



Low-Frequency First: Eliminating Floating Artifacts in 3D Gaussian Splatting

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<https://jcwang-gh.github.io/EFA-GS>

Motivation

- **3D Gaussian Splatting (3DGS)** is an explicit learning-based 3D representation method that enables efficient rendering and achieves high visual quality simultaneously.

3DGS-based Reconstruction



Ground Truth

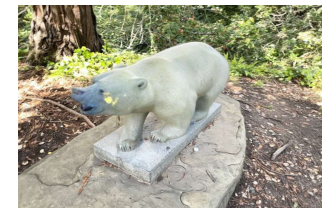


Reconstruction Results

3DGS-based Editing



Ground Truth



Editing Results

Motivation

- However, 3DGS is also sensitive to noise and sometimes produce artifacts, which significantly degrade visual fidelity.

3DGS-based Reconstruction



Ground Truth



Reconstruction Results

3DGS-based Editing



Ground Truth



Editing Results



Motivation

- Previous researches find that depth-based regularization methods can eliminate these artifacts. However, they still have some limitations. (e.g. erosions of delicate details)

3DGS-based Reconstruction



Ground Truth

Reconstruction
Results

Depth Regularization
Results

We need to find the cause of these artifacts and design a method to solve this issue!

Preliminary: Frequency View

➤ *Relation between 3DGS attributes and frequency:*

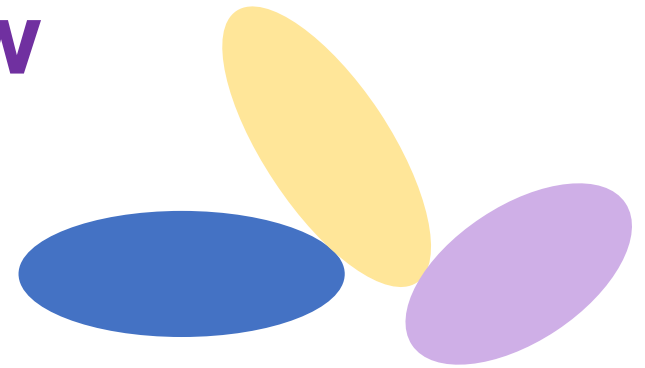
In 3DGS, the expression of Gaussian primitive is:

$$\mathcal{G}(x) = \frac{1}{(2\pi)^{\frac{3}{2}} |\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x-p)^T \Sigma^{-1}(x-p)\right),$$

which can be represented as a weighted sum of different frequency components:

$$\mathcal{G}(x) = \frac{1}{(2\pi)^3} \int_{\mathbb{R}^n} \mathcal{F}(\mathcal{G}(x), \omega) e^{i\omega^T x} dx,$$

p represents the center location. The covariance matrix $\Sigma = RSS^T R^T$, R and S are the rotation and scaling matrix, they are represented by a quaternion q and a 3D vector s respectively.



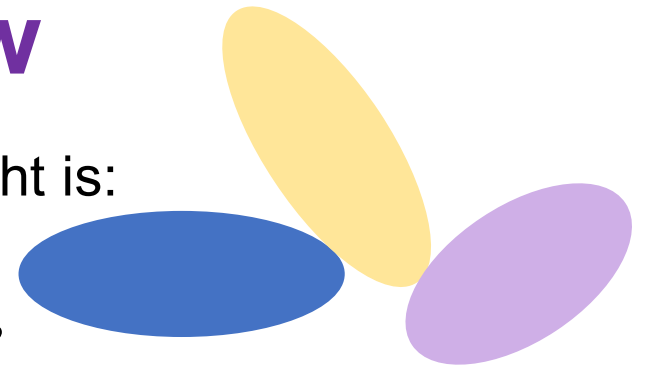
Preliminary: Frequency View

Given an angular frequency ω , the corresponding weight is:

$$|\mathcal{F}(\mathcal{G}(x), \omega)| = \exp\left(-i\omega^T p - \frac{\omega^T \Sigma \omega}{2}\right),$$

which decays as the norm of the angular frequency $|\omega|$ increases due to the positive-definiteness property of Σ .

