

ResGS: Residual Densification of 3D Gaussian for Efficient Detail Recovery

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Figure 1. We propose ResGS, a pipeline to boost the rendering quality of 3D-GS [26] while improving efficiency. (a) The 3D-GS densification methods, split and clone, rely on threshold-based selection, in our analysis leads to a trade-off. (b) Our ResGS employs a single densification method, residual split, that adaptively addresses under-reconstruction and over-reconstruction. (c) 3D-GS tends to generate Gaussians with sizes in small variation and low rendering quality. (d) From the same initialization, our method can **capture fine details and retrieve sufficient geometry** effectively while **reducing redundancy**.

Abstract

Recently, 3D Gaussian Splatting (3D-GS) has prevailed in novel view synthesis, achieving high fidelity and efficiency. However, it often struggles to capture rich details and complete geometry. Our analysis highlights a key limitation of 3D-GS caused by the fixed threshold in densification, which balances geometry coverage against detail recovery as the threshold varies. To address this, we introduce a novel densification method, **residual split**, which adds a down-scaled Gaussian as a residual. Our approach is capable of adaptively retrieving details and complementing missing geometry while enabling progressive refinement. To further support this method, we propose a pipeline named ResGS. Specifically, we integrate a Gaussian image pyramid for progressive supervision and implement a selection scheme that prioritizes the densification of coarse Gaussians over time. Extensive experiments demonstrate that our method achieves SOTA rendering quality. Consistent performance improvements can be achieved by applying our residual split on various 3D-GS variants, underscoring its versatility and potential for broader application in 3D-GS-based applications.

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1. Introduction

Novel View Synthesis (NVS) has continued to be a hot topic throughout the years. Traditional methods like point clouds and meshes [4, 9, 15] can achieve high rendering speed but often lack fidelity. On the other hand, neural volumetric approaches [1, 33, 34] can achieve high fidelity for novel views but significantly sacrifice rendering efficiency. Recently, 3D-GS [26] has shown both high fidelity and fast rendering speed. Initialized from point clouds generated by Structure-from-Motion (SfM) [41, 42], 3D-GS represents the scene using a set of anisotropic Gaussian ellipsoids, associated with attributes for geometry (mean, scale, rotation) and appearance (opacity, color). The rendering process projects these 3D Gaussians to the camera plane through a tile-based rasterizer, thus achieving fast rendering speed and high fidelity.

However, 3D-GS still suffers from setbacks, often fail-

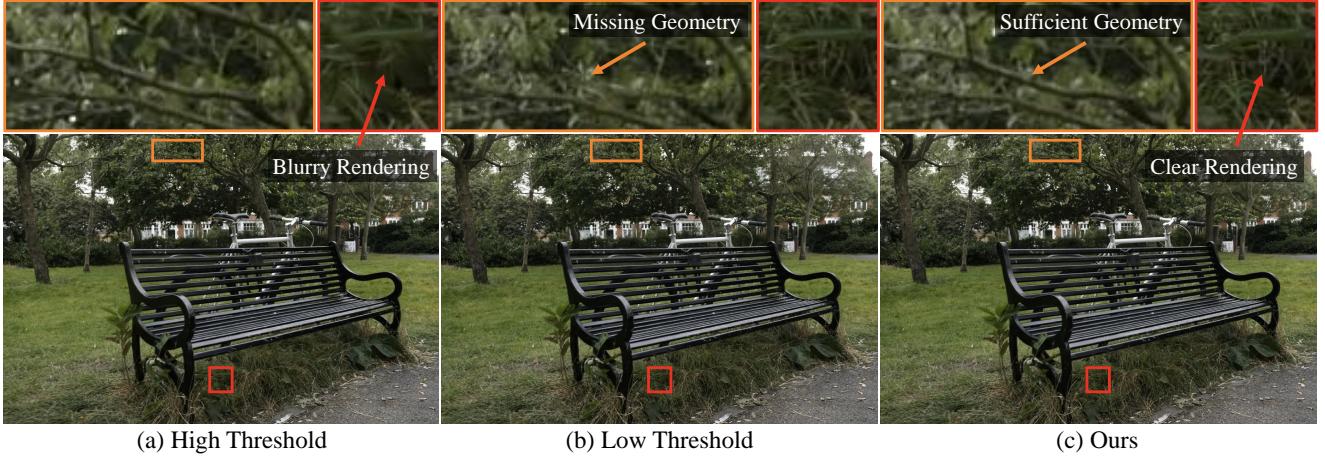


Figure 2. **An illustration of the limitation of 3D-GS densification method.** (a), (b) and (c) represents 3D-GS with a high threshold, 3D-GS with a low threshold, and 3D-GS with densification method replaced as residual split. We provide visualizations of the final rendered image. A high threshold ensures sufficient structural coverage but causes over-reconstruction, leading to blurry rendering. Conversely, a low threshold mitigates blurry rendering but results in under-reconstruction, compromising coverage and creating a difficult trade-off. Our method, however, adaptively tackles both issues without facing this trade-off.

ing to capture fine details and recover complete geometry, as shown by red and orange rectangles in Fig. 1 and Fig. 2. We investigate the underlying reason for these issues and observe that the densification method in 3DGS faces a trade-off. As illustrated in Fig. 1 (a), during densification in 3DGS [26], the selection between split, designed to address over-reconstruction (where Gaussians cover too much area, resulting in a lack of detail), and clone, aimed at under-reconstruction (missing geometry), is based on a predefined threshold τ_s . The Gaussians whose scale $s = \max(s_x, s_y, s_z)$ is larger than the threshold undergo split, while those below it use clone. As a result, the reconstruction process is highly sensitive to the chosen threshold. As highlighted by the red rectangles in Fig. 2 (a), a high threshold results in insufficient split, which prevents the model from capturing fine details, leading to blurry artifacts. On the other hand, a lower threshold reduces clone operations, leading to missing geometry, as illustrated in the orange boxes in Fig. 2 (b). This dilemma limits the rendering quality. Furthermore, 3D-GS tends to first split and then clone, resulting in objects being fitted with Gaussians of similar scales. As highlighted by the blue rectangles in Fig. 1, 3D-GS fits textureless areas with excessive number of small Gaussians, which is redundant.

