

Event-guided HDR Reconstruction with Diffusion Priors

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Abstract

Events provide High Dynamic Range (HDR) intensity change which can guide Low Dynamic Range (LDR) image for HDR reconstruction. However, events only provide temporal intensity differences and it is still ill-posed in over-/under-exposed areas due to missing initial reference brightness and color information. With strong generation ability, diffusion models have shown their potential for tackling ill-posed problems. Therefore, we introduce conditional diffusion models to hallucinate missing information. Whereas, directly adopting events and LDR image as conditions is complicated for diffusion models to sufficiently utilize their information. Thus we introduce a pre-trained events-image encoder tailored for HDR reconstruction and a pyramid fusion module to provide HDR conditions, which can be efficiently and effectively utilized by the diffusion model. Moreover, the generation results of diffusion models usually exhibit distortion, particularly for fine-grained details. To better preserve fidelity and suppress distortion, we propose a fine-grained detail recovery approach using a histogram-based structural loss. Experiments on real and synthetic data show the effectiveness of the proposed method in terms of both detail preservation and information hallucination.

1. Introduction

Extending the dynamic range of an image (usually with low dynamic range, LDR) to record the brightness of real scenes plausibly is particularly useful for daily photography and computer vision tasks. High dynamic range (HDR) imaging can be, in the most direct way, achieved by utilizing neural networks to hallucinate missing information in over-/under-exposed areas [4, 5, 22, 25], as shown in Figure 1 (a), which is challenging to faithfully recover

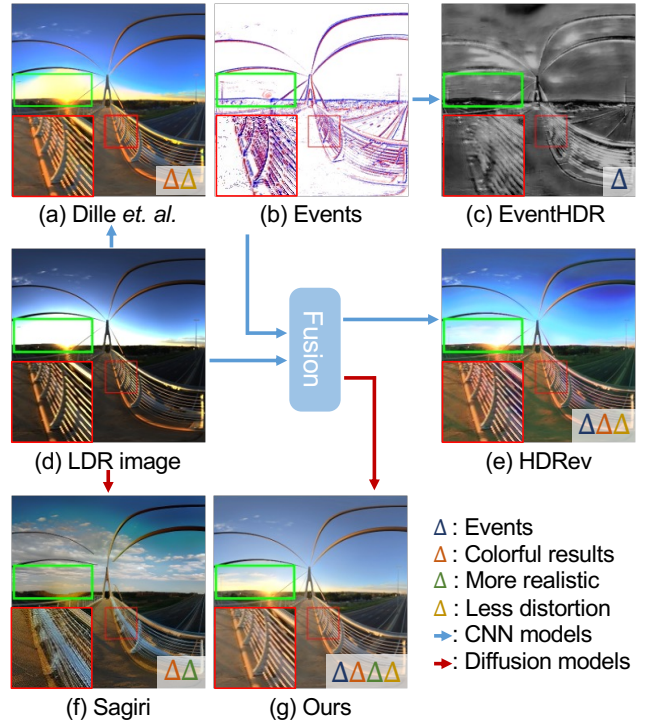


Figure 1. HDR image can be recovered by only using a single LDR image (d) as input (e.g., Dille *et al.* [4]), which is a difficult problem as shown in (a). With only events (b) as input, event-to-image reconstruction (e.g., EventHDR [54]) (c) recovers an HDR scene without color. Event-guided HDR methods (e.g., HDRRev [49]) (e) take both events and the LDR image as input, which recovers colorful HDR scenes with moderate details. Diffusion-based methods (e.g., Sagiri [22]) (f) take the LDR image (and optionally the text prompt) as input showing visually pleasing results but may have challenges in maintaining consistent contents with the original scene. The proposed method (g) takes events and the LDR image as input and leverages the diffusion priors to recover a plausible and realistic HDR image with rich details and less distortion. scene details without any auxiliary information. Neuro-morphic cameras, such as event cameras, are proven to be helpful in providing additional details for HDR purpose [29, 33, 54]. Event cameras capture intensity changes

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by triggering events asynchronously, which inherently contains HDR information (*e.g.*, 120 dB for DAVIS340), and events can be directly converted to HDR images, as demonstrated by EventHDR [54] in Figure 1 (c). The event-to-image reconstruction [29, 33, 54] can recover details in over-/under-exposed regions, but fail to provide colorful results due to lacking color information.

To generate colorful HDR images, event-guided HDR reconstructions [13, 14, 49] take both LDR image and events as inputs, complementarily learning to predict color and intensity in over-/under-exposed areas, as demonstrated in Figure 1 (e). They can reconstruct HDR information, *e.g.*, the cloud in the green box, and provide colorful results. Although regression models are adopted to build the relationship between the predicted pixel values and its neighboring pixels, those methods cannot recover proper intensity, especially when the LDR image has large over-/under-exposed areas. Because absolute HDR intensity (events only contain thresholded radiance changes) and color information are still missing in these regions, it is difficult for regression models to appropriately hallucinate their values.