R is an orthogonal matrix, so S determines the frequency components of a Gaussian primitive. ***A larger Gaussian contains relatively more low frequency information and vice versa.***



Preliminary: Frequency View

➤ **Nyquist-Shannon Sampling Theorem:** The sampling rate must be **at least twice the bandwidth** (the highest frequency) ν of a band-limited signal to reconstruct the signal without aliasing.

Previous work [1] provided a method to estimate the sampling rates of Gaussians

$$\nu \propto \max_{k=1, \dots, N} \left(\mathbf{1}_k(p_i) \cdot \frac{f_k}{d_k} \right),$$

f and d are the focal length and depth respectively. The sampling interval T is the inverse of sampling rate

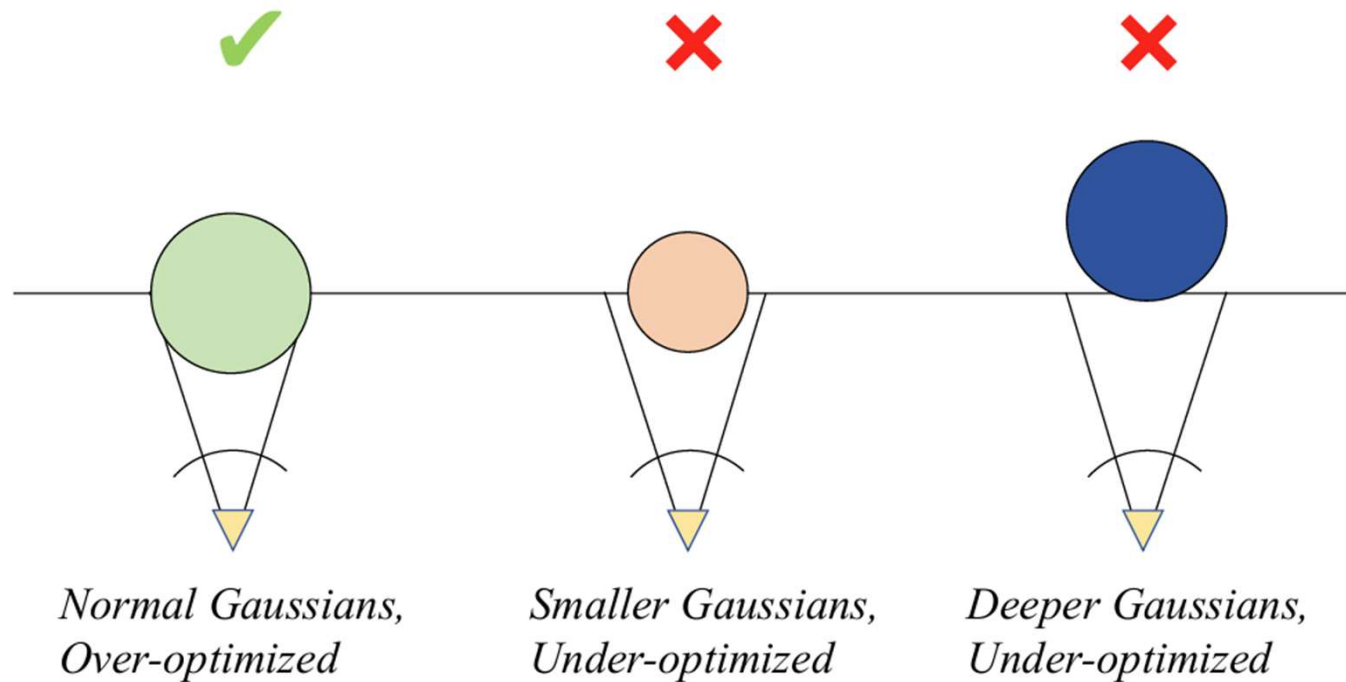
$$T = \frac{1}{\nu},$$

Where $\mathbf{1}_k$ is an indicator denoting the visibility of Gaussians.