To tackle the aforementioned problems, we propose residual split, a novel densification method avoiding a constant scale threshold to decide clone or split. As illustrated in Fig. 1 (b), the core idea is to generate an asymmetric, downsampled replica as a residual for Gaussians undergoing densification. Thus, our method progressively fits the target shape, with Gaussians adaptively capturing details or covering geometry as needed. Furthermore, we propose a coarse-

to-fine training pipeline to supplement the progressiveness of our residual split. Specifically, we structure training in stages, using multi-scale images for gradual supervision. This enables our model to focus on recovering the overall structure in the early stages, gradually refining and retrieving fine details in the later stages. We also develop a progressive Gaussian selection scheme for densification, which gradually encourages coarser Gaussians to undergo further refinement.

Our contributions are summarized as follows:

- We propose a novel densification method for 3D Gaussians based on a residual strategy to overcome the limitations of fixed threshold for determining split or clone in 3D-GS;
- We develop a coarse-to-fine training pipeline, ResGS, for progressive guidance to complement residual split;
- Our method achieves SOTA rendering quality in NVS on three datasets, including Mip-NeRF360 [1], Tanks&Temples [27], and DeepBlending [20]. Furthermore, applying residual split to multiple 3D-GS variants consistently brings performance improvements, demonstrating that our new densification method is more effective than densification with a fixed scale threshold.

2. Related Work

2.1. Novel View Synthesis

Novel view synthesis (NVS) aims to acquire novel view images for a scene through a set of multi-view images. As a pioneer, NeRF [33] introduced an MLP-based implicit representation. More specifically, it uses an MLP to predict the color and opacity of a point in a scene and uses dif-

ferentiable volume rendering to render images. Due to its photo-realistic quality, it has been extensively studied recently. Many variants have been designed to fit challenging tasks such as representing 4D scenes [14, 17, 35, 36], few-shot reconstruction [6–8, 24, 29, 53] and anti-aliasing [1, 2]. However, NeRF-based methods often suffer from long training and rendering time. Therefore, many works [21, 22, 37, 38] have been proposed to extend NeRF into real-time rendering. For example, EfficientNeRF [22] introduced valid sampling and pivotal sampling techniques to accelerate NeRF’s rendering during both training and inference phases.

Recently, 3D-GS [26] has stirred an evolution in the field by achieving both high-fidelity and real-time rendering. Due to its high performance, many works have enabled 3D-GS into many downstream tasks such as SLAM [32, 47], 3D generation [10, 43, 50, 58], 4D scene modeling [18, 28, 45, 48], and surface reconstruction [16, 23].

However, the original 3D-GS still has limitations and myriad works have been proposed to increase the render quality and efficiency of 3D-GS. Mip-Splatting [52] introduced a 2D dilation filter and a 3D smoothing filter to mitigate aliasing and artifacts caused by changes in focal length. Scaffold-GS [31] proposed the concept of neural Gaussians which is to tie Gaussians around an anchor and use an MLP to predict its attributes. Thus, the model is more robust to significant view changes and can improve rendering quality. AbsGS [49] discovered that when accumulating the view space gradients used in densification through pixels, there could be a collision, for gradients at various pixels might have different positivities. They applied an absolute function before summing through pixels to mitigate the issue. Pixel-GS [56] analyzed 3D-GS artifacts from the pixel perspective and introduced a method to select Gaussians for densification based on this analysis. GaussianPro [11] introduced a progressive propagation strategy to propagate Gaussians to under-initialized areas. To reduce redundancy and increase rendering quality, Mini-Splatting [13] proposed a densification and simplification algorithm to re-organize Gaussians’ spatial positions.

With the emergence of numerous works focused on optimizing NeRF and 3D-GS, progressive training schedules—proven effective in multiple scenarios [3, 19, 25, 40] have earned attention.

2.2. Progressive Training in NVS

Several progressive training schedules have been explored upon NeRF-based methods. BungeeNeRF [46] captured different levels of details in large city-scale datasets by gradually adding closer views to the training views and appending residual blocks to the MLP throughout the training process. Pyramid NeRF [57] proposed a progressive subdivision of the scene while utilizing an image pyramid

to gradually add high-frequency information to the scene. BARF [30] proposed a scheduling approach to progressively incorporate higher frequency components in positional encoding, enabling the training of NeRFs without requiring camera poses.

Recently, with the prevalence of 3D-GS, many progressive training pipelines have been proposed. Octree-GS [39] proposed an Octree-based 3D-GS approach, and the Octree depth is progressively deepened. FreGS [54] designed a progressive frequency regulation for 3D-GS which is to calculate the loss of rendered images in the frequency domain and gradually add higher frequency components. Not long ago, MVGS [12] introduced a multi-view regulated training strategy that employs an image pyramid to add detailed information progressively. Although they achieved high performance on rendering quality, they require more massive GPU memory and storage than mainstream methods.

In summary, existing works to optimize 3D-GS primarily concentrate on aspects such as supervision [12, 54], selecting Gaussians for densification [49, 56], and modifying the structure [31, 39] of 3D-GS. None of these approaches address the limitations of the 3D-GS densification method directly or propose an improved alternative.

3. Our Method

3.1. Preliminaries

3D Gaussian Splatting. The 3D-GS work[26] represents a 3D scene with a set of anisotropic 3D Gaussians for fast and high-quality rendering. Each Gaussian primitive consists of two parameters, mean μ and covariance matrix Σ , representing its position and shape:

$$G(\mathbf{x}) = e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x}-\boldsymbol{\mu})}. \quad (1)$$

To model the positive semi-definite property of the covariance matrix Σ , a scaling matrix \mathbf{S} and a rotation matrix \mathbf{R} is used as:

$$\boldsymbol{\Sigma} = \mathbf{R} \mathbf{S} \mathbf{S}^T \mathbf{R}^T, \quad (2)$$

where a 3D vector \mathbf{s} is used for the scaling matrix \mathbf{S} .

Furthermore, each Gaussian also contains a spherical harmonics coefficients SH and opacity o . In rendering, tile-based rasterization is applied: 3D Gaussians $G(\mathbf{x})$ are projected as 2D Gaussians $G'(\mathbf{x})$ on the image plane. A view-dependent color c is then derived from SH , and the 2D Gaussians are sorted by depth and rendered using alpha-blending:

$$C(\mathbf{x}) = \sum_{i \in N_{\mathbf{x}}} c_i \alpha_i(\mathbf{x}) \prod_{j=1}^{i-1} (1 - \alpha_j(\mathbf{x})), \quad (3)$$

