

# AdR-Gaussian: Accelerating Gaussian Splatting with Adaptive Radius

XINZHE WANG\*, Shanghai Jiao Tong University, China

RAN YI\*, Shanghai Jiao Tong University, China

LIZHUANG MA†, Dept. of Computer Science and Engineering, Shanghai Jiao Tong University, China



Fig. 1. Our method achieves a significant improvement in rendering speed for the 3D Gaussian Splatting model with equivalent or better quality. The key to this performance is the lossless early culling of Gaussian-Tile pairs based on adaptive radius of projected Gaussians, which narrows the rendering range for each Gaussian by removing tiles with low splatting opacity. Additionally, we propose a load balancing approach to further accelerate rendering.

3D Gaussian Splatting (3DGS) is a recent explicit 3D representation that has achieved high-quality reconstruction and real-time rendering of complex scenes. However, the rasterization pipeline still suffers from unnecessary overhead resulting from avoidable serial Gaussian culling, and uneven load due to the distinct number of Gaussian to be rendered across pixels, which hinders wider promotion and application of 3DGS. In order to accelerate Gaussian splatting, we propose *AdR-Gaussian*, which moves part of serial culling in *Render* stage into the earlier *Preprocess* stage to enable parallel culling, employing adaptive radius to narrow the rendering pixel range for each Gaussian, and introduces a load balancing method to minimize thread waiting time during the pixel-parallel rendering. Our contributions are threefold, achieving a rendering speed of 310% while maintaining equivalent or even better quality than the state-of-the-art. Firstly, we propose to early cull Gaussian-Tile pairs of low splatting opacity based on an adaptive radius in the Gaussian-parallel *Preprocess* stage, which reduces the number of affected tile through the Gaussian bounding circle, thus reducing unnecessary overhead and achieving faster rendering speed. Secondly, we further propose early culling based on axis-aligned bounding box for Gaussian splatting, which achieves a more significant reduction in ineffective expenses by accurately calculating the Gaussian size in the 2D directions. Thirdly, we propose a balancing algorithm for pixel thread load, which compresses

the information of heavy-load pixels to reduce thread waiting time, and enhance information of light-load pixels to hedge against rendering quality loss. Experiments on three datasets demonstrate that our algorithm can significantly improve the Gaussian Splatting rendering speed.

CCS Concepts: • Computing methodologies → Rendering; Rasterization.

Additional Key Words and Phrases: Novel view synthesis, Gaussian splatting, Real-time rendering, Bounding box

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## 1 INTRODUCTION

Novel view synthesis (NVS) aims to generate photorealistic rendering results of novel views given a set of input views, which has attracted significant attention due to its wide applications in various domains, including model design [Chen et al. 2023a; Tang et al. 2023], autonomous driving [Cao et al. 2024; Matsuki et al. 2023], and virtual reality [Qian et al. 2023; Wang et al. 2023]. The 3D Gaussian Splatting (3DGS) model [Kerbl et al. 2023] is a recent 3D representation that employs a set of 3D Gaussian ellipsoids to model 3D scenes, achieving high-quality real-time rendering of complex scenes. However, the Gaussian rasterization pipeline suffers from unnecessary overhead resulting from avoidable serial Gaussian culling and uneven load due to the distinct number of Gaussian to be rendered across pixels, which limits the rendering speed of 3D Gaussian and hinders its wider applications.

The Gaussian rasterization pipeline currently suffers from unnecessary overhead and uneven load due to the following reasons, which are mainly related to the *Render* stage that performs pixel-parallel point-based rendering in the pipeline: (1) *Unnecessary overhead of serial culling*: Gaussian-Pixel pairs with low splatting opacity

\*Both authors contributed equally to this research.

†Corresponding author.

Authors' Contact Information: Xinzhe Wang, Shanghai Jiao Tong University, China, [hirozwang@sjtu.edu.cn](mailto:hirozwang@sjtu.edu.cn); Ran Yi, Shanghai Jiao Tong University, China, [ranyi@sjtu.edu.cn](mailto:ranyi@sjtu.edu.cn); Lizhuang Ma, Dept. of Computer Science and Engineering, Shanghai Jiao Tong University, China, [ma-lz@cs.sjtu.edu.cn](mailto:ma-lz@cs.sjtu.edu.cn).

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are culled serially during the *Render* stage, but some of the serial culling could be performed in parallel, thus current culling method results in a significant performance penalty for the Gaussian-serial-based alpha blending. (2) *Uneven load across pixel threads*: Since the *Render* stage calculates the color of each pixel in parallel, and the number of Gaussian to be rendered serially for each pixel are different, different pixel threads face distinctly different loads (computational time), which causes long thread waiting time and low rendering efficiency. The existing approaches [Fan et al. 2023; Girish et al. 2023; Hamdi et al. 2024; Lee et al. 2023] that accelerate rendering by reducing the total number of Gaussian sacrifices the rendering quality, and fails to effectively handle the aforementioned problems, leaving room for further improvements of rendering speed.

To address these issues, we propose *AdR-Gaussian*, which employs lossless early culling with adaptive radius and axis-aligned bounding box tailored for Gaussian Splatting to narrow the rendering pixel range of each Gaussian, and proposes a load balancing method to minimize thread waiting time. Our *AdR-Gaussian* consists of two phases: a early-culling phase and a load balancing phase. Firstly, we propose to move part of serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage. We early cull Gaussian-Tile pairs with low splatting opacity during *Preprocess* stage, which is conducted in parallel for each Gaussian. Specifically, we propose *adaptive radius* and *axis-aligned bounding box* for Gaussian Splatting to early cull Gaussian-Tile pairs, which achieves acceleration of Gaussian rendering without rendering quality loss. Furthermore, to address the issue of uneven computational costs across different pixel threads in Gaussian rendering, we propose a *load balancing* algorithm for pixel threads. By quantifying the variance of the number of rendered Gaussian required for each pixel, we reduce the number of Gaussian for heavy-load pixels to reduce thread waiting time, and increase that for light-load pixels to hedge against the quality loss, achieving higher rendering efficiency.

