EaDeblur-GS: Event assisted 3D Deblur Reconstruction with Gaussian Splatting

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Abstract. 3D deblurring reconstruction techniques have recently seen significant advancements with the development of Neural Radiance Fields (NeRF) and 3D Gaussian Splatting (3DGS). Although these techniques can recover relatively clear 3D reconstructions from blurry image inputs, they still face limitations in handling severe blurring and complex camera motion. To address these issues, we propose Event-assisted 3D Deblur Reconstruction with Gaussian Splatting (EaDeblur-GS), which integrates event camera data to enhance the robustness of 3DGS against motion blur. By employing an Adaptive Deviation Estimator (ADE) network to estimate Gaussian center deviations and using novel loss functions, EaDeblur-GS achieves sharp 3D reconstructions in real-time, demonstrating performance comparable to state-of-the-art methods.

Keywords: 3D Gaussian Splatting \cdot Event Cameras \cdot Neural Radiance Fields

1 Introduction

Reconstructing 3D scenes and objects from images has long been a research hotspot in computer vision and computer graphics. The advent of Neural Radiance Fields (NeRF) [4] has brought revolutionary advancements in photorealistic novel view synthesis. Recently, The introduction of 3D Gaussian Splatting (3DGS) [1] has revolutionized 3D scene representation using Gaussian ellipsoids, achieving high-quality 2D rendering and faster speeds. However, in real-world applications, factors like camera shake and shutter speed often lead to image blurriness and inaccurate camera poses estimation, challenging the clear neural volumetric representation.

Therefore, several methods have been developed to handle blurriness in NeRFs and 3DGS. NeRF's deblurring technology has undergone relatively early development, with Deblur-NeRF [3] being the first framework to tackle this issue, which utilized an analysis-by-synthesis approach to recover sharp NeRFs from blurry inputs. MP-NeRF[8] further enhances this by introducing a multi-branch fusion network and prior-based learnable weights to handle extremely blurry or unevenly blurred images. But the NeRF-based methods always consume extensive training time and rendering time. Some methods based on 3DGS has

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been developed because of its advantages in rendering and training speed. For instance, Wenbo Chen et al. [9] proposed Deblur-GS, which models the problem of motion blur as a joint optimization involving camera trajectory and time sampling. B. Lee et al. [2] assign the corrections on the rotation and scaling matrix of 3D gaussians by using a small MLP, enhancing the clarity of scenes reconstructed from blurred images. Nonetheless, these methods can only achieve clear 3D reconstruction results with mildly blurred input images. Consequently, additional data sources like event cameras have been introduced into 3D deblurring reconstruction. Event cameras, a bio-inspired sensor, offers high temporal resolution and has advantages in motion deblur. For NeRFs, EventNeRF [7] used event integration and color simulation for colored 3D representations, while Qi et al. [6] combined blurred images with event streams using innovative loss functions and the Event Double Integral (EDI) approach. For 3DGS, Yu proposed EvaGaussian[10], which enhanced 3DGS with assistance of event streams.

Despite achieving excellent performance in 3D deblurring reconstruction, the aforementioned methods still have limitations. For instance, RGB single-modality deblurring 3DGS and NeRF are often effective only in mildly blurred or simple camera motion scenarios. When input images are severely blurred, these methods usually fail to reconstruct 3D objects and can only produce relatively clear 2D renderings from certain angles. On the other hand, techniques using event cameras for NeRF 3D reconstruction are limited by NeRF's training and rendering speed. Additionally, methods that incorporate event data into 3DGS deblurring reconstruction face challenges, such as inaccurate camera motion trajectory estimation.

To overcome these limitations, we propose a novel integration of event streams with 3DGS, namely Event-assisted 3D Deblur Reconstruction with Gaussian Splatting(EaDeblur-GS), aiming to guide the learning of better 3D Gaussian representations and tackle issues arising from blurry inputs.

Our contributions are summarized as follows:

- We propose Event-assisted 3D Deblur Reconstruction with Gaussian Splatting (EaDeblur-GS), which incorporates blurry RGB images and event streams into Gaussian Splatting to recover sharp 3D representations.
- We introduce a novel Adaptive Deviation Estimator(ADE) network to simulate the shaking motion during exposure accurately by estimating the deviations of Gaussians.
- We comprehensively evaluate the proposed method and compare it with several baselines, demonstrating that our EaDeblur-GS achieves performance comparable to state-of-the-art methods while enabling real-time sharp image rendering.