$$\alpha_i(\mathbf{x}) = c_i G'_i(\mathbf{x})$$

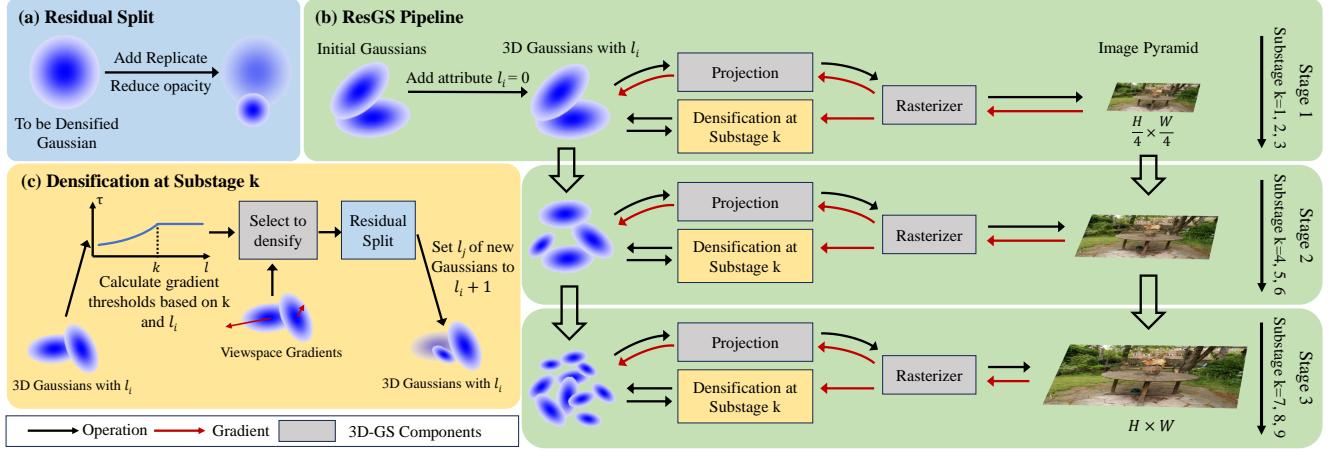


Figure 3. **Overview of our ResGS pipeline.** (a) The core of our pipeline, residual split, involves adding a downscaled replicate and then reducing the opacity of the original Gaussian. (b) We assign initial Gaussians a temporary attribute $l_i = 0$ for densification selection, which is discarded after training. Next, the pipeline is split into L ($L = 3$) stages, with each stage trained on images downsampled using an image pyramid. Furthermore, we divide a single stage evenly into K ($K = 3$) substages for use in selecting Gaussians to densify. (c) The points selected for densification are determined by the substage k , l_i and viewspace gradients of Gaussians. residual split is performed upon selected Gaussians, and l_j would be assigned to new Gaussians.

where \mathbf{x} is a pixel position in the rendered image, $C(\mathbf{x})$ the color of the pixel, and $N_{\mathbf{x}}$ the number of Gaussians that covers \mathbf{x} .

During the training process, 3D Gaussians are periodically densified. 3D-GS calculates the average viewspace gradients ΔL_i over a certain number (e.g. 100) of iterations to determine whether to perform densification. If ΔL_i exceeds threshold τ , a split or clone action is triggered. The split operation addresses over-reconstruction, where excessive space is covered, while clone addresses under-reconstruction, where additional spatial coverage is needed. To determine whether to split or clone, 3DGS[26] sets a threshold $\tau_s = kR$, where k is a predefined factor and R is the scene extent. Split occurs when the scale $s = \max(s_x, s_y, s_z)$ of a Gaussian surpasses a threshold τ_s . Clone is applied when $s < \tau_s$.

3.2. ResGS

We propose ResGS, a coarse-to-fine pipeline to boost the rendering quality of 3D-GS with a novel residual densification method. Fig. 3 shows the overview of our method. We propose a novel densification method, residual split, (Sec. 3.2.1), to tackle the limitations of the 3D-Gs densification method. Furthermore, we introduce a split-stage supervision schedule to add information to the scene gradually (Sec. 3.2.2). We also design a Gaussian selection scheme that progressively encourages densification for coarse Gaussians to enhance details, as described in Sec. 3.2.3.

3.2.1. Residual Split

The core idea of our densification method is to generate asymmetrically downsampled Gaussians as residuals to supplement those requiring densification. The newly added Gaussian adaptively enhances the reconstructed model, allowing the scene to be progressively refined. The method is named as residual split. As illustrated in Fig. 3 (a), for a to-be-densified Gaussian G_i , our densification method consists of two steps. Firstly, we add a down-scaled replicate G_j . Specifically, its opacity o_j , rotation \mathbf{R}_j , spherical harmonics coefficients SH_j would be same as G_i , μ_j is sampled using the original 3D Gaussian as a PDF for sampling, and \mathbf{S}_j is defined as \mathbf{S}_i divided by a set factor λ_s :

$$\begin{aligned} \mathbf{S}_j &= \frac{1}{\lambda_s} \mathbf{S}_i \\ \mathbf{R}_j &= \mathbf{R}_i, \quad SH_j = SH_i, \quad o_j = o_i \\ \mu_j &\sim \mathcal{N}(\mu_i, \Sigma_i) \end{aligned} \quad (4)$$

where Σ_i is the covariance matrix of G_i . Then, to tackle the density increase in the overlap of the two Gaussians, we reduce the opacity of the original Gaussian. This is accomplished by multiplying its opacity by a specified factor β :

$$o'_i = \beta o_i \quad (5)$$

Unlike clone and split which involve hardcoded threshold-based selection, residual split can fill in missing geometry and recover details adaptively without requiring a trade-off, as shown in Fig. 2 (c). For areas where details are challenging to recover, our model initially forms

a coarse shape. In subsequent iterations, small-scale residual Gaussians are progressively added to refine and reveal finer details. Conversely, in regions lacking geometry, our model adds residual Gaussians to fill in and complete the missing structure. Moreover, our method’s asymmetrical approach with hierarchical Gaussians of varying scales enables efficient shape fitting. As illustrated by the blue rectangles in Fig. 1, this hierarchy allows us to fill textureless regions with a few large, coarse Gaussians, significantly reducing redundancy. Consequently, our approach delivers higher rendering quality while using fewer Gaussians.