In summary, we make the following contributions:

- We propose *AdR-Gaussian*, a novel Gaussian Splatting rendering acceleration method, which moves part of serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage, and balances load across different pixel threads.
- We early cull Gaussian-Tile pairs with low splatting opacity during the Gaussian-parallel *Preprocess* stage based on adaptive radius, defined as the bounding circle radius of an ellipse constructed by minimum splatting opacity, which achieves acceleration without rendering quality loss.
- We propose early culling based on axis-aligned bounding box tailored for Gaussian Splatting, which achieves different extents of culling in horizontal and vertical directions, and further improves culling efficiency.
- We propose a load balancing algorithm for pixel thread, which reduces the variance of the number of Gaussian to be rendered serially for each pixel, to reduce thread waiting time and further accelerate rendering.

Experiments on three datasets demonstrate our approach significantly enhances the Gaussian Splatting rendering speed, achieving 310% acceleration on average, while achieving equivalent or superior rendering quality. Specifically, for complex scenes in the

Mip-NeRF360 dataset [Barron et al. 2022], our method attains an average 590FPS rendering speed on a single NVIDIA RTX3090 GPU.

## 2 RELATED WORKS

We first present a brief overview of traditional novel view synthesis approaches, followed by a discussion on the neural radiance fields (NeRF) and the 3D Gaussian Splatting (3DGS) model. Given that both of the latter two fields are extensive, we focus on the rendering acceleration methods, which are most pertinent to our work. For a more comprehensive information and analysis, readers are referred to recent surveys [Chen and Wang 2024; Tewari et al. 2022].

### 2.1 Traditional Novel View Synthesis

Early novel view synthesis methods often rely on physical principles, such as light field sampling interpolation [Gortler et al. 1996; Levoy and Hanrahan 1996], mesh representation [Buehler et al. 2001; Debevec et al. 1996], and voxel representation [Flynn et al. 2019; Mildenhall et al. 2019]. However, these methods are based on discrete sampling and suffer from issues including poor reconstruction quality, dependence on initialization data, and high spatial complexity. With the development of neural networks, methods such as signed distance fields [Jiang et al. 2020; Park et al. 2019], 3D occupancy fields [Niemeyer et al. 2020], and differentiable rendering [Sitzmann et al. 2019] have been introduced to model 3D scenes from 2D images through implicit representation. Nevertheless, for the synthesis of high-resolution and high-quality novel views in complex geometric scenes, all these methods proved challenging until the introduction of NeRF.

### 2.2 Fast NeRF Rendering

NeRF [Mildenhall et al. 2021] employs 5D parameters including position and camera direction to obtain RGBA information via multi-layer perceptron (MLP). However, due to the use of volume rendering approach and the complexity of MLP, NeRF is inefficient, thus lots of research focus on accelerating its rendering speed.

NSVF [Liu et al. 2020] introduces Octree with empty space skipping and early ray termination strategy to minimize invalid sampling. RT-Octree [Shu et al. 2023] uses low-SPP Monte Carlo rendering to reduce arbitrary sampling followed by denoising. KiloNeRF [Reiser et al. 2021] distills the large MLP into thousands of smaller MLPs, thereby reducing MLP query costs. Other approaches cache information using data structures [Hedman et al. 2021; Yu et al. 2021] or hash encoding [Hu et al. 2023; Reiser et al. 2023], further reducing query costs by minimizing MLP usage. Furthermore, some work also employs GPU-friendly implementations [Chen et al. 2023b] to achieve even faster rendering speeds.

However, these real-time NeRF rendering often sacrifice other metrics, such as slower training caused by the establishing and updating of data structures. In contrast, the recently proposed 3DGS model achieves high-quality and real-time rendering, and fast training through differentiable, GPU-friendly Gaussian ellipsoids, and our method aims to further improve the rendering speed of 3DGS.

### 2.3 Fast 3DGS Rendering

The 3DGS model [Kerbl et al. 2023] is a recent explicit 3D representation employing a set of 3D Gaussian ellipsoids, which simultaneously achieve high-quality rendering, competitive training time, and real-time rendering. The 3DGS model trains and fits the scene via Gaussian's differentiability, and achieves efficient rendering through Gaussian's explicit structure. Owing to its high-quality real-time rendering capability, a large amount of application researches have emerged [Szymanowicz et al. 2023; Wu et al. 2023; Zhou et al. 2024], while a few efforts focus on optimizing its storage [Niedermayr et al. 2024] or synthesis quality [Yu et al. 2023].

Some recent researches accelerate the rendering speed of 3DGS by reducing the number of Gaussian. EAGLES [Girish et al. 2023] suppresses the frequency of Gaussian densification via convergence curve, thereby directly decelerating the growth rate of Gaussian number. GES [Hamdi et al. 2024] introduces learning tendency from low frequency to high frequency, limiting the creation of Gaussian for high-frequency information. Additionally, other methods reduce the overall number of Gaussian by pruning those with lower significance. LightGaussian [Fan et al. 2023] assesses Gaussian importance based on its volume, opacity, and the number of pixel affected, under which high-ratio pruning retains decent quality. C3DGS [Lee et al. 2023] employs Gaussian scaling and opacity to generate removal mask, and incorporates masking loss into the loss function to strike a balance between synthesis quality and rendering speed.

However, current fast 3DGS rendering methods lack attention to the optimization of rasterization pipeline of 3DGS, which often result in limited improvements in rendering speed and degenerated quality caused by the reduction of Gaussian number. In contrast, our *AdR-Gaussian* focuses on optimizing the rasterization pipeline of 3DGS, and can significantly accelerate rendering with equivalent or better quality.

## 3 PRELIMINARIES AND ANALYSIS

### 3.1 3D Gaussian Representation

As an explicit 3D representation, 3DGS utilizes a set of 3D Gaussian ellipsoids with geometric and material properties to model the scene.