[1] Yu, Z., Chen, A., Huang, B., Sattler, T., & Geiger, A. (2024). Mip-splatting: Alias-free 3d gaussian splatting. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 19447-19456).

Analysis

- There are 2 key factors determining if a Gaussian can be sufficiently optimized: **scale (frequency bandwidth)** and **depth (sampling interval)**.
- For each Gaussian, if its scale is **larger** than the sampling interval, it is probably **over-optimized**; **otherwise** it is probably **under-optimized**.



Analysis

➤ **Hypothesis:** Low quality initialization can be viewed as accurate initialization with noise.

We conduct experiments using both clean and noisy initialization to estimate the impact of low-quality initialization. We also record the average scalings of Gaussians.



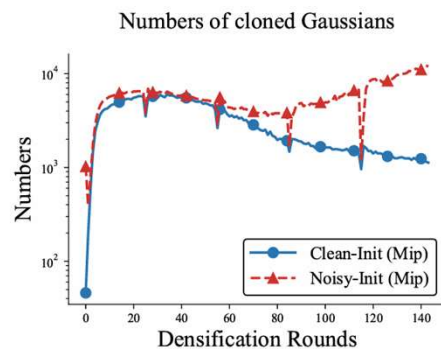
(a) Clean init. (b) Noisy init. (c) Noisy init (training). (d) Noisy init with EFA-GS.

PSNR	ship [10]		kitchen [11]	
	Train	Test	Train	Test
Clean init (Mip-splatting)	33.94	29.74	34.74	32.03
Noisy init (Mip-splatting)	34.02	27.53	33.68	28.39
/Clean - Noisy/ (Mip-splatting)	0.08	2.21	1.06	3.64
Clean init (EFA-GS, simple)	32.88	30.66	31.54	31.23
Noisy init (EFA-GS, simple)	32.89	29.73	31.33	29.48
/Clean - Noisy/ (EFA-GS, simple)	0.01	0.93	0.21	1.75

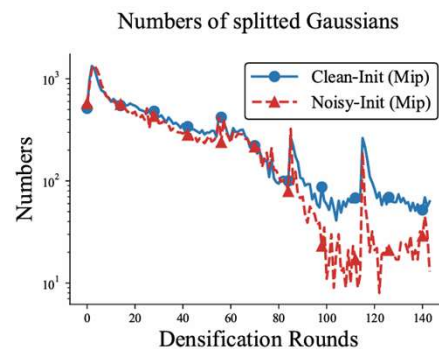
Analysis

Furthermore, we also conduct sparse-view experiments to explore the relation between under-optimized Gaussians and artifacts. These experiments indicate that:

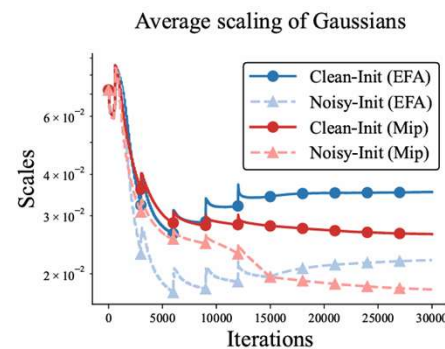
- Corrupted initialization results in excessive shrinkage of most Gaussians.
- Floating artifacts harm more severely to the visual quality of testing views.
- Under-optimized Gaussians are related with the existence of artifacts.



(a) Numbers of cloned Gaussians.



(b) Numbers of splitted Gaussians.