3.2.2. Image Pyramid as Supervision

Reinforcing progressive training in our densification method, we designed a coarse-to-fine supervision schedule that gradually integrates information into the scene. Specifically, based on the original multi-view training pictures, we build an image pyramid $\{IP_i\}_{i=1}^L$ consisting of L layers. IP_i corresponds to the set of images at different viewpoints in layer i . IP_L is the set of original pictures:

$$IP_i = \{P_i^v\}_{v \in V} \quad (6)$$

where V is the set of viewpoints and P_i^v refers to the picture at viewpoint v in the i^{th} layer. Let (H_L^v, W_L^v) be the resolution of P_L^v , and (H_i^v, W_i^v) represent the resolution of P_i^v . Then there is:

$$(H_i^v, W_i^v) = (H_L^v / 2^{L-i}, W_L^v / 2^{L-i}) \quad (7)$$

Correspondingly, our training process is divided into L stages. At stage i , we train our model under the supervision of IP_i , increasing the resolution of the training pictures throughout the stages. Due to the variation of frequency bandwidth in different levels in the image pyramid, high-frequency information is gradually added to the scene. Thus, we can force our model to learn coarse and low-frequency features at early stages and construct an overall structure of the whole scene. At later stages, the focus shifts to capturing high-frequency components, carving details above the coarse expression. Through coarse-to-fine supervision, the model can obtain a division of focus throughout the training process and capture more information from the training images.

3.2.3. Varying Gradient Threshold

To further emphasize the progressiveness of our pipeline, an incremental approach for selecting Gaussians to densify is designed. Specifically, as iterations progress, the model’s focus gradually shifts toward finer details. To support this, we aim to encourage the densification of coarse Gaussians to capture more detail over time. Due to the asymmetry of our residual split, we can expect the generated Gaussians to be finer than the original ones. This allows us to track the

relative fineness level of Gaussians, denoted as l_i . We assign l_i of initial Gaussians to 0. If the level of the Gaussian being densified is l_i , we assign the newly added Gaussian a level of $l_i + 1$. Thus, as l_i gets higher, Gaussians tend to be smaller and finer.

A single stage is then divided evenly into K substages, creating $L \times K$ substages in total. The gradually increasing substage can be seen as an indicator of the scene details level. At substage k , we promote additional densification for Gaussians with $l_i < k$ and prioritize those at lower levels, achieved by applying varying gradient thresholds. Specifically, the threshold $\tau_{k,i}$ for a Gaussian G_i is set as:

$$\tau_{k,i} = \begin{cases} \tau, l_i \geq k \\ \frac{\tau}{\alpha^{k-l_i}}, l_i < k \end{cases} \quad (8)$$

where τ is a set threshold and $\alpha > 1$ is a chosen value.

4. Experiments

4.1. Experiment Settings

Following previous works [13, 26, 31, 39, 49, 54], evaluation of our model was done on three datasets, including all nine scenes from Mip-NeRF360 [1], two scenes from Tanks&Temples [27], and two scenes from DeepBlending [20]. The test and train splits follow those of the original 3D-GS [26], and the image resolution is also maintained as in 3D-GS.

Three commonly used metrics were used to quantify the fidelity of rendered images: PSNR, SSIM [44], and LPIPS [55]. We also report the memory consumption as an indicator of the number of Gaussians.

We trained three versions of our model: two with AbsGS [49], leveraging its enhanced indication of Gaussians for densification—one standard version and one small version with higher gradient thresholds—and a third version using 3D-GS as the baseline. We applied the periodic opacity reduction from AbsGS across all three versions, as it proved to be a more effective alternative to the opacity reset used in 3D-GS. Additionally, we extended this reduction beyond the densification phase, finding it further minimized redundancy without compromising fidelity. Following all 3D-GS-like methods, we trained our model for 30k iterations. The densification stops at 12000 iterations. For the version with AbsGS, τ was set to 0.00067, the small version to 0.0016; for the version with 3D-GS, τ was set to 0.00028. L was set to 3 and K was set to 3. Our first stage lasts for 2500 iterations, the second stage for 3500 iterations, and the rest iterations are in the last stage. α was set to $2^{\frac{1}{3}}$, λ_s was set to 1.6 and β was set to 0.3. The loss function remains the same as in 3D-GS [26], consisting of a combination of

Table 1. **Quantitative comparison to previous methods on real-world datasets.** Our method achieves SOTA in the Mip-NeRF360 dataset and comparable results with SOTA on the Tanks&Temples and Deep Blending datasets. * indicates results generated by retrained models for different rendering resolution.

Dataset Method Metrics	Mip-NeRF360				Tanks&Temples				Deep Blending			
	PSNR ↑	SSIM ↑	LPIPS ↓	Mem.	PSNR ↑	SSIM ↑	LPIPS ↓	Mem.	PSNR ↑	SSIM ↑	LPIPS ↓	Mem.
Plenoxels	23.08	0.626	0.463	2.1GB	21.08	0.719	0.379	2.3GB	23.06	0.795	0.510	2.7GB
Instant-NGP	25.59	0.699	0.331	48MB	21.92	0.745	0.305	48MB	24.96	0.817	0.390	48MB
Mip-NeRF360	27.69	0.792	0.237	8.6MB	22.22	0.759	0.257	8.6MB	29.40	0.901	0.245	8.6MB
Scaffold-GS*	27.69	0.812	0.225	176MB	23.96	0.853	0.177	87MB	30.21	0.906	0.254	66MB
Octree-GS*	27.52	0.812	0.218	124MB	24.52	0.866	0.153	84MB	30.41	0.913	0.238	93MB
3D-GS	27.21	0.815	0.214	734MB	23.14	0.841	0.183	411MB	29.41	0.903	0.243	676MB
AbsGS	27.49	0.820	0.191	728MB	23.73	0.853	0.162	304MB	29.67	0.902	0.236	444MB
Pixel-GS*	27.52	0.822	0.191	1.32GB	23.78	0.853	0.151	1.06GB	28.91	0.892	0.250	1.09GB
FreGS	27.85	0.826	0.209	-	23.96	0.849	0.178	-	29.93	0.904	0.240	-
Mini-Splatting-D	27.51	0.831	0.176	1.11GB	23.23	0.853	0.140	1.01GB	29.88	0.906	0.211	1.09GB
Ours-Small (AbsGS)	27.94	0.830	0.191	342MB	24.33	0.862	0.150	187MB	30.01	0.906	0.234	289MB
Ours (3D-GS)	28.00	0.831	0.187	600MB	24.26	0.865	0.141	354MB	29.93	0.903	0.232	596MB
Ours (AbsGS)	28.00	0.833	0.174	698MB	24.38	0.867	0.132	351MB	29.91	0.902	0.227	586MB

\mathcal{L}_1 and D-SSIM losses. All experiments were done on an NVIDIA RTX3090 GPU.