The geometry of each Gaussian is defined by its center position  $\mathbf{X}_0$ , and a 3D covariance matrix  $\Sigma$  defined in world space [Zwicker et al. 2001]:

$$G(\mathbf{X}) = e^{-\frac{1}{2}(\mathbf{X}-\mathbf{X}_0)^T \Sigma^{-1} (\mathbf{X}-\mathbf{X}_0)}, \quad (1)$$

where  $\mathbf{X}$  is a sampling point and the covariance matrix is further decomposed into a scaling and a rotation matrix.

The material information of each Gaussian includes opacity attribute  $\sigma$ , and spherical harmonics (SH) (representing color). To render from a specific perspective, based on the concept of Elliptic Weighted Average (EWA) [Zwicker et al. 2002], the splatting opacity  $\alpha$  for each Gaussian-Pixel pair is calculated by the opacity  $\sigma$ , Gaussian-pixel 2D distance  $\mathbf{x}$  and projected covariance matrix  $\Sigma'$ :

$$\alpha = \sigma e^{-\frac{1}{2}\mathbf{x}^T \Sigma'^{-1} \mathbf{x}}. \quad (2)$$

With Gaussian color  $c$  calculated from SH, and splatting opacity  $\alpha$ , the color of each pixel is calculated by alpha blending  $N$  related

Gaussians:

$$C = \sum_{i \in N} c_i \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j). \quad (3)$$

Such an alpha blending idea is based on the neural point-based approach [Kopanas et al. 2021], and has achieved very high efficiency through a tile-based soft rasterizer.

### 3.2 Gaussian Rasterization

Inspired by the soft rasterization approaches [Lassner and Zollhöfer 2021], the Gaussian rasterization adopts a tile-based and sorting renderer. The screen is firstly splitted into  $16 \times 16$  tiles. And then each Gaussian is linked to the tiles it overlaps with. The Gaussians in each tile are sorted by view space depth, and then the color is calculated by alpha blending.

**3.2.1 Rasterization Pipeline.** The rasterization pipeline consists of six stages: *Preprocess*, *InclusiveSum*, *DuplicateWithKeys*, *SortPairs*, *IdentifyTileRanges*, and *Render*. Their roles are as follows:

1) *Preprocess* stage: preprocesses each Gaussian in parallel to obtain the perspective-related data needed for rendering.

2-3) *InclusiveSum* and *DuplicateWithKeys* stages: process each Gaussian in parallel. For each Gaussian, these stages obtain the information of which tiles it covers.

4-5) *SortPairs* and *IdentifyTileRanges* stages: aim to sort the Gaussians in each tile by depth, and determine the start and end indices of the Gaussian within each tile for rendering.

6) *Render* stage: calculates the color of each pixel in parallel, using a point-based approach to sequentially render the Gaussians within the corresponding tile by alpha blending.

**3.2.2 Rasterization Costs Analysis.** The computational cost  $\mathcal{E}$  required in the Gaussian rasterization pipeline can be categorized into three parts, depending on the degree of GPU parallelism:

$$\mathcal{E} = \mathcal{E}_g + \mathcal{E}_n + \mathcal{E}_p, \quad (4)$$

where (1)  $\mathcal{E}_g$  denotes the Gaussian-level parallel cost of the 1-3th stages, for preprocessing Gaussians to obtain their color and other perspective related attributes; (2)  $\mathcal{E}_n$  represents the Gaussian-Tile pair parallel cost of the 4-5th stages, for identifying Gaussian range for each tile; and (3)  $\mathcal{E}_p$  represents the pixel-level parallel cost of the 6-th stage, for the point-based rendering.

Due to the serial alpha blending of Gaussians in the *Render* stage, and the complexity of calculating the splatting color for each Gaussian-Pixel pair, this stage has the largest computational time proportion, i.e.,  $\mathcal{E}_p$  takes the largest proportion (over 50%) in  $\mathcal{E}$ . To accelerate the *Render* stage, we propose *AdR-Gaussian*, which culs pairs of Gaussian-Tile with low splatting opacity earlier in *Preprocess* stage, and balances the computational costs of pixel thread.

## 4 METHOD

### 4.1 Overview

Our main goal is to reduce the computational cost  $\mathcal{E}$  of the Gaussian rasterization pipeline (Sec. 3.2), which can be decomposed into three types of costs as in Eq. (4). Among these three types of costs, the pixel-level parallel cost  $\mathcal{E}_p$  of the *Render* stage (Sec. 3.2.1) takes the largest proportion. This is because the pixel-parallel *Render* stage