2 Method

As shown in Fig.1, our method starts with the input of blurry RGB images and the corresponding event streams. We first employ the Event Double Integral (EDI) technique [5] to generate a set of latent sharp images. These images

are then processed by COLMAP to achieve enhanced initial reconstruction and precise camera pose estimation. From this enhanced reconstruction, we create a set of 3D Gaussians. Subsequently, the positions of these Gaussians and the estimated camera poses are fed into our proposed ADE network to determine the positional deviations of the Gaussians. These adjusted 3D Gaussians are then projected onto each viewpoint, including corresponding latent viewpoints, to produce sharp image renderings. Furthermore, we integrate a Blurriness Loss to simulate the generation of authentic blurry images, and an Event Integration Loss to guide the Gaussian model in accurately capturing the true shapes of objects. This allows the model to learn precise 3D volume representations and achieve superior 3D reconstructions. The overview of our method is illustrated in Fig.1.

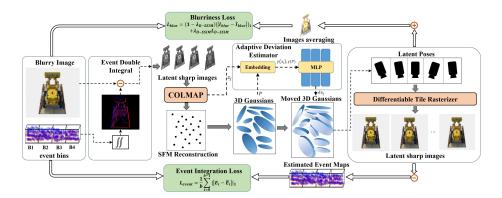


Fig. 1. The overview of EaDeblur-GS

In the following sections, we detail how the ADE network estimates deviations, followed by an in-depth introduction to blurriness loss and event integration loss.

2.1 Adaptive Deviation Estimator

Motion blur caused by camera shake impedes sparse initial reconstruction due to unclear input images. To mitigate this issue, we employ the EDI method [5], which combines blurry images and corresponding event streams. The EDI model transforms a blurry image I_{blur} into multiple sharp images I_0, \dots, I_k , under the assumption that the blurry image is the temporal average of latent sharp images, each represented by the accumulated events. Given a blurry image and its corresponding event bins $\{B_k\}_{k=1}^b$, the sharp image of viewpoint I_0 and each latent sharp image I_k can be expressed as:

$$I_0 = \frac{(b+1)I_{blur}}{1 + e^{\Theta \sum_{i=1}^1 B_i} + \dots + e^{\Theta \sum_{i=1}^b B_i}}.$$
 (1)

$$I_k = \frac{(b+1)I_{blur}e^{\Theta\sum_{i=1}^k B_i}}{1 + e^{\Theta\sum_{i=1}^l B_i} + \dots + e^{\Theta\sum_{i=1}^b B_i}}.$$
 (2)

We then utilize COLMAP to estimate the poses of EDI-processed sharp images $\{\mathbf{P}_k\}_{k=0}^b = \text{COLMAP}(\{I_k\}_{k=0}^b)$, which also results in a more accurate initial sparse point cloud.

Inspired by [9] and [2], we represent latent poses as displacements of Gaussian ellipsoid centers x_j . To estimate the deviations of Gaussians in this context, we employ Adaptive Deviation Estimator network, which is consisted of a small Multi-Layer Perceptron (MLP) $\mathcal{F}\theta$ with three hidden linear layers and an embedding layer which transforms low-frequency positional information into high-frequency expressions. The ADE $\mathcal{F}\theta$ takes the EDI-predicted poses $\mathbf{P}kk=0^b$ and original positions of Gaussians x_j to estimate deviations:

$$\{(\delta x_j^{(i)})\}_{i=1}^l = \mathcal{F}_\theta\Big(\gamma(x_j), \gamma(P)\Big)$$
(3)

where l means the number of estimated latent poses, and $\delta x_j^{(i)}$ denotes the i-th predicted position offset of j-th Gaussian. We then obtain extra l sets of 3D Gaussians $\{\{\hat{x}_j^{(i)}\}_{i=1}^l\}_{j=1}^{N_G}$ by adjusting the positions of the original 3D Gaussians, where N_G is the number of Gaussians, $\hat{x}_j^{(i)}$ represents the position offset scaled by $\lambda_p : \delta x_j^{(i)}$ by $\lambda_p . \hat{x}_j^{(i)} = x_j + \lambda_p \delta x_j^{(i)}$. This method computes l different sets of 3D Gaussians for each viewpoint, which can be rasterized to l sharp latent images $\{I_i\}_{i=0}^l$. Additionally, we rasterize an image with original Gaussians positions as the image rendered from original viewpoint. During forward rendering process, the MLP network and multiple rendering are not necessary, ensuring real-time inference speed comparable to original 3D Gaussian.

2.2 Loss Functions

Blurriness loss. To model the motion blur process during exposure time, we take the average sum of rendered images as follows:

$$\hat{I}_{blur} = \frac{1}{b+1} \sum_{i=0}^{b} I_i, \quad I_i = \text{Rasterize}(\{G(\hat{x}_j^{(i)})\}_{j=1}^{N_G})$$
 (4)

where I_i is a sharp image generated by the estimated corrections, I_{blur} is the estimated blurry image. The blurriness loss is computed as the difference between estimated blurry image and input blurry image I_{blur} , combined with a D-SSIM loss as follows:

$$L_{blur} = (1 - \lambda_{D-SSIM}) \|I_{blur} - \hat{I}_{blur}\|_{1} + \lambda_{D-SSIM} L_{D-SSIM}$$
 (5)

where we set $\lambda_{D-SSIM} = 0.2$ for all experiments.