4.2. Comparisons

To quantitatively assess the visual quality of our method, we compared with several 3D-GS variants: 3D-GS [26], Scaffold-GS [31], Octree-GS [39], FreGS [54], AbsGS [49], Pixel-GS [56] and Mini-Splatting-D [13]. Note that Scaffold-GS and Octree-GS use a latent representation rather than the original 3D-GS representation. Some radiance-field-based methods are also selected for comparison, including Plenoxels [51], Instant-NGP [34] and Mip-NeRF360 [1]. Note that the resolution of Mip-NeRF360 dataset images varies across different works. Following the resolution setup in the 3D-GS work, we retrain some models on the Mip-NeRF360 dataset. Additionally, for works that did not report their storage, we obtained and reported it based on their released code. As shown in Table 1, our method achieves SOTA performance across all metrics on the Mip-NeRF360 dataset. On the Tanks&Temples dataset, we also achieve the best SSIM and LPIPS metrics, which closely reflect human perception. In the Deep Blending dataset, our method performs comparably to the best results of existing approaches. Additionally, our model variant without AbsGS [49] maintains similar performance to the full model, with only a slight reduction in LPIPS. Notably, our smaller model version achieves strong performance with reduced memory usage, showcasing the efficiency and scalability of our approach.

In Fig. 5, we present qualitative comparisons between our method and several 3D-GS variants [26, 49, 56] across various scenes, including both indoor and outdoor settings. It is evident that our model captures finer details, as shown in the second, third, and fourth rows, constructs missing geometry more effectively (last row), and achieves more ac-

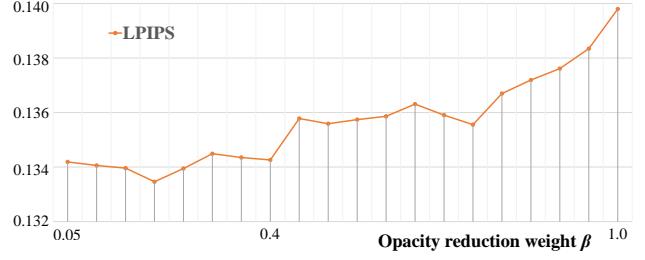


Figure 4. **Impact of the opacity reduction weight β for residual split.**

curate geometry reconstruction (first row).

4.3. Analysis

4.3.1. Residual Split

Analyzing β . To analyze the impact of different opacity reduction weights β on rendering quality, we tested our model upon the Tanks&Temples dataset while applying different β . All the models are trained with similar storage. The results are shown in Fig. 4. While β is sampled in the range of (0.05, 1.0), the LPIPS scores do not differ much when $\beta < 0.4$. A notable performance drop (increasing LPIPS) is observed.

Compatibility. We analyze the compatibility of our novel densification method by replacing split and clone in multiple 3D-GS variants [13, 26, 49, 56] with residual split. The hyper-parameters were kept the same as in the original pipelines. The results are shown in Table 2. The table shows that our method leads to a notable increase in PSNR metrics across all pipelines, while for other metrics, some exhibit improvements, and others remain approximately the same. Additionally, memory consumption is reduced after incor-

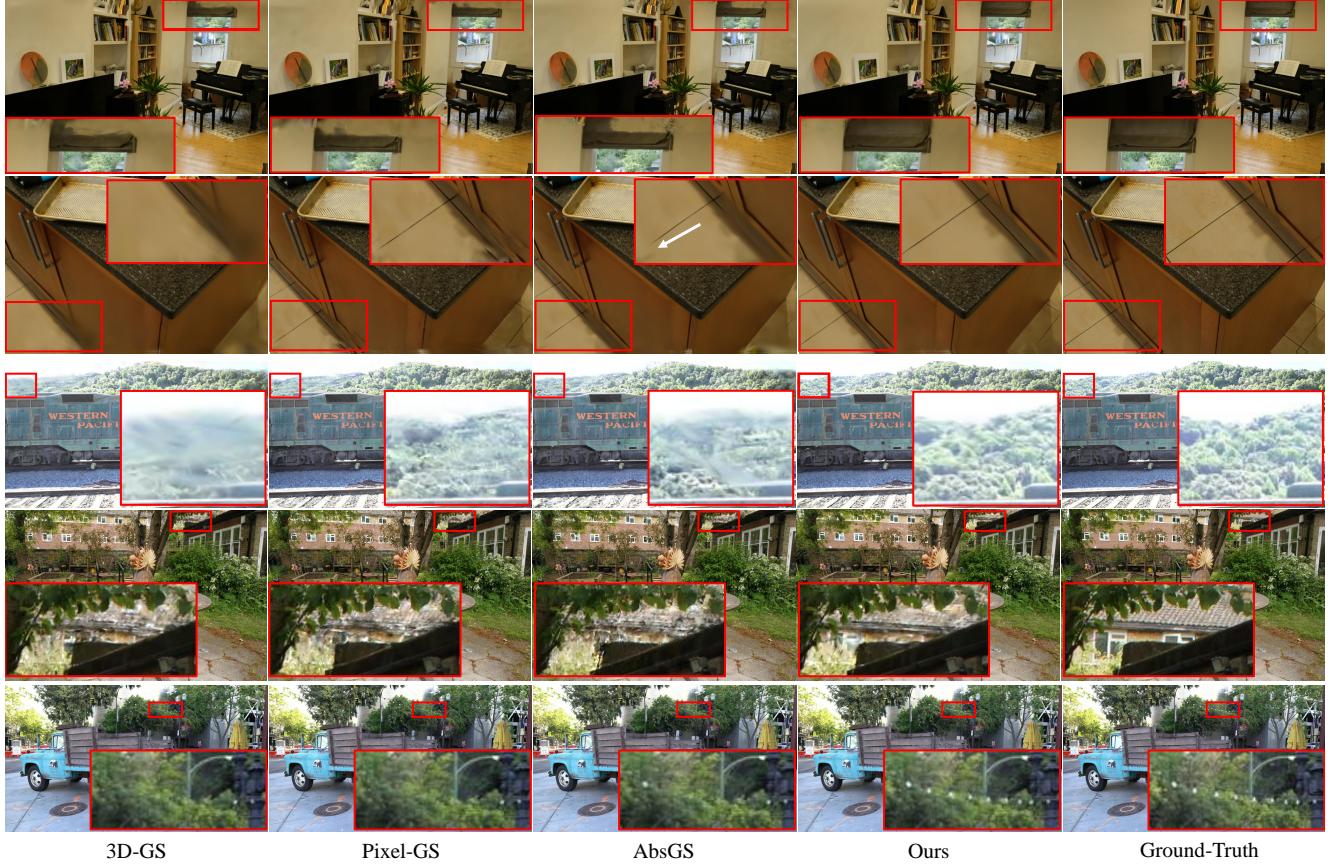


Figure 5. **Qualitative comparisons of ResGS with three 3D-GS variations on a variety of indoor and outdoor scenes.** Our approach captures more intrinsic details and acquires more complete geometry in complex scenes.