Diffusion models [16, 38–40] are emerging generative models that show great potential for generating plausible and high-quality images. Even if for ill-posed problems, they can provide visually pleasing results thanks to the expressive power of diffusion priors. Diffusion models have also been adopted for image restoration [24, 44, 50]. Recent attempts, *e.g.*, Sagiri [22], have shown the potential of diffusion priors for HDR reconstruction by providing more visually realistic details in over-exposed areas, *e.g.*, the cloud in the sky of Figure 1 (f). However, the generated HDR images still cannot appropriately keep the fidelity of the original scene, and additional distortion are brought into well-exposed regions, as shown by the red box in Figure 1 (f).

To reconstruct visually pleasing and faithful HDR images with less distortion, we introduce events to provide differential HDR intensity and adopt conditional diffusion models [51] to compensate for the ill-posed nature of hallucinating missing information and constrain the generative model to be consistent with the original scene. Specially, we focus on solving the following two key problems via employing diffusion models in event-guided HDR reconstruction: **1) Condition extraction:** Since events and LDR image are two different modalities of visual representation, directly adopting them as conditions is non-compatible for the conditional diffusion models to conduct effective fusion. Inspired by the modality alignment of HDRev [49], we introduce an event-image encoder and a pyramid fusion module to fuse events and LDR image in different resolutions and provide conditions to guide the generation process. **2) Details preservation:** Applying diffusion models to HDR reconstruction [22, 24] suffers from fine-grained detail distortion, as shown in Figure 1 (f). Such artifacts become

more obvious when LDR images are high quality and have large well-exposed areas. To refine the fine-grained details and make them consistent with LDR images and events, we design a refinement module with histogram-based structure loss. The proposed method is validated on both synthetic and real data and outperforms existing methods by providing fidelity-preserving HDR reconstruction, as illustrated in Figure 1 (g), with the following technical contributions:

- integrating events and the conditional diffusion models to recover missing information faithfully;
- adopting the pretrained event-image encoder and pyramid fusion to effectively apply conditions; and
- designing the refinement module and histogram-based structure loss to further strengthen fine-grained details.

2. Related works

Image-based HDR reconstruction Many approaches leverage the capabilities of neural networks to directly hallucinate HDR information from training data, such as CNNs [5, 6, 9], Generative Adversarial Networks (GANs) [41], and diffusion models [7, 22]. Liu *et al.* [25] incorporates the LDR image formulation pipeline into its hallucination process to perform step-by-step prediction. For a more comprehensive view, we refer to GTA-HDR [2]. Since information is unavoidably missing in over-/under-exposed areas, the above methods only rely on hallucination, which may not correspond to real scenes.

Event-based HDR reconstruction Benefiting from the HDR property of event cameras, previous works reconstruct HDR images from events with recurrent neural networks [33, 34, 54] or GANs [29, 42]. Since events only record logarithmic irradiance changes, it’s difficult to reconstruct color images. To reconstruct color HDR images, Han *et al.* [13, 14] adopted a hybrid camera system to capture events and frame, enabling event-guided HDR reconstruction. Yang *et al.* [49] treated events and frame as different modalities and proposed multi-modalities alignment and fusion to provide HDR videos. Other methods [27, 36] incorporate events and bracketed exposure for HDR reconstruction, while long-exposed images bring blurry artifacts. The proposed method takes events and LDR image as input, incorporating diffusion models to compensate for realistic and faithful information in over-/under-exposed areas.

Generative priors Generative Priors capture the underlying data distribution, enabling the generated images to follow real-world image distribution. GAN [10] has shown its potential to leverage generative priors for image restoration [20, 21, 31]. Recently, diffusion models [16, 38–40] have widely adopted as effective generative priors for producing realistic images [30, 35, 43, 51], which also demonstrate strong potential for image restorations [24, 44, 50], specifically, for HDR image reconstruction from bracketed exposure [12, 17, 47]. There are some attempts [11, 22] to