Event Integration Loss. Leveraging the high time-resolution event stream, we adopt an Event Integration Loss to guide the network in learning a fine-grained

Table 1. Quantitative analysis. The results in tha table are the averages of six synthetic scenes from E2NeRF. We use bold to mark the best result.

Image Deblur	GS	Deblurring-GS	${ m E^2NeRF}$	Ours
PSNR	22.15	22.70	29.77	30.08
SSIM	0.878	0.8427	0.960	0.9366
FPS	160	160	2	160

sharp 3D reconstructions. We integrate the events polarities between two input frames as follows:

$$\mathbf{E}(t) = \int_{t_0}^{t_0 + \delta t} \mathbf{e}(t)dt. \tag{6}$$

where δt is time interval between two input frames. The logarithm difference between the last rendered frame and first rendered frame of multiple rendered frames $\{I_i\}_{i=0}^l$ gives the estimated event integration maps $\tilde{\mathbf{E}}(t)$. The event integration loss is then:

$$L_{event} = \|\mathbf{E}(t) - \widetilde{\mathbf{E}}(t)\|_1 \tag{7}$$

The final loss function is the combination of the blurriness loss and event integration loss as follows:

$$L = L_{blur} + \lambda_{event} L_{event} \tag{8}$$

3 Experiments

3.1 Comparisons and Results

To evaluate the effectiveness of using event data to aid in deblurring RGB images, we compare our method with the original Gaussian Splatting (GS), which utilizes blurry images as input and supervision. Since COLMAP fails with only blurry images, we estimate the initial point cloud using EDI-deblurred images.

We also compare our method with Deblurring 3D Gaussian Splatting (Deblurring-GS) to highlight the advantages of incorporating event data. Additionally, we benchmark our approach against Event Enhanced Neural Radiance Fields from Blurry Images (E^2 NeRF), the state-of-the-art method that leverages event data for deblurring RGB images.

Our evaluation metrics include Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Frames Per Second (FPS). All methods are tested on the synthetic data from E²NeRF, which includes perfectly sharp images from the same viewpoint as blurry input images with corresponding event streams. The implementation details are provided in the supplementary materials.

The quantitative comparison results are presented in Table 1 and the qualitative comparison is also provided in Supplementary materials. Our results demonstrate that our method achieves performance comparable to the current

Table 2. Ablation study to validate the effectiveness of losses. "w" represents "with" and "wo" represents "without". " L_{blur} " denotes the blurriness loss function. " L_{event} " denotes the event integration loss.

Loss Function	wo $L_{blur}\&L_{event}$	w L_{blur} wo L_{event}	w $L_{blur} \& L_{event}$
PSNR	22.92	31.80	31.83
SSIM	0.886	0.9490	0.9488

Table 3. Ablation study to analyze the contribution of ADE module. "w" represents "with" and "wo" represents "without".

Latent Pose Estimation	wo MLP	w MLP
PSNR	28.76	31.83
SSIM	0.9347	0.9488

state-of-the-art model in terms of PSNR and SSIM, while maintaining real-time rendering capabilities with noticeable FPS. The advantage of using event data for deblurring RGB images is further evidenced by comparing Deblurring 3D Gaussian Splatting with our method, showing a significant increase in PSNR.

3.2 Ablation studies

Blurriness loss and Event Integration Loss. To validate the effectiveness of training losses, we conduct the experiments on the "hotdog" scene from E²NeRF dataset. The results in the Tab.2 demonstrates that both proposed losses significantly improve the deblurring performance, with the event integration loss further slightly enhancing sharp rendering quality.

With/Without MLP Latent Poses Estimation We conduct the experiments to further analyze the contribution of ADE module. Using initial latent poses estimated by COLMAP with EDI preprocessed images, we compare results with and without the ADE network. As shown in Table 3, the ADE module improves all evaluation metrics, indicating its effectiveness in estimating latent poses during exposure. Further ablations are provided in the supplementary materials.

4 Conclusion

In this paper, we introduce Event-Assisted 3D Deblur Gaussian Splatting (EaDeblur-GS), which integrates event data and RGB images to achieve sharp neural 3D representations. We propose an Adaptive Deviation Estimator network to estimate latent poses during exposure by computing Gaussian deviations. Our method, evaluated against state-of-the-art techniques and through extensive ablation studies, shows significant improvements over the original 3D Gaussian Splatting and performance comparable to Event-RGB deblur NeRF (E²NeRF).

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