Table 2. **Analyzing residual split upon multiple 3D-GS variants.** The performance consistently increases on these pipelines, indicating that our Residual split outperforms the split and clone strategy using a fixed threshold.

Dataset Method Metrics	Mip-NeRF360				Tanks&Temples				Deep Blending			
	PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem
3D-GS	27.21	0.815	0.214	734MB	23.14	0.841	0.183	411MB	29.41	0.903	0.243	676MB
3D-GS + residual split	27.44	0.813	0.216	586MB	23.76	0.845	0.178	318MB	29.75	0.902	0.240	546MB
AbsGS	27.49	0.820	0.191	728MB	23.73	0.853	0.162	304MB	29.67	0.902	0.236	444MB
AbsGS + residual split	27.71	0.827	0.185	712MB	24.05	0.857	0.161	285MB	29.68	0.905	0.234	421MB
Pixel-GS*	27.52	0.822	0.191	1.32GB	23.78	0.853	0.151	1.06GB	28.91	0.892	0.250	1.09GB
Pixel-GS + residual split	27.62	0.821	0.191	1.00GB	24.05	0.856	0.148	754MB	29.75	0.899	0.235	914MB
Mini-Splatting-D	27.51	0.831	0.176	1.11GB	23.23	0.853	0.140	1.01GB	29.88	0.906	0.211	1.09GB
Mini-Splatting-D + residual split	27.64	0.831	0.176	1.04GB	23.49	0.853	0.140	967MB	29.94	0.903	0.210	1.02GB

porating residual split compared to the original pipeline. This underscores our method’s ability to improve rendering quality and reduce redundancy, while also demonstrating its compatibility and potential for broader application across 3D-GS-oriented works as an effective alternative to split and clone.

4.3.2. Split-Stage Schedule

To evaluate the functionality of our split-stage training schedule, visualizations of intermediate results are pre-

sented in Fig. 6. At the early stages, due to the absence of high-frequency information, our model captures the overall structure of the scene, using a few large, coarse Gaussians to represent it. As training progresses to later stages, more intricate information is revealed, allowing finer details to be carved out.

4.3.3. Ablation Studies

To assess the effectiveness of individual modules in our proposed pipeline—residual split, image pyramid as supervi-



Figure 6. **Impact of the split-stage schedule.** We show the Gaussian ellipsoids and the rendered images at the end of Stage 1, Stage 2, and the final stage. Our model constructs a coarse structure in the early stages and refines details in the later stages.

Table 3. **Ablation Study on our pipeline.** Here, **IP** denotes image pyramid supervision, **RS** represents using residual split for densification, and **VT** indicates applying varying gradient threshold. Each component contributes to our method’s effectiveness.

Dataset Method Metrics	Mip-NeRF360		
	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
Base	27.41	0.817	0.189
Base + IP	27.54	0.823	0.182
Base + RS	27.66	0.825	0.183
Base + RS + IP	27.88	0.831	0.178
Base + RS + IP + VT (full)	28.00	0.833	0.174

sion, and varying gradient threshold—ablation studies on the Mip-NeRF360 [1] dataset were conducted. For the varying gradient threshold, we only conducted studies on its removal, as it is highly interdependent with the other two modules. The results are shown in Table 3. It is evident that both residual split and the image pyramid supervision individually enhance the quality of our baseline, and combining them results in even better performance. Additionally, applying the varying gradient threshold further boosts performance. In conclusion, each module contributes to improved results.

4.4. Discussions and Limitations

Our results show that our method significantly improves rendering quality on the Mip-NeRF360 [1] and Tanks&Temples [27] datasets. However, for Deep Blending [20], our method did not yield a significant boost in perfor-

mance. This variation is primarily due to the challenges specific to each dataset: Mip-NeRF360 and Tanks&Temples require capturing fine textures and recovering missing geometry, whereas Deep Blending on managing occlusions and preventing overfitting to training views. Our method mainly contributes to retrieving fine details and geometry and does not address the issue of overfitting and occlusion, suggesting it to be a topic for future optimization.

5. Conclusion

In this paper, we analyzed the limitations of the current 3D-GS densification method. To address these issues, we propose residual split, a residual empowered densification method that adaptively handles various cases and fits the scene progressively. Additionally, we introduce ResGS, a coarse-to-fine 3D-GS pipeline to supplement residual split. Specifically, we use an image pyramid for supervision to gradually recover the overall structure to fine details during Gaussian optimization. We also design a Gaussian selection scheme to further densify coarse Gaussians progressively. Experiments show our pipeline achieves SOTA rendering quality while residual split is highly compatible with other 3D-GS variants.

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ResGS: Residual Densification of 3D Gaussian for Efficient Detail Recovery

Supplementary Material

6. More Experiment Results

In this section, we give more experimental results of our work.

Variance of PSNR on Deep Blending Dataset. A notable variance in the PSNR metrics of our method is observed on the Deep Blending [20] dataset. We tested our method on the Deep Blending dataset 10 times and reported the average performance and population standard deviation. The results are shown in Table 4. The table demonstrates that the PSNR scores on the Deep Blending dataset exhibit a notable variance. The underlying reason, as discussed in our limitations, is that our method does not address issues related to occlusion and overfitting, making the Deep Blending dataset particularly challenging for our approach. This highlights opportunities for future optimization and improvement. Furthermore, we report the average performance and population standard deviation over 10 runs for the other two datasets, Mip-NeRF360 [1] and Tanks&Temples [27], as presented in Table 5 and Table 6, respectively. The PSNR metrics for these two datasets do not show a notable variance, showcasing the robustness of our method in most scenarios.

Further Analyzing Residual Split on 3D-GS. In our paper, we tested the compatibility of our residual split across multiple pipelines without modifying any hyper-parameters. Here, we present the results of applying residual split to 3D-GS [26] while adjusting the densification threshold τ to maintain the same storage size as 3D-GS, further demonstrating the capability of our method to enhance rendering quality. The results are shown in Table 7, showing that our method yields a further performance increase.

