BeSplat: Gaussian Splatting from a Single Blurry Image and Event Stream Gopi Raju Matta Trisha Reddypalli Kaushik Mitra



Goal



To synthesize high-quality, sharp images from a single blurry image and its corresponding event stream by leveraging event information to accurately estimate the motion trajectory and restore fine details with enhanced clarity along the camera's trajectory.

Background and Motivation

- >Accurate 3D scene recovery from blurry images is vital but challenging for single views.
- >Event cameras provide high temporal resolution, complementing blurry images effectively.
- \succ Gaussian Splatting enables fast training, real-time rendering, and sharp 3D reconstruction.

Key contributions

- \succ Conceptualized single-image motion deblurring a novel view synthesis problem using as Splatting Gaussian and event stream information.
- >Incorporated event loss to accurately estimate camera motion and address the ill-posed nature of single-image deblurring.
- >Achieved faster training, reduced GPU memory usage, and real-time rendering, producing sharp, high-quality novel images along the camera trajectory.

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Qualitative Results

Synthetic Dataset



Real Dataset



Illustration

- sharp 3D scene.
- Gaussian splats are optimized by photometric and event losses.
- \gg Sharp images along the camera generated jointly bv representation and motion trajectory.



Dataset (GB)

	Camera↓	Lego↓	Letter↓	Plant↓	Toys↓	Average↓
BeNeRF [29]	8.65	8.65	8.65	8.65	8.65	8.65
Ours	1.45	1.45	1.45	1.45	1.45	1.45

Dataset (hh:mm)

	Camera↓	Lego↓	Letter↓	Plant↓	Toys↓	<i>Average</i> ↓
BeNeRF [29]	06.20	06.25	06.25	06.30	06.25	06.25
Ours	01.30	01.25	01.30	01.35	01.30	01.30

(c) Comparison of Deblurring Methods Based on PSNR, SSIM, and LPIPS Metrics

	Livingroom			Tanabata			
	PSNR ↑	SSIM ↑	LPIPS↓	PSNR ↑	SSIM↑	LPIPS↓	
DeblurGANv2 [25]	29.26	.8121	.2087	20.09	.4964	.3934	
MPRNet [64]	28.57	.7937	.2621	18.20	.4258	.4173	
NAFNet [7]	29.92	.8306	.2268	18.96	.4665	.3908	
Restormer [63]	29.48	.8262	.2391	18.82	.4596	.4248	
EDI [41]	32.61	.8871	.0904	24.87	.7564	.1039	
BeNeRF [29]	37.11	.9370	.0632	32.14	.9015	.0515	
Ours	35.14	.9111	.1189	29.15	.8626	.1015	



 \succ The method takes a blurry image and event stream as input to estimate camera motion and reconstruct a

 \succ Camera motion is modeled with a B'ezier spline, and minimizing

> trajectory are optimizing scene the

Quantitative Results

(a) Memory Usage Comparison with BeNeRF on Real

(b) Training Time Comparison with BeNeRF on Real