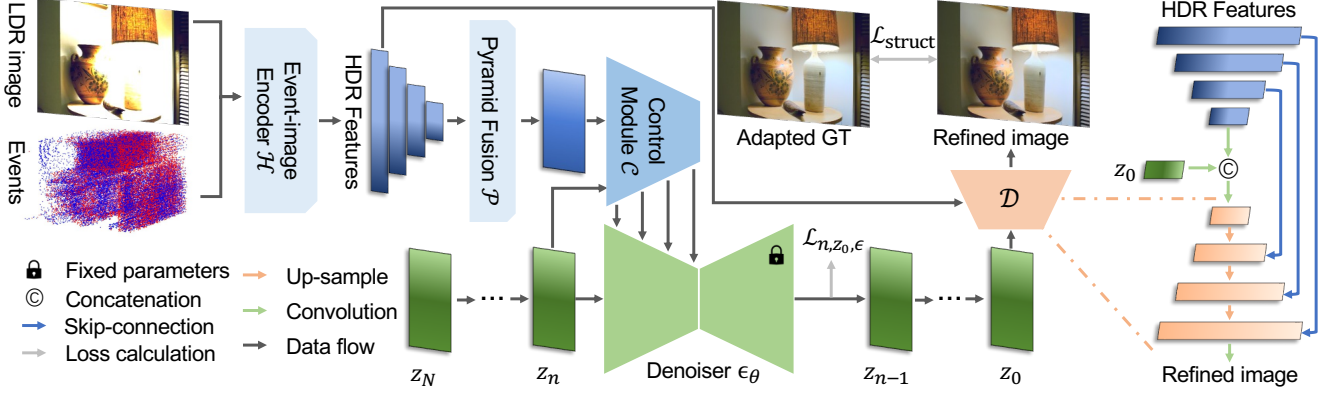


Figure 2. Pipeline of the proposed method consists of three parts: diffusion model and denoising process (green part), event-image conditioning (blue part), and detail refinement (orange part). The blue part fuses LDR image and events to generate injected features for Denoiser as described in Section 3.2. The green part adopts the injected features as conditions to estimate noise from latent z_t step by step with fixed pretrained parameters. To refine the distortion of denoised images, the refinement module in the orange part, whose architecture is shown on the right, is proposed to leverage the HDR features and denoised latent z_0 . Considering the uncertainty of diffusion results in color and brightness, we introduce structure loss, which adopts adaptive Ground Truth (GT) as the supervision target, as described in Section 3.3. After refinement, we obtain a plausible and realistic refined image without distortion.

take advantage of diffusion models to generate HDR images from single LDR image, while it cannot provide faithful reconstruction due to the inevitable dynamic clipping.

3. Proposed Method

Section 3.1 introduces basic concepts about diffusion models and event cameras. The pipeline of the proposed method is illustrated in Figure 2. The green part is the pretrained latent diffusion model, which performs denoising in latent space step by step with the injected feature from the blue part. The blue part is the proposed event-guided conditioning and generation process, which adopts an event-image encoder and a pyramid fusion to utilize events and the LDR image efficiently and effectively, as described in Section 3.2. The orange part is the fine-grained detail enhancement based on the Variant Auto Encoder (VAE) decoder, which learns to refine fine-grained details by the proposed histogram-based structure loss as described in Section 3.3. Training details are described in Section 3.4.

3.1. Preliminary

Diffusion models Diffusion models [16, 35, 39] can generate realistic high-quality images by diffusing and denoising processes. Latent diffusion models [35] are a type of diffusion models that perform those processes on latent space. During training, the latent diffusion models project the clean image into the latent space with a VAE encoder as z_0 , then diffuse z_0 by adding Gaussian noise for n steps to get the noisy latent z_n . Adding noise in one step is as:

$$z_n = \sqrt{a_n}z_{n-1} + \sqrt{1 - a_n}\epsilon_{n-1}, \quad (1)$$

where $n \in [1, N]$ means the n -th diffusion step, N is the total diffusion steps, $\epsilon_n \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is the added noise, a_n is

the pre-defined parameter of the noise scheduler. Defining $\bar{a}_n = \prod_{i=1}^n a_i$, the closed form equation of Eq. (1) [16] is:

$$z_n = \sqrt{\bar{a}_n}z_0 + \sqrt{1 - \bar{a}_n}\epsilon, \quad (2)$$

where $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. The denoising process trains a denoiser ϵ_θ to estimate the noise ϵ usually by minimizing Mean Square Error (MSE) $\mathcal{L}_{n,z_0,\epsilon} = \|\epsilon - \epsilon_\theta(z_n, n)\|$. As the variable z_n will be an approximately standard Gaussian distribution when n is large enough, during inference, the denoising process often starts from an i.i.d. noise z_N and generates a clean image z_0 using ϵ_θ over N steps.

Event triggering and stacking Event cameras trigger an event (t, x, y, p) when illuminance changes of pixel (x, y) in the logarithm domain over a predefined threshold η in time t , where the polarity $p \in \{-1, 1\}$ indicates the decrease and increase of the illuminance. Mathematically, an event is generated when the following inequation occurs:

$$\|\log I_{x,y}(t) - \log I_{x,y}(t_{\text{ref}})\| \geq \eta, \quad (3)$$

where $I_{x,y}(t)$ is the illuminance at time t , $I_{x,y}(t_{\text{ref}})$ is the reference illuminance level, t_{ref} is the last event triggered time of pixel (x, y) , η is a pre-defined event threshold. We convert the stream-like events to tensors using voxel grid [53], which encodes temporal information in a C -channel 3D volume by discretizing event timestamps into C temporal bins. Following Rebecq *et al.* [33, 34], k -th event (t_k, x_k, y_k, p_k) distributes its polarity p_k to the two closest temporal bins related to its normalized timestamp by:

$$E_j^{x,y} = \sum_{x_k=x, y_k=y} p_k \max(0, 1 - |\tilde{t}_k - j|), \quad (4)$$

where $\tilde{t}_k = \frac{C-1}{\Delta t}(t_k - t_0)$ is the normalized timestamp, $\Delta t = \max_k(t_k) - t_0$ is the time span of events, t_0 is the start timestamp, and $j \in [0, C-1]$ is the index of the bin.