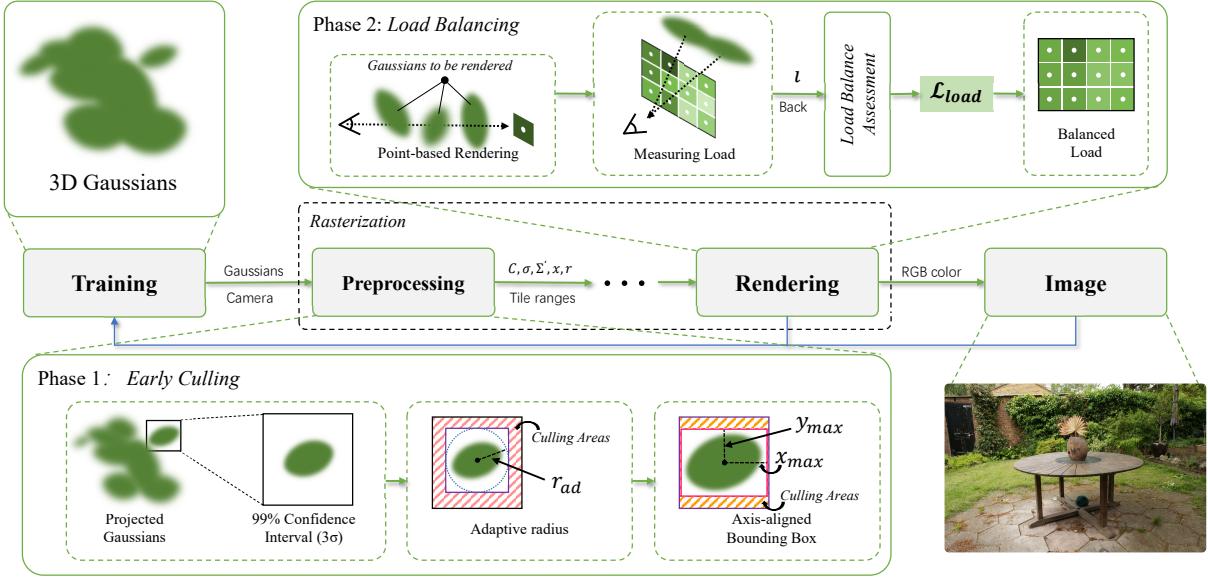


Fig. 2. Pipeline overview. We propose *AdR-Gaussian*, designed to accelerate the rendering process of 3DGS. In this approach, we propose to move part of serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage. We early cull Gaussian-Tile with low splatting opacity based on adaptive radius, which is the bounding circle radius of the ellipse constructed by minimum splatting opacity. Furthermore, we employ *axis-aligned bounding box* tailored for Gaussian Splatting to improve culling efficiency. To address the uneven load issue, we propose a load balancing algorithm for pixel threads, which reduces the number of Gaussian for heavy-load pixels to reduce thread waiting time, and increases that for light-load pixels to hedge against quality loss.

has a high degree of seriality in the handling of Gaussians, *i.e.*, to calculate pixel color based on alpha blending, it necessitates the sequential traversal of all Gaussians within the corresponding tile. Therefore, we aim to accelerate the pixel-parallel *Render* stage, by moving part of serial culling earlier into Gaussian-parallel stages, and balancing the computational costs across parallel pixel threads.

As shown in Fig. 2, the pipeline of our *AdR-Gaussian* consists of two distinct phases:

**Phase 1: Early Culling (Sec. 4.2, 4.3).** We move part of serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage. We early cull Gaussian-Tile pairs with low splatting opacity during *Preprocess* stage, which is conducted in parallel for each Gaussian, and reduces the number of Gaussian-Tile to be processed in the later stages. Specifically, we propose two early culling algorithms: 1) we early cull pairs of Gaussian-Tile with low splatting opacity based on adaptive radius, which is the radius of the bounding circle of an ellipse constructed by minimum splatting opacity. 2) Furthermore, we employ axis-aligned bounding box to improve culling efficiency and achieve higher rendering speed.

**Phase 2: Load balancing (Sec. 4.4).** For *Render* stage, since the color of each pixel is calculated in parallel, and the computational costs of different pixel threads are uneven, the overall efficiency largely depends on heavy-load pixel threads. We propose to balance load across pixel threads, reducing the number of rendered Gaussian for heavy-load pixels to minimize thread waiting, and increasing that for light-load pixels to hedge against quality loss, which achieves more efficient rendering with equivalent or better quality.

## 4.2 Early Culling with Adaptive Radius

Since the Gaussians in each tile are rendered in serial, the *Render* stage takes the largest load proportion, which motivates us to accelerate this stage. We observe that the cull of Gaussians (removing Gaussians of low splatting opacity) are conducted in *Render* stage: The splatting opacity of each Gaussian is calculated by Eq. (2), based on Gaussian-Pixel 2D distance  $\mathbf{x}$ , which is pixel-related, and pixel information can only be obtained from *Render* stage. However, since the process of each Gaussian in *Render* is serial, which makes the culling also serial. We regard the culling process can be parallel, and propose to move part of the culling earlier, into previous *Preprocess* stage to avoid serial culling and enable parallel culling.

Our goal is to early cull pairs of Gaussian-Tile with extremely low splatting opacity in parallel in *Preprocess* stage, to avoid unnecessary serial processing and achieve faster rendering speed. To achieve this, we propose adaptive radius for projected Gaussians, which computes the bounding circle for each Gaussian, and early culls tiles out of bounding circle during the *Preprocess* stage, where Gaussians are processed in parallel. Compared to the original rendering range based on 99% confidence interval (black square), the rendering range of the bounding circle is shown as the purple square in Fig. 3a. Owing to the constraints of the rasterization pipeline, the actual rendering extent is the circumscribed square of the bounding circle.

To get the bounding circle, we compute projected Gaussian's adaptive radius based on the splatting opacity, instead of the original 99% confidence interval (calculated from the standard deviation of a 2D Gaussian distribution). Although the splatting opacity  $\alpha$  is yet unknown during the *Preprocess* stage, we know a lower bound of

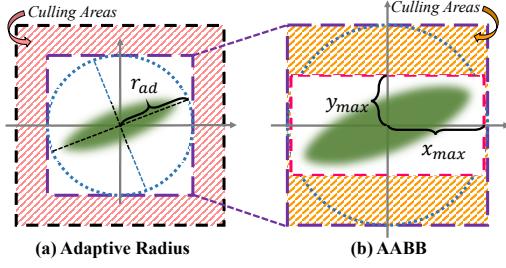


Fig. 3. The rendering range of early culling approaches: (a) Adaptive Radius, (b) AABB for Gaussian. The original rendering range, i.e., the bounding box of 99% confidence interval, is shown as the black square, which will be further culled in *Render* stage based on splatting opacity. We propose to early cull in *Preprocess* stage with (1) adaptive radius, which is the bounding circle (blue) radius of an ellipse constructed by minimum splatting opacity, and remove the redundant red areas, resulting in a smaller rendering range (in purple); and (2) we further propose to cull with axis-aligned bounding box (in rose red) for Gaussian Splatting, which achieves different extents of culling in 2D directions, significantly accelerating rendering speed.