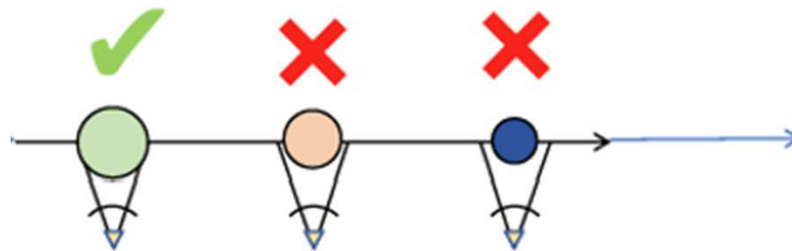
(c) Average scalings of Gaussians.

Mip-splatting	PSNR
8-Views	17.38
12-Views	18.44
16-Views	20.74

Analysis

- **Proposition:** In low-quality initialization scenarios, under-optimized Gaussians would be more sensitive to noise and more likely to become floating artifacts than over-optimized ones in the optimization process.

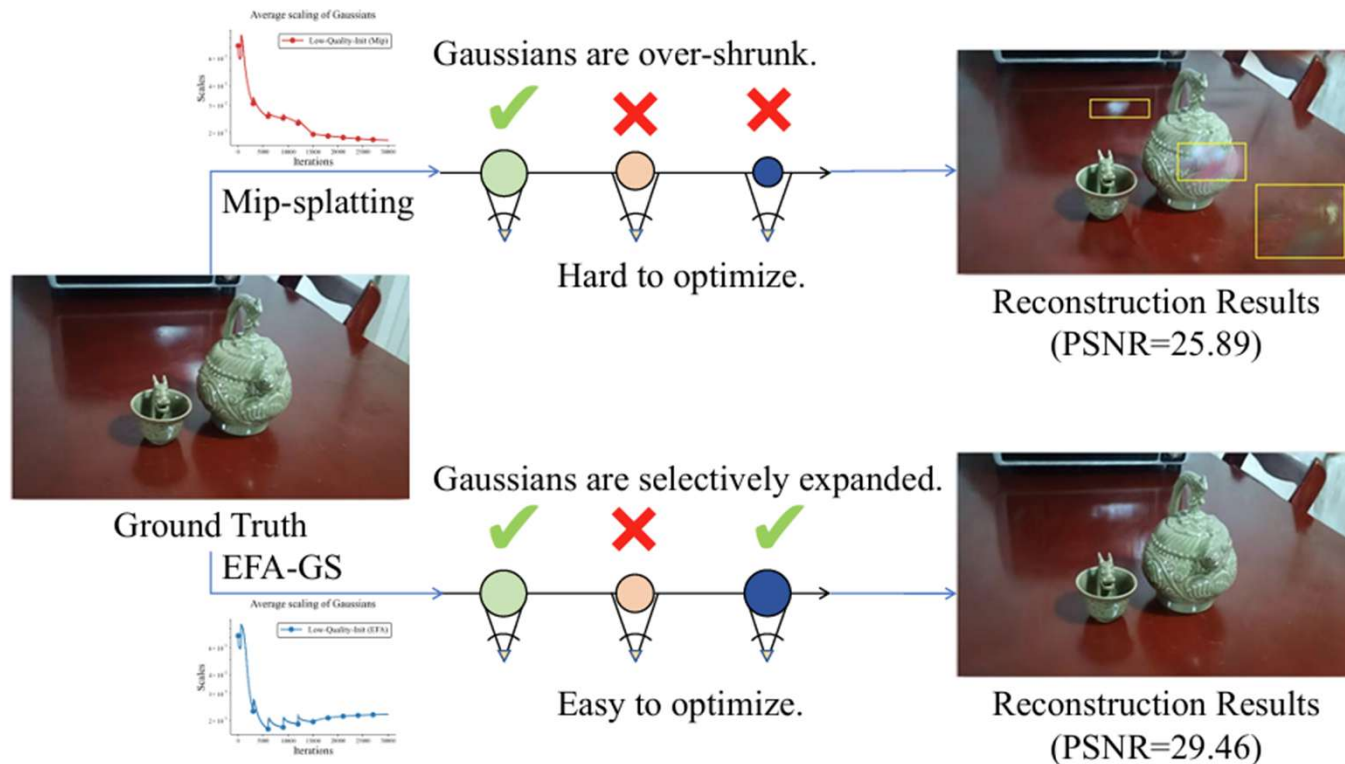
Gaussians are over-shrunk.