Periodic Opacity Reduction. 3D-GS [26] often encounters redundancy issues, which we categorize into two main causes: the first is the use of an excessive number of small-scale Gaussians to represent coarse areas, and the second is the overlap between Gaussians, resulting in redundant Gaussians that contribute minimally to the rendered image. Our residual split can solve the first issue but does not address the second. To tackle the second issue, as mentioned in our experiment settings, we implemented the periodic opacity reduction technique in [5, 49]. Specifically, the opacity of Gaussians is periodically reduced, causing the opacity of those that contribute little to the rendered image to diminish to a negligible value, allowing them to be

effectively pruned. Additionally, we extended this operation to occur after the densification stage, discovering that it further reduces redundancy without compromising fidelity. Here, we present the experimental results of our method without extending the periodic opacity reduction operation, as shown in Table 8. From the table, we can observe that extending the periodic opacity reduction operation effectively reduces redundancy without compromising the fidelity of the rendered images. Furthermore, when the operation is not extended and the gradient threshold is adjusted to maintain storage approximately equal to our full model, the rendering quality shows only a slight decrease in LPIPS metrics. This indicates that while extending the operation can enhance the performance of our method, its overall impact on the performance improvement is relatively minor.

Per Scene Results. We present the per-scene results of the used metrics in Table 9-14. For works that did not report per-scene results, we obtained and reported them using their released code. The works selected for comparison are mainly the same as in the paper: 3D-GS [26], Scaffold-GS [31], Octree-GS [39], AbsGS [49], Pixel-GS [56], Mini-Splatting-D [13], Plenoxels [51], Instant-NGP [34] and Mip-NeRF360 [1]. Note that we did not show the results of FreGS [54] since they did not report their per-scene results or release their code. Works retrained on the Mip-NeRF360 [1] are marked with a *.

Image Resolution of Mip-NeRF360 Dataset. In our paper, we mentioned that the image resolution on the Mip-NeRF360 [1] dataset varies across different works. 3D-GS [26] uses the provided “images_4”, the official downscaled 4 times images from the dataset, for outdoor scenes and “images_2” for indoor scenes. Most works [13, 49, 54] follow the 3D-GS setting, but Scaffold-GS [31], Octree-GS [39], Pixel-GS [56] uses different settings. Specifically, Scaffold-GS and Octree-GS downscale original images to 1.6K resolution, while Pixel-GS downscale original images by a factor of 4 for outdoor scenes and 2 for indoor scenes during the training process, instead of using the provided downscaled images. This discrepancy results in differences in experimental settings. To further demonstrate the performance of our method, we provide its results under the two different settings, as shown in Table 15 and 16. The tables show that our method prevails even under these alternate settings.

Table 4. Average and standard deviation results of three metrics on the Deep Blending dataset.

Method	Metrics	Deep Blending					
		PSNR ↑		SSIM ↑		LPIPS ↓	
Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev
Ours-Small (AbsGS)		29.71	0.211	0.903	0.002	0.235	0.002
Ours (3D-GS)		29.64	0.205	0.900	0.003	0.233	0.002
Ours (AbsGS)		29.68	0.173	0.900	0.002	0.228	0.002

Table 5. Average and standard deviation results of three metrics on the Mip-NeRF360 dataset.

Method	Metrics	Mip-NeRF360					
		PSNR ↑		SSIM ↑		LPIPS ↓	
Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev
Ours-Small (AbsGS)		27.93	0.010	0.830	0.001	0.191	0.001
Ours (3D-GS)		27.99	0.011	0.831	0.001	0.187	0.001
Ours (AbsGS)		27.99	0.011	0.833	0.001	0.174	0.001

Table 6. Average and standard deviation results of three metrics on the Tank&Temples dataset.

Method	Metrics	Tank&Temples					
		PSNR ↑		SSIM ↑		LPIPS ↓	
Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev
Ours-Small (AbsGS)		24.21	0.081	0.862	0.001	0.151	0.001
Ours (3D-GS)		24.26	0.058	0.864	0.001	0.141	0.001
Ours (AbsGS)		24.27	0.063	0.866	0.001	0.133	0.001

Table 7. Results of residual split upon 3D-GS with varied gradient threshold.

Dataset	Method	Mip-NeRF360				Tanks&Temples				Deep Blending			
		PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem
3D-GS		27.21	0.815	0.214	734MB	23.14	0.841	0.183	411MB	29.41	0.903	0.243	676MB
3D-GS + residual split		27.48	0.815	0.213	722MB	23.85	0.846	0.174	374MB	29.83	0.901	0.238	640MB

Table 8. Results of our method without extended periodic opacity reduction. Here, No EPOR refers to our method trained without applying the extended periodic opacity reduction. No EPOR + CT refers to the model without the extended periodic opacity reduction but with an adjusted gradient threshold to ensure that the final storage size is approximately the same as our full model with extended periodic opacity reduction.

Dataset	Method	Mip-NeRF360				Tanks&Temples				Deep Blending			
		PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem	PSNR ↑	SSIM ↑	LPIPS ↓	Mem
Ours (No EPOR)		28.02	0.833	0.173	973MB	24.32	0.867	0.130	591MB	29.86	0.902	0.227	911MB
Ours (No EPOR + CT)		28.00	0.833	0.181	608MB	24.35	0.866	0.139	380MB	29.96	0.904	0.230	564MB
Ours (full)		28.00	0.833	0.174	698MB	24.38	0.867	0.132	351MB	29.91	0.902	0.227	586MB

Table 9. Per-scene PSNR metrics of Mip-NeRF360 dataset.

Method	Scenes	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
Plenoxels		21.91	20.10	23.49	20.66	22.25	27.59	23.62	23.42	24.67
Instant-NGP		22.17	20.65	25.07	23.47	22.37	29.69	26.69	29.48	30.69
Mip-NeRF360		24.31	21.65	26.88	26.18	22.93	31.47	29.45	31.99	33.40
Scaffold-GS*		25.07	21.36	27.35	26.64	22.93	32.04	29.50	31.63	32.71
Octree-GS*		25.05	21.33	27.58	26.41	22.81	32.09	29.48	30.89	31.71
3D-GS		25.25	21.52	27.41	26.55	22.49	30.63	28.70	30.32	31.98
AbsGS		25.29	21.35	27.48	26.71	21.99	31.61	29.03	31.62	32.32
Pixel-GS*		25.21	21.49	27.42	26.84	22.09	31.45	29.05	31.65	32.53
Mini-Splatting-D		25.55	21.50	27.67	27.11	22.13	31.41	28.72	31.75	31.72
Ours-Small (AbsGS)		25.62	21.80	27.72	27.27	22.90	32.41	29.32	31.95	32.48
Ours (3D-GS)		25.55	22.07	27.71	27.12	22.82	32.48	29.41	32.09	32.74
Ours (AbsGS)		25.62	21.78	27.82	27.19	22.57	32.51	29.50	32.26	32.78

Table 10. Per-scene SSIM metrics of Mip-NeRF360 dataset.