splatting opacity, which is a predefined minimum splatting opacity constant  $\alpha_{low}$  set in the original 3DGS model:  $\alpha_i \geq \alpha_{low}$ , where  $\alpha_i$  is the splatting opacity of Gaussian  $i$  at the current pixel. By substituting Eq. (2) into this inequality, we get the following expression:

$$\mathbf{x}^T \Sigma'^{-1} \mathbf{x} \leq 2 \ln \left( \frac{\sigma_i}{\alpha_{low}} \right). \quad (5)$$

Since 2D distance  $\mathbf{x}$  can be expressed as its 1D components  $(x, y)$ , and covariance  $\Sigma'$  can be expressed as  $[\Sigma'_X, \Sigma'_{XY}; \Sigma'_{XY}, \Sigma'_Y]$ , inequality Eq. (5) represents an ellipse, wherein  $x, y$  serve as variables:

$$Ax^2 + By^2 + Cxy + D \leq 0, \quad (6)$$

where

$$\begin{aligned} A &= \Sigma'_Y, \quad B = \Sigma'_X, \quad C = -2\Sigma'_{XY}, \\ D &= -2 \left( \Sigma'_X \Sigma'_Y - \Sigma'_{XY}^2 \right) \ln \left( \frac{\sigma_i}{\alpha_{low}} \right). \end{aligned}$$

We then define the adaptive radius of a projected Gaussian as the bounding circle radius of this ellipse, i.e., half of the ellipse's major axis length. According to the standard equation of ellipse, the half length of an ellipse's major axis is equal to the square root of the reciprocal of the smaller eigenvalue  $\lambda_{ad}$  of the ellipse's covariance matrix  $\Sigma_{ad}$ :  $r_{ad} = \sqrt{1/\lambda_{ad}} = \sqrt{2D/(-(A+B) + \sqrt{(A-B)^2 + C^2})}$ . By substituting coefficients, adaptive radius is formulated as follows:

$$r_{ad} = \sqrt{2\lambda'_{max} \ln \left( \frac{\sigma_i}{\alpha_{low}} \right)}, \quad (7)$$

where  $\lambda'_{max}$  is the larger eigenvalue of the projected covariance  $\Sigma'$ , which has been computed earlier for the 99% confidence interval (Detailed formula are presented in Supplementary materials).

Finally, there may be situations where the Gaussian opacity is high or the predefined minimum splatting opacity is low, resulting in an adaptive radius  $r_{ad}$  that exceeds the original radius  $r_o$  determined

based on the 99% confidence interval. Therefore, the final value of the 2D Gaussian radius should be the minimum of these two values:

$$r = \min(r_{ad}, r_o). \quad (8)$$

By performing early culling based on adaptive radius in *Preprocess* stage in a parallel manner, we can save some computation costs caused by serial culling during *Render* stage.

#### 4.3 Early Culling with Axis-aligned Bounding Box for Gaussian Splatting

Although the adaptive radius significantly reduces unnecessary overhead in Gaussian splatting rasterization, it cannot effectively cull pairs of Gaussian-Tile with low splatting opacity in the minor axis direction (Fig. 3b, regions marked in orange), as the radius is determined by the major axis. To address this issue, we propose axis-aligned bounding box for Gaussian splatting, which achieves a more significant reduction in ineffective expenses by accurately calculating the Gaussian size in the 2D directions.

For a projected Gaussian, we further cull the tiles based on the axis-aligned bounding box of the ellipse (Eq. (6)) constructed by the minimum splatting opacity  $\alpha_{low}$ . Specifically, half of the bounding box's width  $w$  and height  $h$  equal to the maximum values in the two coordinate directions of the ellipse,  $x_{max}$  and  $y_{max}$ , respectively. We first define a function  $F$  for the ellipse:  $F = Ax^2 + By^2 + Cxy + D$ .

Based on the ellipse function, we calculate the corresponding partial derivatives in two coordinate directions respectively:

$$\frac{\partial F}{\partial x} = 2Ax + Cy, \quad \frac{\partial F}{\partial y} = 2By + Cx. \quad (9)$$

Based on geometric properties of ellipse, when the ellipse function's partial derivative with respect to one coordinate direction is 0, the coordinate value in another direction attains its extremum. To get the extremum of the ellipse on both coordinates, we let the two derivatives to be 0, and substitute the two coordinate relationships into the ellipse function, and solve  $x_{max}$  and  $y_{max}$  as follows:

$$x_{max} = \sqrt{2\Sigma'_X \ln \left( \frac{\sigma_i}{\alpha_{low}} \right)}, \quad y_{max} = \sqrt{2\Sigma'_Y \ln \left( \frac{\sigma_i}{\alpha_{low}} \right)}. \quad (10)$$

Compared to bounding circle with adaptive radius, the axis-aligned bounding box for Gaussian splatting can achieve different extents of culling in horizontal and vertical directions, thereby obtaining different tile ranges for the two directions. Furthermore, similar to the adaptive radius for bounding circle, we take the original radius as the upper limit:

$$r_x = \min(x_{max}, r_o), \quad r_y = \min(y_{max}, r_o). \quad (11)$$

With this approach, the Gaussian rendering range can align with the axis-aligned bounding box, significantly reducing rendering overhead and achieving more efficient rendering.

#### 4.4 Load Balancing for Pixel-parallel Splatting

*Uneven Load Issue.* Based on the point-based rendering, the *Render* stage of Gaussian rasterization has a pixel-parallel and Gaussian-serial architecture: the color calculation of each pixel is conducted in parallel, each pixel corresponding to a pixel thread; while in each pixel thread, the Gaussians are rendered sequentially. Although the



Fig. 4. Visualization of pixel load in Truck dataset. Brighter pixels represent heavier load and darker pixels represent lighter load, which clearly shows the uneven load across pixel threads.

early cull by adaptive radius and axis-aligned bounding box can accelerate *Render* stage by reducing the number of serial Gaussian, the rendering efficiency is still limited by the *uneven load (computational time)* across pixel threads (an example shown in Fig. 4):

1) Uneven load across tiles: Since a 3D scene usually has different frequency information in different regions, where regions with higher frequency requires more Gaussians, the number of Gaussian of each tile varies, leading to uneven load among different tiles.