Reconstruction Results

Method

We propose our EFA-GS, an enhanced 3DGS in order to effectively mitigate floating artifacts. EFA-GS consists of the Low-Frequency Come-First (LFCF) algorithm and some strategies.



Method

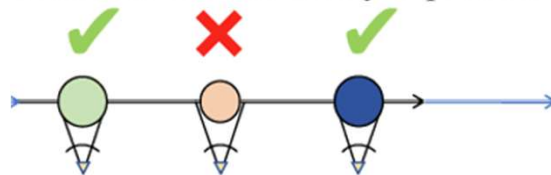
➤ **LFCF algorithm:** The core idea of LFCF algorithm is to selectively expand Gaussians during training.

Both the expanding and shrinking operations are implemented as

$$s' = s \cdot c,$$

where c is a 3D vector controlling expansion or shrinkage.

Gaussians are selectively expanded.



Easy to optimize.



Reconstruction Results

Algorithm 1 LFCF algorithm

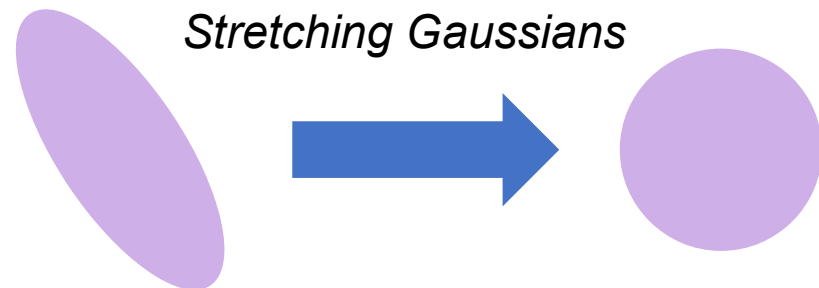
Require: previous gradients $PGrad(\cdot)$, current gradients $Grad(\cdot)$, enlarging factor $s(\cdot)$, processing threshold τ , opacities $\alpha(\cdot)$, opacity threshold ϵ , splitting threshold $\eta(\cdot)$

```
1: for  $i^{th}$  Gaussian in all Gaussians do
2:   if  $Grad(i) > \tau$  then
3:     if  $Grad(i) > PGrad(i)$  then
4:       ExpandGaussian( $i, s(i)$ )
5:     else
6:       ShrinkGaussian( $i$ )
7:       SplitGaussian( $i$ )
8:     end if
9:   end if
10:   $PGrad(i) \leftarrow Grad(i)$ 
11: end for
12: for  $i^{th}$  Gaussian in all Gaussians do
13:   if  $\alpha(i) < \epsilon$  then
14:     RemoveGaussian( $i$ )
15:   end if
16: end for
```

Method

We design several strategies to preserve delicate details by controlling c . Here are 2 main strategies:

- **Depth-based Strategy:** We observe that deeper Gaussians have lower sampling rates and are more difficult to optimize, so we assign **deeper Gaussians lower enlarging factors**.
- **Scale-based Strategy:** The strategy treats scaling factors of different axes differently. To preserve the Gaussian volume, we design a volume-preserving setting $\prod_i c_i = 1$