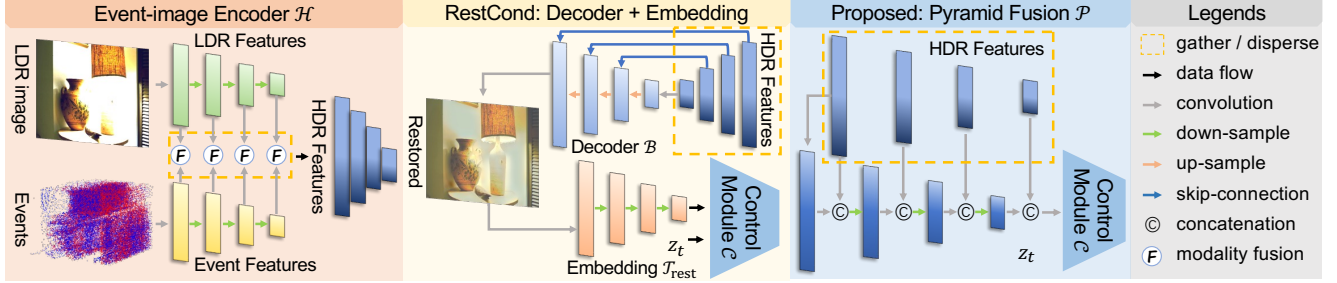


Figure 3. Pipeline of the event-guided conditioning process, with comparison to conditioning using HDRRev [49] restored image. Directly concatenating events and LDR image cannot fully utilize events, thus we introduce an event-image encoder to fuse them as shown in the orange part. The HDRRev [49] restored images by decoding HDR features can serve as input to the embedding module, as shown in the yellow part. The proposed pyramid fusion module, as shown in the blue part, fuses different levels HDR features to provide conditions.

3.2. Event-guided Conditioning and Generation

To hallucinate missing information for HDR reconstruction, previous methods mainly come in two ways: adopting better hallucination models (*e.g.*, diffusion models [22]) or introducing HDR sensors (*e.g.*, event cameras [13, 14, 49]). Diffusion models generate high-quality and realistic images by modeling real-world image distributions with diffusion priors. Event cameras provide differential HDR intensity, making events well-suited as conditions for diffusion models to generate more accurate details in over-/under-exposed areas, thereby compensating the dynamic range of LDR images. Thus we propose to leverage both event cameras and diffusion models to hallucinate realistic HDR images to be more consistent with real scenes.

To generate images corresponding to conditions, conditional models [18, 51] are proposed to generate features injected into specific layers of the well-trained denoiser. ControlNet [51] is one of the widely conditional models for image restoration [24, 44, 45], which generates and injects features for each down-sample and middle layers of the denoiser. As illustrated in the interaction between the blue and green parts of Figure 2, we perform feature injection similar to ControlNet. In the green part, we utilize Stable Diffusion [35] V1.5 as the pretrained denoiser ϵ_θ to denoise from the initial latent z_N step by step. The generated image is obtained by decoding the estimated initial latent $\hat{z}_0$ with VAE decoder. With an image-like input, ControlNet employs an embedding module to generate conditions, then adopts a control module to obtain injected features. However, it is challenging for the embedding module to effectively fuse LDR image with events and extract useful information.

Events record temporal intensity changes, making them distinct from LDR images. Directly concatenating stacked events E and LDR images I_{LDR} together as the input for the embedding module $\mathcal{T}_{\text{con}}$ introduces HDR information, where the conditioning process¹ is:

$$\mathcal{E}_{\text{ConCond}}(I_{\text{LDR}}, E) = \mathcal{T}_{\text{con}}([I_{\text{LDR}}, E]), \quad (5)$$

$[\cdot]$ denotes concatenation. But it cannot fully utilize HDR information encoded in events, *e.g.*, decoration and cable

in over-exposed areas cannot be accurately reconstructed in Figure 4 (d). Therefore, a specifically designed HDR information extraction model is needed. HDRRev [49] performs event-guided HDR reconstruction through representation alignment and feature fusion, which addresses the modality gap between events and LDR images. It performs representation alignment through pre-training to obtain modality-specific encoders as shown in the orange part of Figure 3. The LDR image and events are encoded into modality-specific features, represented by green features (LDR image) and yellow features (events), respectively. Those two features are fused through the fusion module to obtain HDR features. The restoration process can be written into:

$$I_{\text{restored}} = \mathcal{B}(\mathcal{H}(I_{\text{LDR}}, E)), \quad (6)$$

where $\mathcal{B}$ and $\mathcal{H}$ are the decoder and encoder in HDRRev [49]. The restoration process utilizes events to recover more details, as shown by Figure 4 (e), which offers a better reconstruction of the decoration and cable than (d). The intuitive way to better utilize events for conditioning is adopting I_{restored} as input for the embedding module $\mathcal{T}_{\text{rest}}$ as shown in the yellow part of Figure 3. The conditioning process¹ is:

$$\mathcal{E}_{\text{RestCond}}(I_{\text{LDR}}, E) = \mathcal{T}_{\text{rest}}(\mathcal{B}(\mathcal{H}(I_{\text{LDR}}, E))). \quad (7)$$

Diffusion models improve image quality as shown by the improved shape and color of the table in Figure 4 (f) compared to (e). Adopting I_{restored} as conditions (“RestCond”) better utilizes events and provides more details than “ConCond”, *e.g.*, the decoration in Figure 4 (f) is better than (d).