2) Uneven load within tiles: Within a tile, for a certain Gaussian, different pixels have different splatting opacity due to different distances to Gaussian center. Since the front-to-back blending will be stopped when the accumulated opacity exceeds a threshold, the actual number of rendered Gaussian is different across pixels.

Based on the nature of GPU thread waiting, uneven load across pixel threads leads to lower rendering efficiency [Liu and Vinter 2015]. To address the uneven load issue, we propose a *load balancing* algorithm for Gaussian splatting. We first reduce the number of Gaussian to be rendered for heavy-load pixels, and to address the rendering quality decrease caused by fewer Gaussians, we further increase the number of Gaussian to be rendered for light-load pixels.

*Pixel Loads Distribution.* We first compute the distribution of load of each pixel thread, which is equivalent to the distribution of the number of Gaussian  $\ell_i$  to be rendered for each pixel :

$$\ell_i = \sum_{j \in N} \mathbb{1}(G_j, p_i), \quad (12)$$

where  $N$  denotes the overall number of Gaussian and  $\mathbb{1}(G_j, p_i)$  is an indicator representing whether Gaussian  $j$  contributes to pixel  $i$ .

*Load Balancing Loss.* Given that the rendering efficiency under uneven loads hinges on heavy-load threads, to improve speed, the loads for these pixel threads need to be reduced. Meanwhile, encouraging light-load threads to enhance their information by increasing Gaussians to be rendered will not compromise efficiency. Thus, our load balancing strategy aims to reduce the number of Gaussian to be rendered in heavy-load pixels, and increase that in light-load pixels. We adopt the standard deviation to estimate the difference of loads across pixels, and design the load balancing loss as follows:

$$\mathcal{L}_{load} = std_{i \in HW}(\ell_i), \quad (13)$$

where  $H, W$  denotes the screen size and  $std$  represents standard deviation function. The smaller  $std$  indicates more balanced load

distribution, and smaller difference in the number of Gaussian processed serially by each pixel thread, thus higher rendering efficiency.

*Total Loss.* To balance synthesis quality and rendering speed, we incorporate the load balancing loss with L1-Loss and SSIM-Loss into the overall loss function, and the total loss is formulated as:

$$\mathcal{L} = \lambda_{L1}\mathcal{L}_{L1} + \lambda_{ssim}\mathcal{L}_{ssim} + \lambda_{load}\mathcal{L}_{load}, \quad (14)$$

where  $\lambda_{L1}$ ,  $\lambda_{ssim}$ ,  $\lambda_{load}$  are the weight coefficients of the L1 loss, SSIM loss, and load balancing loss, respectively. The numerical values satisfy  $\lambda_{L1} + \lambda_{ssim} + \lambda_{load} = 1$ .

## 5 EXPERIMENTS

### 5.1 Experimental Settings

**5.1.1 Datasets and Metrics.** To validate the effectiveness of our method, we utilize the same datasets and metrics as those used in 3DGS [Kerbl et al. 2023]. Specifically, the datasets comprises all scenes from Mip-NeRF360 [Barron et al. 2022], two scenes from Tanks&Temples [Knapitsch et al. 2017], and two scenes from Deep-Blending [Hedman et al. 2018], encompassing both bounded indoor scenes and unbounded outdoor environments. The evaluation metrics include training duration, model size, rendering speed measured in frames per second (FPS), and synthesis quality assessed using PSNR, SSIM [Wang et al. 2004], and LPIPS [Zhang et al. 2018]. We employ identical hyperparameter settings across all experiments, with results reported on a single NVIDIA RTX 3090 GPU.

**5.1.2 Implementation.** Since adaptive radius and load acquisition in our method are based on Gaussian rasterization, these core methods are implemented using CUDA kernels, while load assessment and loss adjustments are handled by PyTorch. For bounding circle with adaptive radius, as the larger eigenvalue  $\lambda'_{max}$  of the projected covariance  $\Sigma'$  is already computed, the only thing we need to do is to multiply it by the opacity coefficient  $2\ln\left(\frac{\sigma_i}{\alpha_{low}}\right)$  instead of 3 to yield the adaptive radius  $r_{ad}$  as in Eq. (7). Note that we maintain a minimum splatting opacity  $\alpha_{low}$  of  $\frac{1}{255}$  for optimal rendering quality, though higher values could further accelerate rendering. Regarding the load balancing approach, to prioritize quality optimization while accelerating rendering, the weight of its loss term  $\lambda_{load}$  is set to 0.45, while the sum weight of remaining loss is reduced to 0.55.

### 5.2 Comparisons

We compare *AdR-Gaussian (Ours-Full* denotes our full method, and **Ours-AABB** denotes AABB-only method) to 3DGS [Kerbl et al. 2023], and state-of-the-art 3DGS faster rendering methods: Light-Gaussian [Fan et al. 2023], C3DGS [Lee et al. 2023], EAGLES [Girish et al. 2023], and GES [Hamdi et al. 2024]. The qualitative and quantitative comparisons are shown in Fig. 5 and Table 1, respectively.

Despite varying amounts and distributions of information across datasets, our *AdR-Gaussian* with only AABB for 3DGS (denoted as **Ours-AABB**) achieves higher rendering efficiency than any existing method on every dataset. Specifically, early culling with AABB has significantly improved the rendering speed to 185% of the baseline (3DGS), with an average rendering speed of 401 FPS on the three test datasets. Moreover, experiments demonstrate *Ours-AABB* outperforms comparison methods in rendering on Mip-NeRF360

Table 1. Quantitative evaluation of our method compared to the latest works, computed over the same full dataset as 3DGS. The bold results represent the best performance, while the underlined results stand for the second-best among all the results obtained in our own experiments. *Ours-AABB* shows the results for our method with only the axis-aligned bounding box for Gaussian splatting.