Experiments

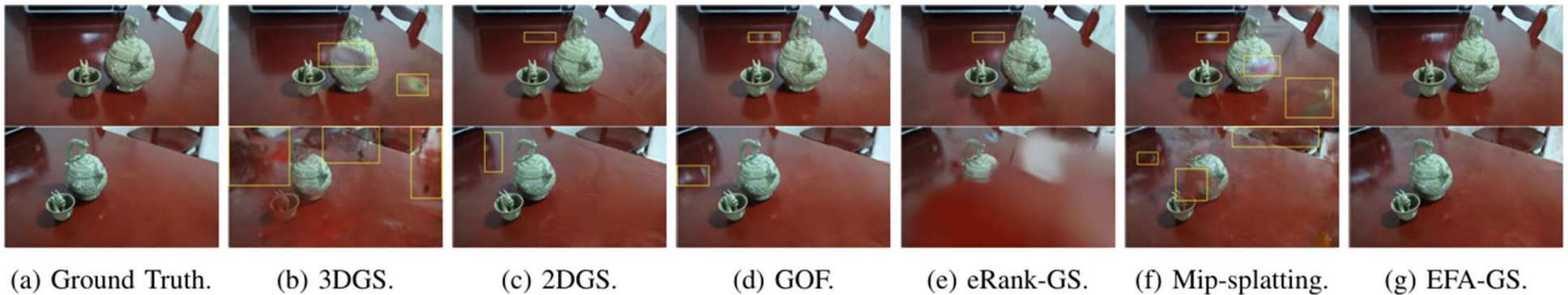
We estimate our EFA-GS on 3D Reconstruction and Editing tasks. For Reconstruction tasks, the experimental settings are:

- Evaluation Metrics: PSNR, LPIPS, SSIM.
- Dataset: Mip-NeRF 360, RWLQ, TanksandTemples.
- Comparison methods: Vanilla 3DGS, Mip-splatting, 2DGS, Gaussian Opacity Fields, eRank-GS.

Experiments

➤ *RWLQ results:* Our EFA-GS achieve state-of-the-art performance and effectively eliminate floating artifacts.

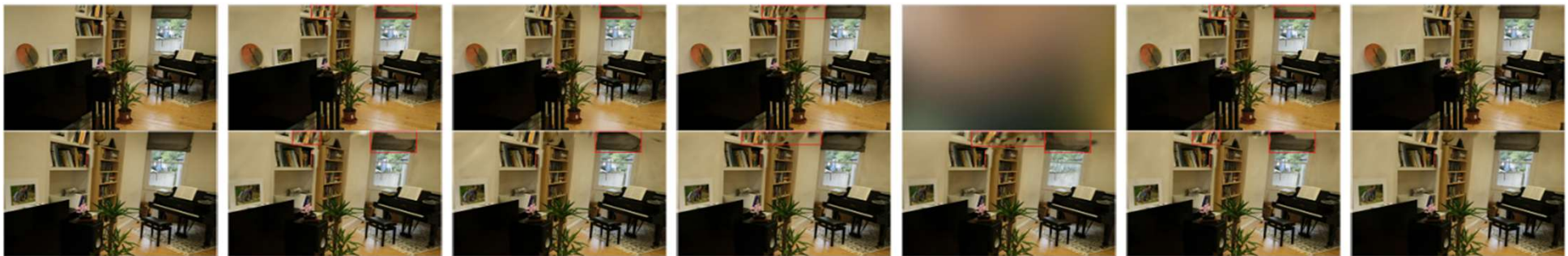
	PSNR↑	SSIM↑	LPIPS↓
2DGS [20]	28.00	0.95	0.16
GOF [24]	27.92	0.95	0.15
eRank-GS [33]	23.16	0.91	0.18
Vanilla 3DGS [1]	27.71	0.95	0.15
EFA-GS(3DGS)	28.70	0.95	0.14
Mip-splatting [9]	26.67	0.94	0.16
EFA-GS(Mip, default)	28.35	0.95	0.15



Experiments

➤ *Mip-NeRF 360 results:* Our EFA-GS effectively preserve delicate details and achieve state-of-the-art performance.