Although HDRRev is an encoder-decoder architecture, the fusion between LDR image and events is performed only in the encoder. Applying I_{restored} as conditions not only suffers from a decoder-encoder redundant computation $\mathcal{T}_{\text{rest}}(\mathcal{B}(\cdot))$ as shown in the yellow part of Figure 3, but also fails to reconstruct details from events, *e.g.*, the shape of table in the red box of Figure 4, and is difficult to adjust the proper brightness of over-exposed areas, *e.g.*, the cloud in Figure 1 (e). The embedding module $\mathcal{T}_{\text{rest}}$ may misunderstand

¹More details are provided in the supplementary materials.

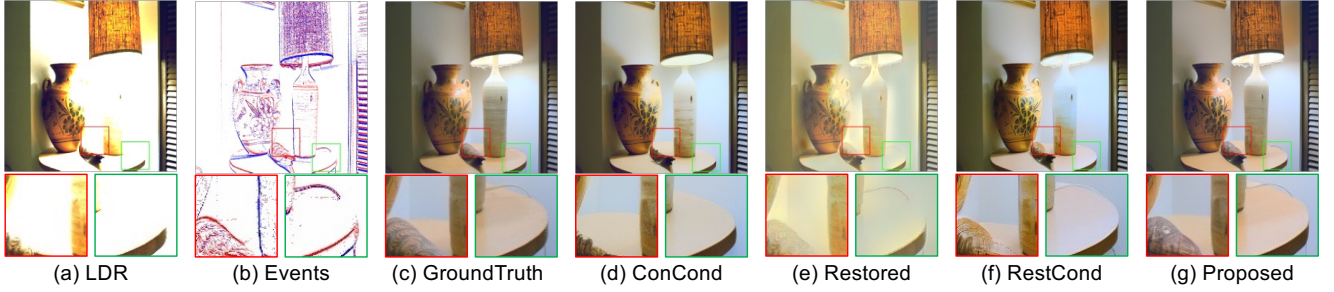


Figure 4. Comparison with different conditioning ways: directly concatenating events and LDR image (“ConCond”) and HDRRev [49] restored image (“RestCond”). “ConCond” (d) cannot fully utilize events in over-exposed areas to reconstruct cable. Illustrated by “RestCond” (f), the unsatisfactory results of decoration and table in “Restored” (e) failed to provide HDR information for conditioning in over-exposed areas. The proposed conditioning module can restore missing information as depicted in (g).

these unsatisfactory areas as shown by the shape of the decoration in the red box of Figure 4 (f).

To mitigate issues of poor brightness adjustment in HDRRev, and leverage its advantage in event-image fusion, we adopt HDR features from each layer of its event-image encoder to provide conditions. Directly adopting HDR features as conditions is not only more efficient, because of removing the redundant decoder-encoder process, but also more effective, because of avoiding introducing unsatisfactory reconstruction from the decoder $\mathcal{B}$. However, the HDR features are pyramidal, in which different levels of visual information are encoded separately. To fuse different level HDR features, we propose a pyramid fusion module $\mathcal{P}$ as shown in the blue part of Figure 3, which fuses different level features with down-sample layers and feature concatenation to provide conditions. More accurate details and colors can be recovered with it as shown in Figure 4 (g). The proposed conditioning process $\mathcal{E}$ consists of an event-image encoder and pyramid fusion module, denoted by:

$$\mathcal{E}(I_{\text{LDR}}, E) = \mathcal{P}(\mathcal{H}(I_{\text{LDR}}, E)). \quad (8)$$

Then the predicted noise is $\epsilon_\theta(z_n, n, \mathcal{C}(\mathcal{E}(I_{\text{LDR}}, E)))$, where $\mathcal{C}$ is the control module derived from ControlNet [51]. With the pretrained denoiser ϵ_θ , we are able to train the control module $\mathcal{C}$ and conditioning process $\mathcal{E}$ to hallucinate HDR images by minimizing the noise loss:

$$\mathcal{L}_{n, z_0, \epsilon_n} = \|\epsilon_n - \epsilon_\theta(z_n, n, \mathcal{C}(\mathcal{E}(I_{\text{LDR}}, E)))\|^2. \quad (9)$$

3.3. Fine-grained Detail Refinement

Although diffusion models can reconstruct realistic HDR images, it suffers from distortion, especially for fine-grained details as shown in Figure 1 (f) and Figure 5 “W/o Refinement”. Therefore, we aim to introduce information from events and LDR image to refine those distortion. Typically, we adopt HDR features from the event-image encoder for refinement. As shown in the orange part of Figure 2, our refinement module is a decoder $\mathcal{D}$ in which the up-sample layers are initialized from the VAE decoder. It fuses HDR features $\mathcal{H}(I_{\text{LDR}}, E)$ with latent z_0 to provide the refined HDR image H :

$$H = \mathcal{D}(\mathcal{H}(I_{\text{LDR}}, E), z_0). \quad (10)$$

By training the refinement module with the Ground Truth (GT), we can refine some distortion as shown in Figure 5 “W/o Structure”. Due to the inconsistent color between GT and diffusion results as illustrated in Figure 5, applying GT as a supervision target brings color artifacts similar to regression-based methods [25, 49] as depicted in the red box of Figure 5 “W/o Structure”. Those artifacts come from the discrepancy between the deterministic GT and the uncertainty in diffusion results during the training process of refinement.² Additionally, it also depicts that the details in diffusion results have been wiped (the road curb in the red box) after this refinement. Because it is easier for the refinement to minimize the total loss by reducing the brightness and color difference than the detail difference.