Method	Scenes	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
Plenoxels		0.496	0.431	0.6063	0.523	0.509	0.8417	0.759	0.648	0.814
Instant-NGP		0.512	0.486	0.701	0.594	0.542	0.871	0.817	0.858	0.906
Mip-NeRF360		0.685	0.584	0.809	0.745	0.631	0.910	0.892	0.917	0.938
Scaffold-GS*		0.755	0.590	0.858	0.765	0.639	0.923	0.910	0.926	0.943
Octree-GS*		0.759	0.597	0.864	0.763	0.643	0.924	0.907	0.916	0.930
3D-GS		0.771	0.605	0.868	0.775	0.638	0.914	0.905	0.922	0.938
AbsGS		0.783	0.623	0.871	0.780	0.617	0.925	0.911	0.929	0.945
Pixel-GS*		0.775	0.633	0.867	0.784	0.630	0.920	0.911	0.929	0.944
Mini-Splatting-D		0.798	0.642	0.878	0.804	0.640	0.928	0.913	0.934	0.946
Ours-Small (AbsGS)		0.792	0.634	0.872	0.802	0.652	0.929	0.914	0.932	0.945
Ours (3D-GS)		0.790	0.639	0.874	0.800	0.650	0.929	0.916	0.934	0.947
Ours (AbsGS)		0.797	0.647	0.876	0.804	0.645	0.931	0.918	0.934	0.948

Table 11. Per-scene LPIPS metrics of Mip-NeRF360 dataset.

Method	Scenes	bicycle	flowers	garden	stump	treehill	room	counter	kitchen	bonsai
Plenoxels		0.506	0.521	0.3864	0.503	0.540	0.4186	0.441	0.447	0.398
Instant-NGP		0.446	0.441	0.257	0.421	0.450	0.261	0.306	0.195	0.205
Mip-NeRF360		0.301	0.344	0.170	0.261	0.339	0.211	0.204	0.127	0.176
Scaffold-GS*		0.233	0.352	0.120	0.236	0.331	0.216	0.203	0.130	0.207
Octree-GS*		0.225	0.340	0.108	0.233	0.310	0.203	0.202	0.141	0.219
3D-GS		0.205	0.336	0.103	0.210	0.317	0.220	0.204	0.129	0.205
AbsGS		0.171	0.270	0.100	0.195	0.278	0.200	0.189	0.121	0.190
Pixel-GS*		0.182	0.263	0.100	0.186	0.280	0.213	0.185	0.120	0.193
Mini-Splatting-D		0.158	0.255	0.090	0.169	0.262	0.190	0.172	0.114	0.175
Ours-Small (AbsGS)		0.175	0.290	0.099	0.188	0.279	0.196	0.184	0.117	0.189
Ours (3D-GS)		0.168	0.295	0.092	0.179	0.280	0.192	0.177	0.114	0.185
Ours (AbsGS)		0.156	0.251	0.089	0.170	0.250	0.187	0.172	0.112	0.179

Table 12. Per-scene PSNR metrics of Tank&Temples and Deep Blending dataset.

Method Scenes	Truck	Train	Dr Johnson	Playroom
Plenoxels	23.22	18.93	23.14	22.98
Instant-NGP	23.38	20.46	28.26	21.67
Mip-NeRF360	24.91	19.52	29.14	29.66
Scaffold-GS	25.77	22.15	29.80	30.62
Octree-GS	26.27	22.77	29.87	30.95
3D-GS	25.19	21.10	28.77	30.04
AbsGS	25.74	21.72	29.20	30.14
Pixel-GS	25.49	22.13	28.02	29.79
Mini-Splatting-D	25.43	21.04	29.32	30.43
Ours-Small (AbsGS)	26.07	22.40	29.64	30.38
Ours (3D-GS)	26.08	22.65	29.54	30.32
Ours (AbsGS)	26.14	22.61	29.51	30.32

Table 15. Results on the Mip-NeRF360 dataset with same setting as Scaffold-GS and Octree-GS.

Method Metrics	Dataset	Mip-NeRF360		
		PSNR ↑	SSIM ↑	LPIPS ↓
Scaffold-GS		27.71	0.813	0.221
Octree-GS		27.73	0.815	0.217
Ours-Small (AbsGS)		28.04	0.831	0.191
Ours (3D-GS)		28.10	0.832	0.187
Ours (AbsGS)		28.14	0.834	0.174

Table 13. Per-scene SSIM metrics of Tank&Temples and Deep Blending dataset.

Method Scenes	Truck	Train	Dr Johnson	Playroom
Plenoxels	0.774	0.663	0.787	0.802
Instant-NGP	0.800	0.689	0.854	0.779
Mip-NeRF360	0.857	0.660	0.901	0.900
Scaffold-GS	0.883	0.822	0.907	0.904
Octree-GS	0.896	0.835	0.912	0.914
3D-GS	0.879	0.802	0.899	0.906
AbsGS	0.888	0.818	0.898	0.907
Pixel-GS	0.883	0.823	0.885	0.899
Mini-Splatting-D	0.890	0.817	0.905	0.908
Ours-Small (AbsGS)	0.889	0.834	0.905	0.907
Ours (3D-GS)	0.890	0.840	0.901	0.905
Ours (AbsGS)	0.893	0.841	0.900	0.905

Table 16. Results on the Mip-NeRF360 dataset with same setting as Pixel-GS.

Method Metrics	Dataset	Mip-NeRF360		
		PSNR ↑	SSIM ↑	LPIPS ↓
Pixel-GS		27.88	0.834	0.176
Ours-Small (AbsGS)		28.21	0.841	0.176
Ours (3D-GS)		28.28	0.843	0.172
Ours (AbsGS)		28.30	0.845	0.160

Table 14. Per-scene LPIPS metrics of Tank&Temples and Deep Blending dataset.

Method Scenes	Truck	Train	Dr Johnson	Playroom
Plenoxels	0.335	0.422	0.521	0.499
Instant-NGP	0.249	0.360	0.352	0.428
Mip-NeRF360	0.159	0.354	0.237	0.252
Scaffold-GS	0.147	0.206	0.250	0.258
Octree-GS	0.118	0.198	0.231	0.244
3D-GS	0.148	0.218	0.244	0.241
AbsGS	0.132	0.193	0.241	0.233
Pixel-GS	0.122	0.180	0.258	0.243
Mini-Splatting-D	0.100	0.181	0.218	0.204
Ours-Small (AbsGS)	0.124	0.177	0.233	0.235
Ours (3D-GS)	0.118	0.164	0.232	0.231
Ours (AbsGS)	0.106	0.159	0.231	0.223