

True Scene-Linear HDR 3D Gaussian Splatting: Neural-Free Game-Engine-Ready HDR Novel View Synthesis

Ziyang Zhang¹ , Hajime Uchimura¹ and Kentaro Suzuki¹

¹Polyphony Digital Inc., Japan

Abstract

We propose a novel method for high dynamic range (HDR) 3D Gaussian Splatting (3DGS) compatible with HDR-capable game engines using linear-space RGB. Existing methods often rely on neural-network-based tone mapping to map linear 3DGS colors to standard dynamic range images, causing poor performance when used directly in linear space. Furthermore, they require multiple-exposure images from the same camera position and viewing angle, which is infeasible for real-world data collection. In contrast, our method learns a true linear-RGB HDR 3DGS representation without requiring any neural network during training or rendering. It supports a unified training pipeline for diverse input formats, including multi-exposure photos, 10-bit HDR images, and log-encoded captures. Experiments show that our approach achieves significantly higher linear-space HDR quality than existing methods, enabling high-quality novel view synthesis in HDR-capable rendering systems, including game engines.

CCS Concepts

• **Computing methodologies** → **Rendering**; **Point-based models**;

1. Introduction

High dynamic range (HDR) images capture broad luminance ranges, preserving fine details in both dark and bright regions. As 3D Gaussian Splatting (3DGS) increasingly enters video-game rendering pipelines, supporting scene-linear HDR RGB in 3DGS has become an important practical feature. Recent HDR 3DGS methods such as HDR-GS and GaussHDR [CXL*24,LKLX25] improve appearance reconstruction across exposure levels. However, existing methods either optimize visual quality mainly through learned tone-mapped outputs, which do not directly ensure correct underlying scene-linear HDR radiance, or perform HDR reconstruction with learned neural tone-mapping modules and auxiliary features. These neural components make the resulting representations less directly compatible with modern game-engine rendering pipelines, which typically expect HDR scene representations to integrate with built-in exposure control, tone mapping, and post-processing systems. In addition, these methods commonly require multi-exposure images from the same camera position and angle, complicating the image capture and limiting their practicality in real applications.

To address such limitations, we propose a game-engine-ready scene-linear HDR 3DGS training method. Our method keeps linear HDR RGB as the learned representation inside 3DGS and does not require any neural networks during training or inference. Our contributions are summarized as follows:

- A novel neural-network-free 3DGS training method that accurately learns a scene-linear HDR representation.

- A unified input processing pipeline that supports a variety of input formats, including single 10-bit HDR images, log-encoded HDR images, and multi-exposure SDR image groups.
- An intensity-aware loss term that enhances detail reconstruction in dark regions.

2. Method

We map all inputs to scene-linear HDR RGB by directly linearizing 10-bit HDR and log-encoded images or applying a classic HDR radiance recovery algorithm to multi-exposure captures taken from a fixed camera pose [DM97]. Direct linear-HDR supervision is unstable because of the large dynamic range, while tone-mapped SDR supervision cannot ensure scene-linear correctness without neural networks. Although training 3DGS models directly in log-color space can improve stability and the learned representation can later be converted to linear color, even small log-domain errors may be amplified during conversion, causing visible artifacts. We therefore retain a scene-linear representation and use S-Log3 [Son14] only as a loss-domain encoding: rendered and ground-truth HDR images are mapped to S-Log3 before loss computation. The training loss combines L1, SSIM [WBSS04], and Charbonnier [Bar19] terms:

$$\mathcal{L} = \mathcal{L}_{\text{dark-}\ell_1} + \lambda_s \mathcal{L}_{\text{SSIM}} + \lambda_c \mathcal{L}_{\text{charb}}, \quad (1)$$

$$\begin{aligned} \mathcal{L}_{\text{dark-}\ell_1} &= \|\Phi_k(\hat{\mathbf{I}}_{\text{SLog3}}) - \Phi_k(\mathbf{I}_{\text{SLog3}})\|_1, \\ \mathcal{L}_{\text{SSIM}} &= 1 - \text{SSIM}(\hat{\mathbf{I}}_{\text{SLog3}}, \mathbf{I}_{\text{SLog3}}). \end{aligned} \quad (2)$$