	PSNR↑	SSIM↑	LPIPS↓
2DGS	27.00	0.81	0.24
GOF	27.33	0.82	0.20
eRank-GS	27.69	0.84	0.20
Vanilla 3DGS	27.58	0.82	0.21
EFA-GS(3DGS)	27.52	0.82	0.21
Mip-splatting	27.92	0.84	0.18
EFA-GS(Mip, default)	27.94	0.84	0.18



(a) Ground Truth.

(b) 3DGS.

(c) 2DGS.

(d) GOF.

(e) eRank-GS.

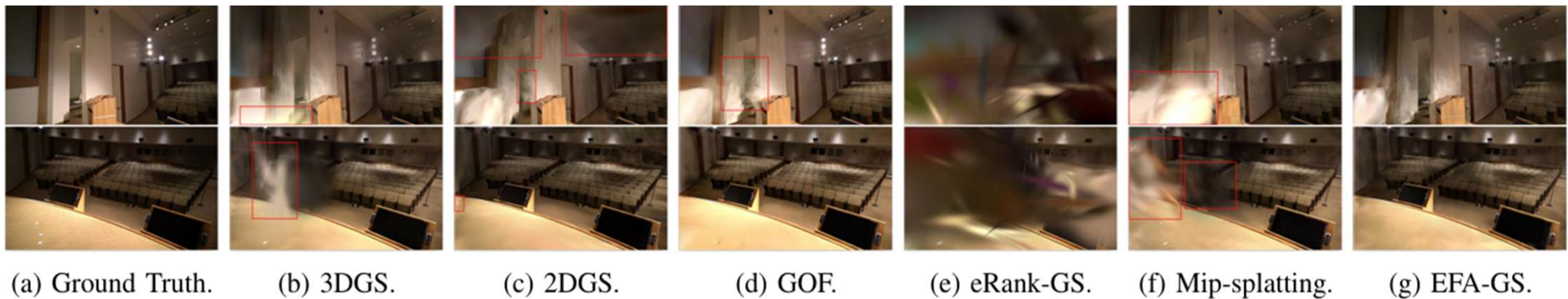
(f) Mip-splatting.

(g) EFA-GS.

Experiments

➤ *TanksandTemples results:* Our EFA-GS effectively mitigate floating artifacts and achieve state-of-the-art performance.

	PSNR↑	Overall SSIM↑	LPIPS↓	Low-Quality Init		
				PSNR↑	SSIM↑	LPIPS↓
2DGS	21.17	0.78	0.32	18.98	0.72	0.41
GOF	19.80	0.77	0.30	17.84	0.67	0.39
eRank-GS	18.43	0.72	0.37	16.37	0.62	0.45
Vanilla 3DGS	21.51	0.79	0.28	19.11	0.69	0.37
EFA-GS(3DGS)	21.69	0.80	0.28	19.45	0.69	0.36
Mip-splatting	20.63	0.78	0.29	18.15	0.67	0.39
EFA-GS(Mip, default)	21.31	0.79	0.28	19.07	0.69	0.37



Experiments

➤ *Ablation Studies:* Each component of EFA-GS is useful: they either improve the visual quality or reduce the computation cost.

➤ *Speed experiments:* EFA-GS efficiently improve visual quality with limited computation costs.

	Depth	Scale	PSNR↑	SSIM↑	LPIPS↓
EFA-GS	✓	✓	27.94	0.84	0.18
EFA-GS(w/o depth)		✓	27.83	0.83	0.18
EFA-GS(w/o scale)	✓		27.91	0.83	0.18
EFA-GS(w/o scale&depth)			27.37	0.83	0.19

EFA-GS Settings	Str 1	Str 2	Str 3	PSNR↑	Time↓
EFA-GS(w/o all str)				32.08	20'22"
EFA-GS(w/o str 1&2)			✓	32.12	20'12"
EFA-GS(w/o str 1)		✓	✓	32.19	20'21"
EFA-GS(w/o str 1&3)		✓		32.18	20'49"
EFA-GS(w/o str 3)	✓	✓		32.50	23'10"
EFA-GS(w/o str 2&3)	✓			32.36	22'53"
EFA-GS(w/o str 2)	✓		✓	32.37	22'40"
EFA-GS	✓	✓	✓	32.56	22'55"

