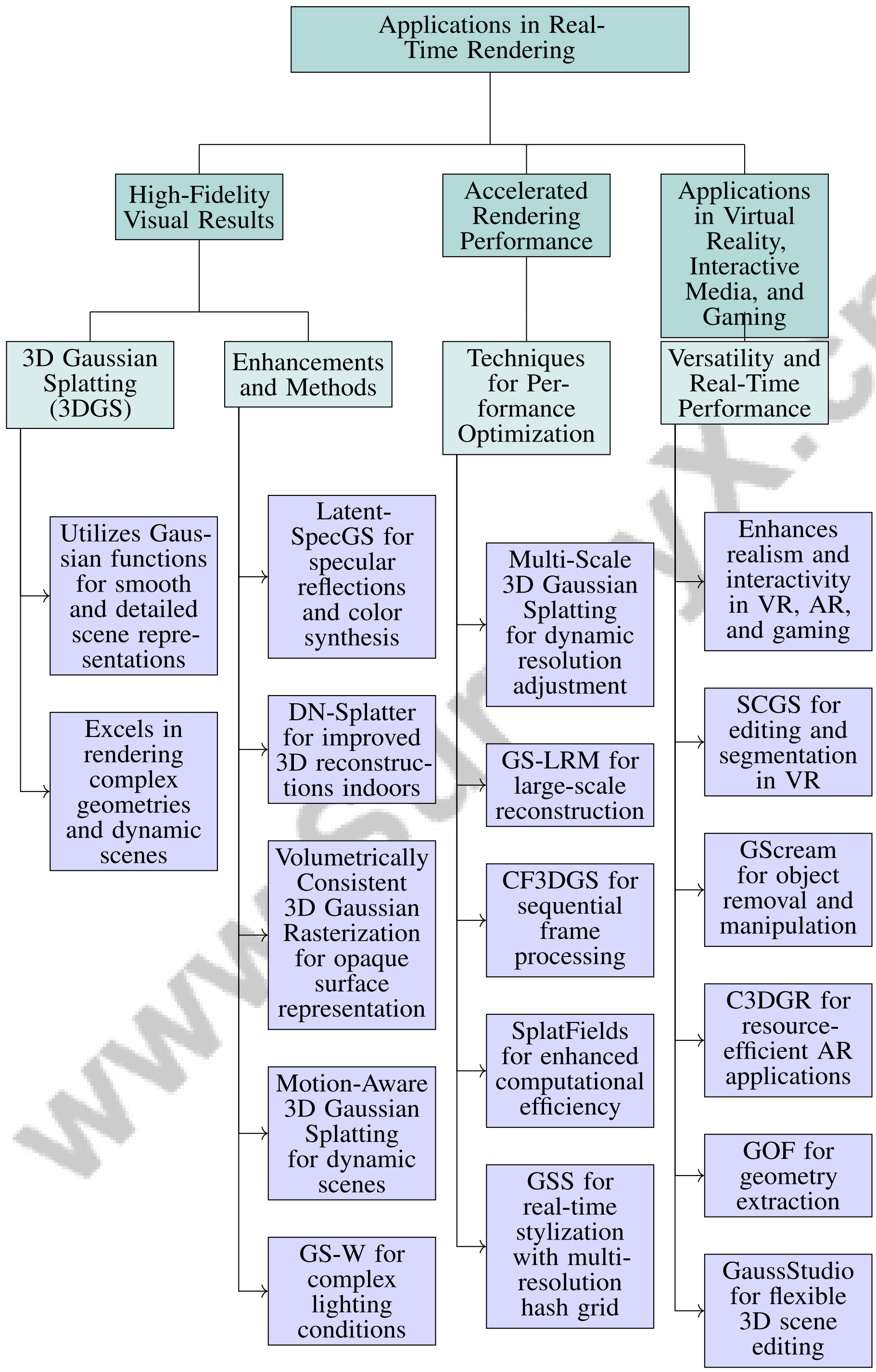

Figure 2: This figure illustrates the hierarchical categorization of applications of 3D Gaussian Splatting (3DGS) in real-time rendering, highlighting its contributions to high-fidelity visual results, accelerated rendering performance, and versatility in virtual reality, interactive media, and gaming.

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