Dataset Method[Metric]	Mip-NeRF360					Tanks&Temples					Deep Blending								
	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓	
LightGaussian	3DGs 34m30s	29m15s	185.85	780.7MB	<u>0.813</u>	<u>27.49</u>	0.220	14m56s	253.39	437.5MB	<u>0.844</u>	<u>23.64</u>	<b>0.178</b>	24m14s	213.00	677.5MB	0.899	29.50	<b>0.246</b>
	C3DGS 37m5s	212.32	<b>58.7MB</b>	0.803	27.03	0.238	17m49s	341.30	<b>33.9MB</b>	0.834	23.41	0.196	28m19s	259.15	<b>52.0MB</b>	0.896	29.12	0.258	
	EAGLES 21m55s	205.22	122.7MB	0.797	26.99	0.247	19m8s	301.95	93.0MB	0.831	23.42	0.202	28m31s	310.19	104.0MB	<u>0.902</u>	<u>29.84</u>	0.257	
	GES 21m50s	177.87	<u>68.11MB</u>	0.805	27.14	0.239	11m22s	300.68	<u>34.0MB</u>	0.836	23.34	0.200	19m41s	195.64	<u>61.5MB</u>	<b>0.907</b>	<b>29.95</b>	0.249	
	Ours-AABB Ours-Full	241.67	332.9MB	0.792	26.95	0.258	10m56s	339.22	214.5MB	0.836	23.36	0.197	19m04s	279.93	367.5MB	0.901	29.60	0.252	

Table 2. Ablation on same full dataset as comparisons. The experimentation begins with the original 3DGS project and sequentially introduces each sub method of ours. The bold results represent the best performance among all the results obtained in our ablation experiments.

Dataset Method[Metric]	Mip-NeRF360					Tanks&Temples					Deep Blending							
	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓	Train↓	FPS↑	Mem↓	SSIM↑	PSNR↑	LPIPS↓
3DGS+Adaptive radius	29m15s	185.85	780.7MB	0.813	27.49	0.220	14m56s	253.39	437.5MB	0.844	23.64	<u>0.178</u>	24m14s	213.00	677.5MB	0.899	29.50	<b>0.246</b>
	28m38s	221.90	782.2MB	0.813	27.50	0.220	14m25s	361.00	439.5MB	0.845	23.68	<b>0.177</b>	23m35s	320.10	678.5MB	0.899	29.51	<b>0.246</b>
	3DGS+AABB	27m49s	<u>336.15</u>	786.7MB	<b>0.814</b>	<u>27.51</u>	<b>0.219</b>	14m3s	419.07	445.5MB	<b>0.846</b>	<u>23.76</u>	0.178	22m51s	449.21	693.0MB	0.899	29.50
3DGS+AABB+Load balance (Ours)	<b>17m44s</b>	<b>589.61</b>	<b>274.3MB</b>	0.783	26.90	0.272	<b>9m2s</b>	<b>718.42</b>	<b>192.0MB</b>	0.832	23.53	0.205	<b>15m32s</b>	<b>716.46</b>	<b>335.5MB</b>	<b>0.901</b>	<b>29.65</b>	0.254

Table 3. Experiments result on the same three dataset for the combination of *Ours-Full* and the pruning startegy in LightGaussian.

Dataset Method[Metric]	Mip-NeRF360		Tanks&Temples		Deep Blending	
	FPS↑	PSNR↑	FPS↑	PSNR↑	FPS↑	PSNR↑
Ours-Full	589.61	26.90	718.42	23.53	716.46	29.65
(+)Pruning	741.12	26.81	1109.70	23.42	1035.37	29.61

and Tanks&Temples datasets. Compared to the baseline 3DGS, we achieve lossless acceleration, which is due to we only early cull Gaussian-Tile pairs that contribute nothing to the final color.

Additionally, our full *AdR-Gaussian* method with both early culling and load balancing (denoted as **Ours-Full**) achieves the highest rendering speed among all methods, 310% on average compared to 3DGS. This is realized by the reduction in the number of Gaussian to be rendered for heavy-load pixels, *i.e.* reduction in thread waiting, which also improves our training speed and model size on every dataset compared to the baseline. Meanwhile, *Ours-Full* can achieve superior quality on *Deep Blending* dataset, because our load balancing also increases the number of Gaussian to be rendered for light-load pixels, which enhances the information on these pixels.

### 5.3 Ablation Studies

To clearly assess the performance of each component of our methods, we conduct ablation studies as follows: we begin with the original 3DGS project, and sequentially add each module: early culling with adaptive radius, and with AABB for 3DGS, and load balancing. The quantitative results are presented in Table 2, where the contribution of each module can be obtained by comparing corresponding rows.

*Adaptive Radius.* The ablation experiment shows that early-culling with adaptive radius enhances rendering speed for all test datasets, without rendering quality loss, and improving training time. Adaptive radius achieves rendering acceleration by moving part of serial culling from the Gaussian-serial *Render* stage earlier into the Gaussian-parallel *Preprocess* stage. Moreover, this method does not

sacrifice rendering quality, achieving slight rendering quality improvement while largely improving speed.

*Axis-aligned Bounding Box.* Experiments on three datasets demonstrate that early culling with axis-aligned bounding box for Gaussian splatting achieves higher FPS, *i.e.*, higher rendering efficiency. Since early-culling with AABB can effectively cull the Gaussian-Tile pairs in the minor-axis direction, which can not be achieved by the bounding circle calculated by adaptive radius, early-culling with AABB moves more serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage, leading to further acceleration. Experiments show that such early culling methods are lossless and suitable for any scene.

*Load Balancing.* Experimental results show load balancing method can further improve speed and multiple metrics despite little sacrifice of quality. Load balancing strategy continuously reduces the number of Gaussian to be rendered for heavy-load pixels with load balancing loss, which enables a comprehensive optimization of rendering speed and other metrics. Additionally, load balancing also enriches information for light-load pixels, which can offset the quality loss. Regarding the application of load balancing in different scenes, it is more suitable for scenes with less high-frequency information, such as the scenes in the *Deep Blending* dataset. The overall acceleration ratio increases with higher information frequency, sacrificing more quality, while local areas with relatively low-frequency information can always achieve more accurate modeling, hedging against the quality loss.