Meanwhile, although the diffusion results suffer from distortion, they already have visually pleasant brightness and color consistent with LDR images. Therefore, we tend to maintain the brightness and color properties of diffusion results and only focus on detail refinement by introducing local histogram matching [46] to adjust the GT to serve as a new supervision target. Local histogram matching [46] is able to adjust the pixel intensity distribution to match the histogram of a target image for each local area, which is suitable for adjusting only color and brightness, and maintaining details of GT. Adopting local histogram matching to adjust ground truth image O to diffusion result H_{diff} is as:

$$O_{\text{adj}} = \text{Hist}(O, H_{\text{diff}}). \quad (11)$$

Our histogram-based structure loss adopts the adjusted image O_{adj} as ground truth and is composed of two losses. The first one is MSE loss:

$$\mathcal{L}_{\text{MSE}}(H, O_{\text{adj}}) = \|H - O_{\text{adj}}\|^2, \quad (12)$$

and the perceptual loss $\mathcal{L}_{\text{perc}}$ based on the feature maps extracted by the pretrained VGG-16 [37] network:

$$\mathcal{L}_{\text{perc}} = \sum_l \|\phi_l(H) - \phi_l(O_{\text{adj}})\|^2 + \|\mathcal{G}_l^\phi(H) - \mathcal{G}_l^\phi(O_{\text{adj}})\|^2, \quad (13)$$

²Diverse diffusion results are shown in the supplementary materials.



Figure 5. Validation for the effectiveness of the structure loss. With only conditioning and diffusion process, the results of “W/o Refinement” suffer from distortion as shown in the green box. Training the refinement module with ground truth, some distortions are refined, but introducing unnatural saturation adjustment and unsatisfactory detail prediction as shown in the red box of “W/o Structure”. We introduce local histogram matching [46] to adjust the brightness and color of ground truth to diffusion results, making the refinement module focus on refining the details. The adapted ground truth is shown in “Adapted GT”. As shown in “Proposed”, by adopting adapted ground truth as a supervision target, the refinement module with structure loss refines distortion with more natural colors and details.

where ϕ_l is the extracted feature from l -th layer of VGG-16, G_l^ϕ is the Gram matrix of ϕ_l . Our structure loss is:

$$\mathcal{L}_{\text{struct}} = \alpha \mathcal{L}_{\text{MSE}} + \beta \mathcal{L}_{\text{perc}}, \quad (14)$$

where $\alpha = 0.01, \beta = 0.001$ are the balance weights of different terms. Using O_{adj} as the supervision target enables the refinement module to focus on fine-grained detail refinement as illustrated in Figure 5 “Complete”, in which the building is undistorted and the road curb is natural.

3.4. Training details

As a large number of paired events, LDR image, and GT is needed for training, we adopt 733 HDR images collected by Yang *et al.* [49] and follow the same data generation process to generate training and testing data with resolution (512, 512). We first simulate 733 HDR videos with random global motion by generating random camera motion trajectories [3]. We utilize the event simulator [32] and virtual camera [6] to simulate the events and LDR images, respectively. The dataset generated from 733 images is separated into training and testing following the setting of Yang *et al.* [49], while 663 for training and 70 for testing. During training, we randomly over- or under-exposed 20% to 50% pixels of the HDR images to generate LDR images.

Other implementation details. The proposed method is implemented with the Pytorch framework and runs on a single NVIDIA GeForce RTX 3090 GPU. For optimization, we use the ADAM optimizer [19] with a linear decay learning rate scheduler starting from step 0 and an initial learning rate of $\gamma = 10^{-5}$. DDIM noise scheduler is adopted both in training and sampling, with training steps $N = 1000$ and linear-scaled beta schedule. We adopt $C = 5$ same to HDRev [49] to apply their pretrain model. During sampling, we adopt classifier-free guidance with guidance scale $u = 1.5$ and inference steps $n = 9$ to obtain our results.

Table 1. Quantitative evaluation of synthetic data on dataset collected by Yang *et al.* [49]. The red metric shows the best performance. $\uparrow (\downarrow)$ means higher (lower) is better.

	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	CIEDE $\downarrow$	FID $\downarrow$	NIQE $\downarrow$
Liu <i>et al.</i> [25]	18.35	0.771	0.276	15.33	78.41	4.02
EventHDR [54]	11.04	0.334	0.447	23.44	182.11	4.58
Sagiri [22]	12.50	0.453	0.414	17.67	83.46	5.35
HDRev [49]	14.05	0.619	0.238	17.69	46.23	3.88
NeurImg [14]	18.53	0.621	0.338	17.42	105.07	4.04
Dille <i>et al.</i> [4]	19.73	0.820	0.243	9.76	76.83	4.22
Ours	25.67	0.926	0.099	6.01	27.09	3.86

4. Experiments

The comparison with existing methods including four categories: event-based EventHDR [54], single-image CNN-based Liu *et al.* [25] and Dille *et al.* [4], single-image diffusion-based Sagiri [22], and event-guided NeurImgHDR [14] and HDRev [49]. Experiments are conducted both on synthetic data and real data, as described in Section 4.1 and Section 4.2 respectively.