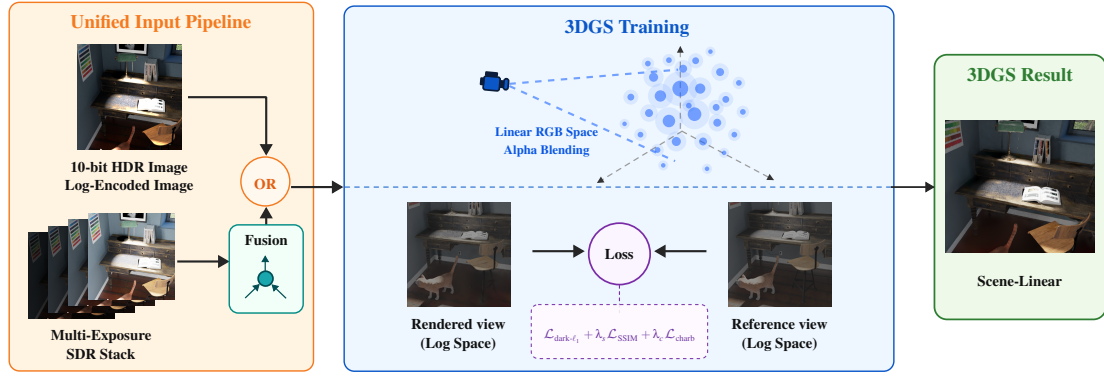


Figure 1: **Overall structure.** We support 10-bit HDR/log-encoded inputs and multi-exposure SDR stacks for training linear-RGB 3DGS.

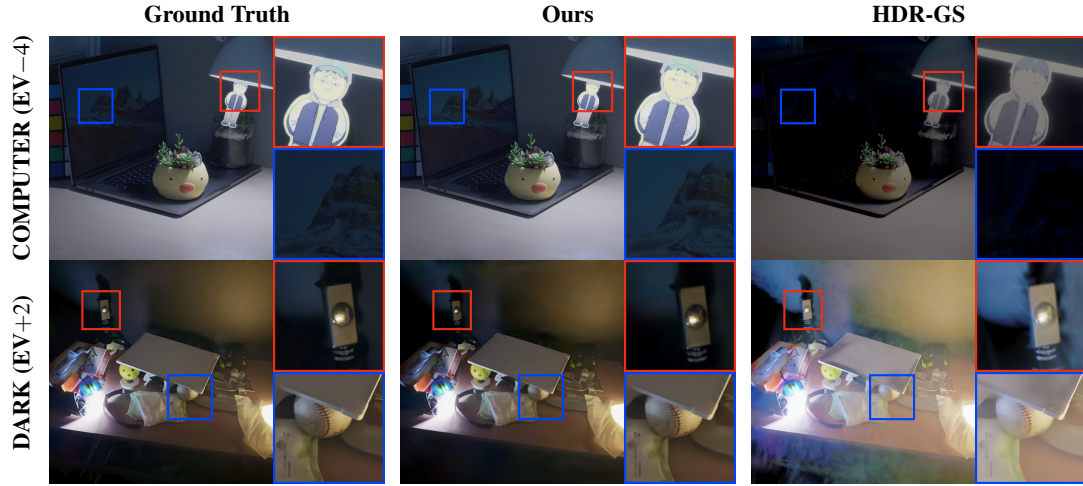


Figure 2: **Visual comparison.** Linear RGB renderings tone-mapped for SDR visualization.

Here, $\hat{\mathbf{I}}_{S\text{Log}3}$ and $\mathbf{I}_{S\text{Log}3}$ denote the rendered and ground-truth images in S-Log3 space, which compresses the HDR range. We define an intensity-aware boosting term as $\Phi_k(x) = \log(1 + kx)/\log(1 + k)$, which emphasizes low-intensity errors because its gradient is larger near $x = 0$; k controls the strength. The Charbonnier term encourages sharper boundaries and dark structures while reducing sensitivity to large HDR errors.

3. Results and Conclusion

In Fig. 2, we compare our method to HDR-GS in two scenes. Overall, our method achieves much better color and intensity correctness. On the COMPUTER scene, we are able to preserve details under high-intensity lighting. In a more challenging scene, DARK, our method shows a strong capability to reconstruct both bright and dark areas. We also compare our method to GaussHDR quantitatively. On COMPUTER at exposure value (EV) = +1, without using any neural networks during training or rendering, our method achieves an L1 reconstruction loss of 0.266 in scene-linear space, which is much lower than calibrated GaussHDR (0.590) in scene-linear space. On DARK, training directly in S-Log3 yields worse sRGB L1 (0.041) than using an S-Log3 loss (0.025). As future work, we are working on more ablation studies and visual compar-

isons while improving the capability of capturing dimmer details and a broader HDR range.

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