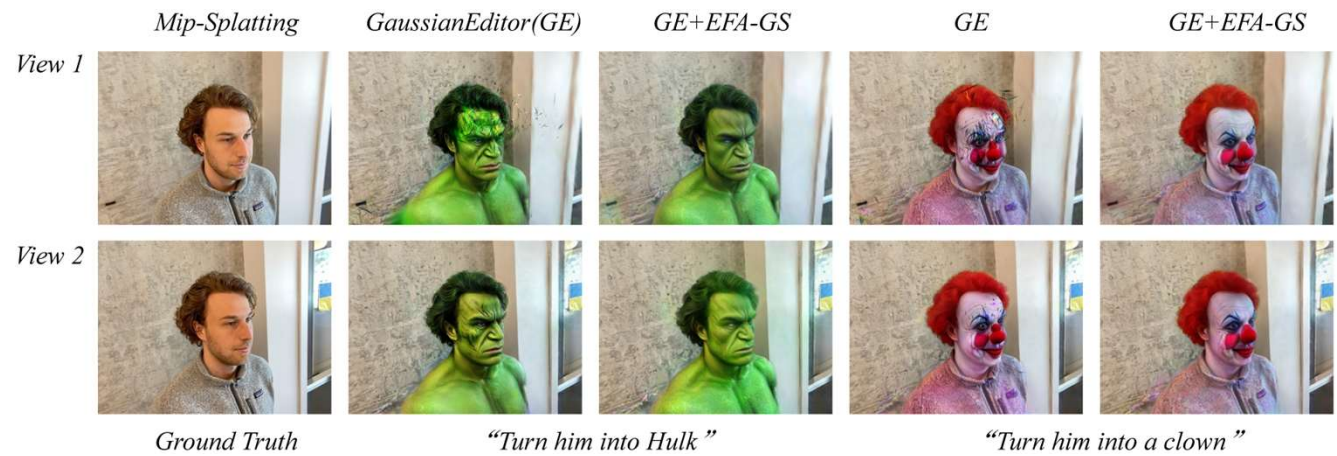
	PSNR↑	SSIM↑	Overall LPIPS↓	Aver Time(min)↓	PSNR↑	SSIM↑	Low-Quality Init LPIPS↓	Aver Time(min)↓
Vanilla 3DGS	21.51	0.79	0.28	32.3	19.11	0.69	0.37	31.5
EFA-GS(3DGS)	21.69	0.80	0.28	29.2	19.45	0.69	0.36	29.0
eRank-GS	18.43	0.72	0.37	75.8	16.37	0.62	0.45	72.0
EFA-GS(eRank)	20.32	0.77	0.31	80.3	17.78	0.65	0.40	77.8
GOF	19.80	0.77	0.30	83.6	17.84	0.67	0.39	78.8
EFA-GS(GOF)	20.57	0.79	0.28	86.9	19.07	0.69	0.37	85.5

Experiments

➤ Hyperparameter Analysis.

PSNR↑	$r = 1$	$r = 2$	$r = 5$
$c_{max} = 1.50$	27.62	27.94	27.90
$c_{max} = 1.75$	27.60	27.87	27.92
$c_{max} = 2.00$	27.58	27.89	27.91

➤ 3D Editing.



Summary

- We propose a theoretical framework to analyze the underlying mechanism of floating artifacts.
- We present EFA-GS to effectively and efficiently mitigate artifacts. EFA-GS consists of LFCF algorithm and other strategies.
- Experiments shows EFA-GS effectively mitigate artifacts in various tasks.



Thanks for Your Listening!

Presented by Jianchao Wang

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<https://jcwang-gh.github.io/EFA-GS>