Metrics For fidelity preserving, we adopt reference metrics including peak signal-to-noise ratio (PSNR), structural similarity (SSIM), the perceptual error with learned perceptual image patch similarity (LPIPS) [52], the Fréchet Inception Distance (FID) [15], and the Color Difference Evaluation 2000 (CIEDE) [26], respectively. A non-reference metric named the Natural Image Quality Evaluator (NIQE) [28] is adopted to evaluate the image quality.

4.1. Evaluation on Synthetic Data

The quantitative evaluation is reported in Table 1. The proposed method outperforms the previous methods in terms of fidelity and structure preservation as shown by reference metrics. Also, our image quality outperforms other methods, as indicated by NIQE [28]. The qualitative evaluation is illustrated in Figure 6. EventHDR [54] reconstructs faithful grayscale HDR images without color. Liu *et al.* [25]

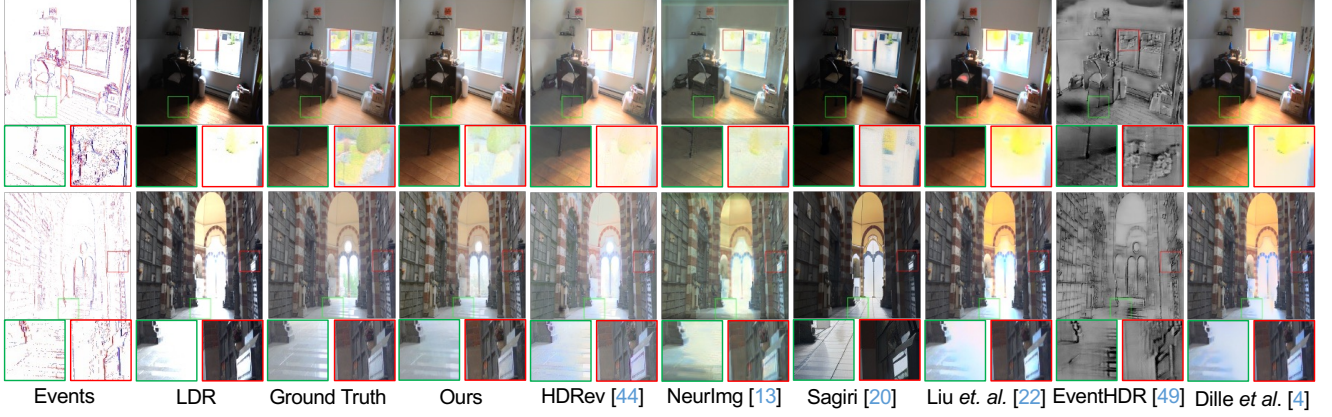


Figure 6. Qualitative evaluation of synthetic data on dataset collected by Yang *et al.* [49].

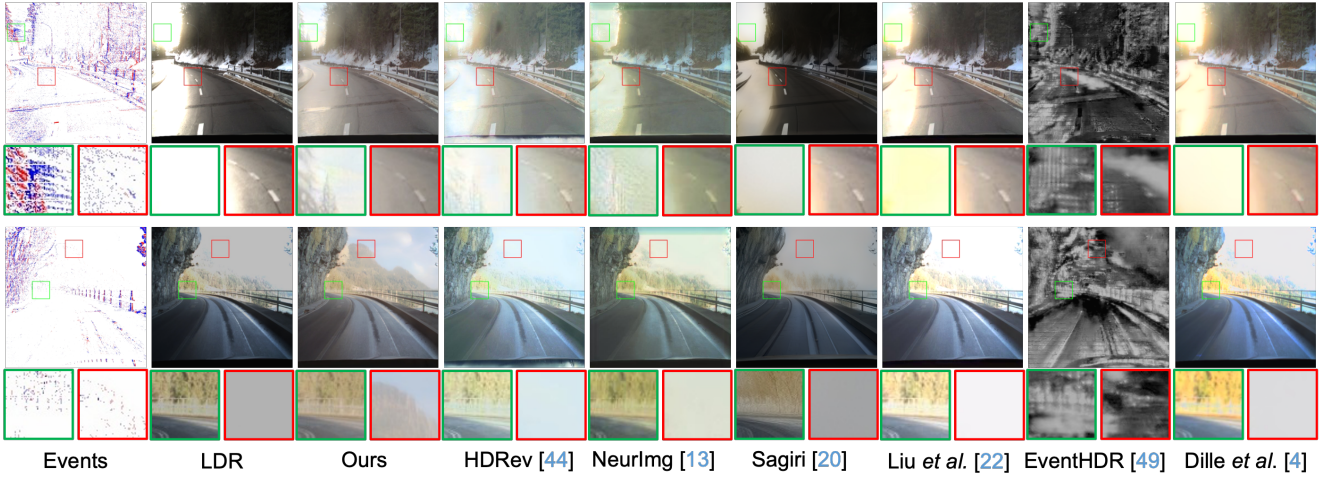


Figure 7. Qualitative evaluation of real data on DSEC [8].