### 5.4 Discussions

**5.4.1 Limitation.** The adjustment of minimum splatting opacity is not fully compatible with the training of 3D Gaussians. Since Gaussian opacity is reinitialized every fixed intervals, setting an splatting opacity threshold higher than this initialized value can result in the culling of all Gaussians, leading to rendering failures. Meanwhile, when only rendering is required, raising the splatting opacity threshold can safely speed up the process.

**5.4.2 Combination.** Our method focuses on the rasterization rather than the representation of 3D Gaussian, allowing for easy integration with other 3DGS methods, including those aimed at accelerating rendering. As shown in Table 3, by adding the pruning strategy in LightGaussian, the rendering speed of *Ours-Full* can be further accelerated with only a minor degeneration of quality.

## 6 CONCLUSION

In this paper, we propose *AdR-Gaussian*, an acceleration for 3D Gaussian Splatting, which achieves a rendering speed of 310% while maintaining equivalent or even better quality than its baseline (3DGS). By moving part of serial culling in *Render* stage earlier into parallel culling in *Preprocess* stage, and balances the load across different pixel threads to minimum thread waiting, *AdR-Gaussian* is able to significantly accelerate the rendering speed of Gaussian Splatting. Compared with state-of-the-art fast rendering methods for 3DGS, our AdR-Gaussian shows much higher rendering efficiency.

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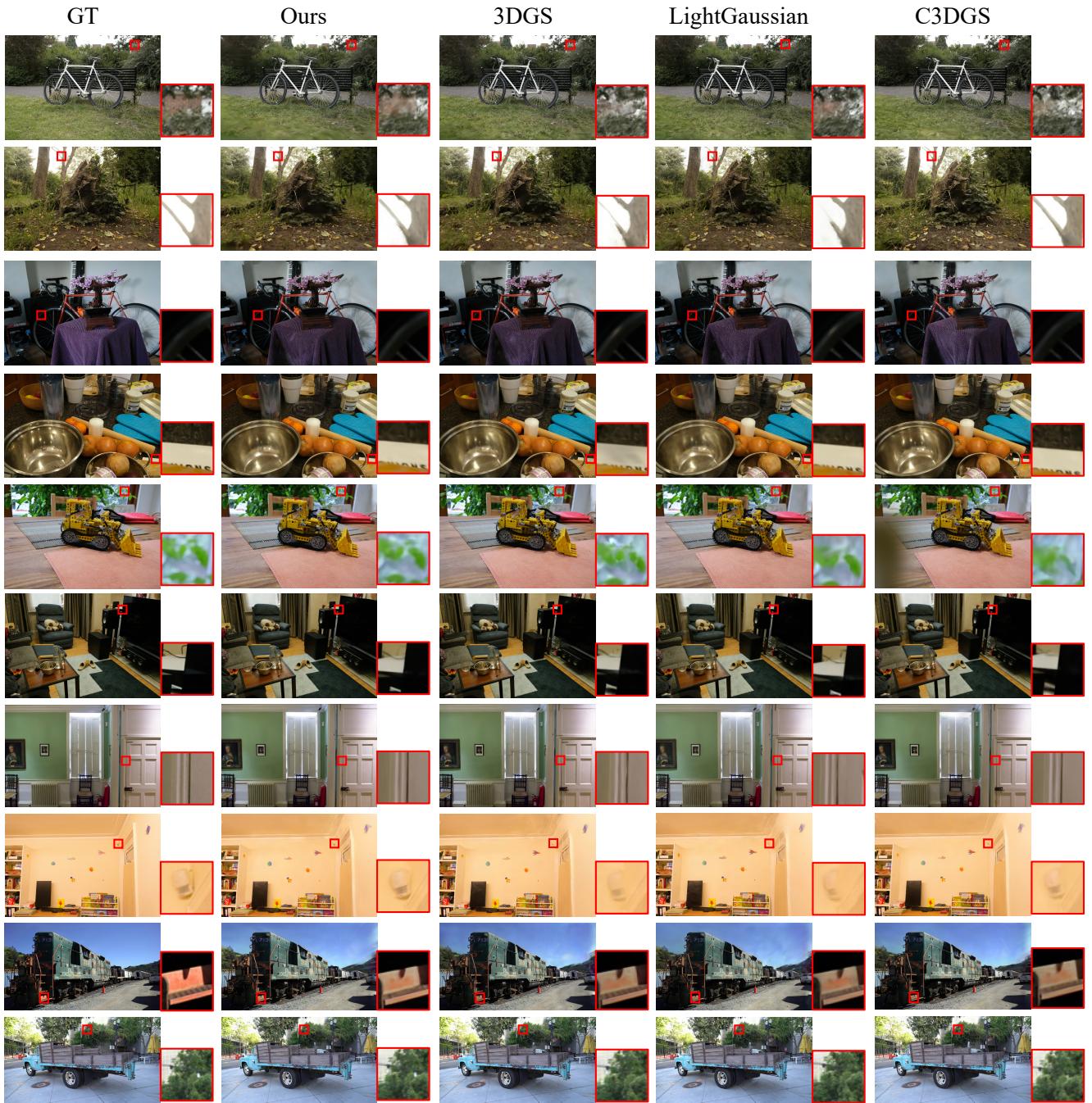


Fig. 5. Our qualitative comparison with 3DGS and recent accelerated rendering methods, where images are from held-out test views. The scenes are, from the top down: *BICYCLE*, *STUMP*, *BONSAI*, *COUNTER*, *KITCHEN*, and *ROOM* from the Mip-NeRF360 dataset; *DRJOHNSON* and *PLAYROOM* from the Deep Blending dataset; *TRAIN* and *TRUCK* from Tanks&Temples dataset. Detailed comparisons are highlighted with red rectangles, where the larger rectangle is the zoomed-in view of the smaller one.