Table 2. Quantitative evaluation (NIQE [28]↓/MANIQA [48]↑/QualiClip [1]↑) of real data. Blue metrics indicate the second-best.

Dataset	Liu <i>et al.</i> [25]	EventHDR [54]	Sagiri [22]	HDRev [49]	NeurImg [14]	Dille <i>et al.</i>	Ours
DSEC [8]	(3.65/0.466)	(4.00/0.270)	(5.87/ 0.617)	(3.41 /0.402)	(3.80/0.570)	(3.63/0.467)	(3.12 / 0.693)
HES-HDR [14]	(5.67/0.335)	(5.52/0.203)	(6.40/ 0.576)	(5.01/0.322)	(4.61 /0.442)	(5.72/0.367)	(4.81 / 0.530)

maintains details from LDR images but is hard to compensate for missing information. Sagiri [22] adopts diffusion models to provide high-quality images but fails to preserve consistency with inputs. NeurImg [14] has difficulty combining events with LDR image to predict over-exposed areas and has noise-like artifacts. HDRev [49] recovers HDR information, while it is difficult to deal with brightness and color adjustment in over-/under-exposed areas. Our method provides natural results and outperforms other methods both on missing information generation and fidelity preservation.

4.2. Evaluation on Real Data

Comparison on DSEC dataset DSEC [8] is a stereo event camera dataset for driving scenarios. We choose parts³ of data recording HDR scenes as our testing data.

³More details are provided in the supplementary materials.

The quantitative evaluation using non-reference metrics is shown in Table 2, indicating that the proposed method achieves higher image quality than others. The qualitative evaluation of the DSEC dataset is depicted in Figure 7. EventHDR [54] fails to restore grayscale results. It’s challenging for Liu *et al.* [25] and Sagiri [22] to hallucinate missing information. NeurImg [14] and HDRev [49] have problems utilizing the HDR information provided by events. The proposed method not only provides realistic and faithful results compared with other methods but also exhibits generation ability even with fewer events.

Comparison on HES-HDR dataset HES-HDR [14] is a hybrid event and spike HDR dataset. Its hybrid event dataset is suitable for our task. Although the non-reference metrics are not the best, we show better recovery ability as shown by qualitative evaluation³. The qualitative evalua-

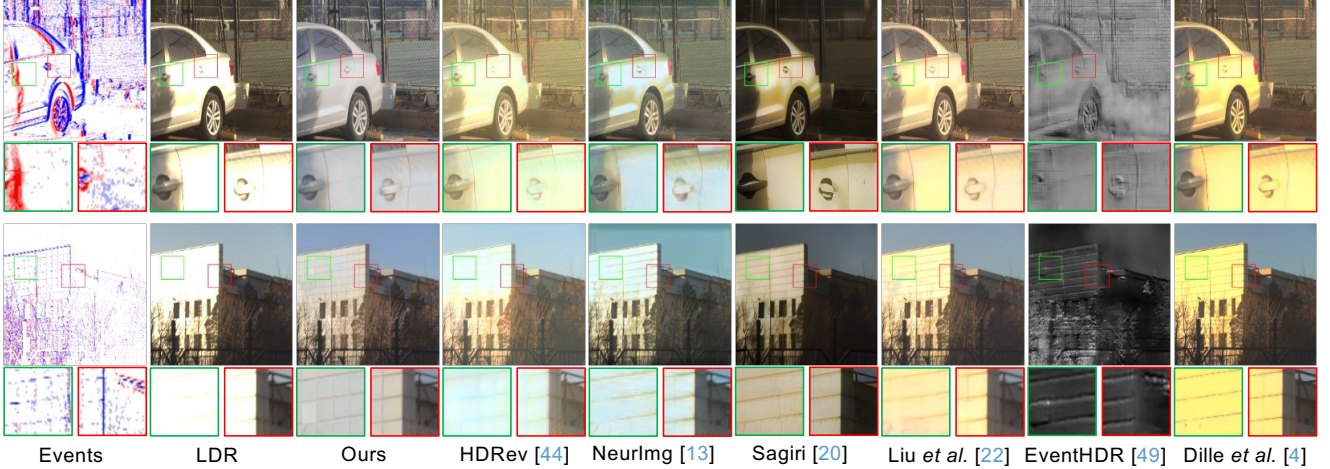


Figure 8. Qualitative evaluation of real data on HES-HDR [14].

Table 3. Ablation studies of synthetic data on the dataset collected by Yang *et al.* [49]. “Proposed*” is calculated with adjusted GT O_{adj} . The red metric shows the best performance among different ablation parts. $\uparrow$ ($\downarrow$) means higher (lower) is better.

	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	CIEDE $\downarrow$	FID $\downarrow$	NIQE $\downarrow$
ConCond	22.60	0.749	0.200	7.48	48.14	4.23
RestCond	20.79	0.725	0.247	9.33	61.74	4.20
W/o Pyramid	21.62	0.728	0.223	8.67	46.99	3.89
W/o Refinement	23.29	0.77	0.170	7.29	38.13	3.63
W/o structure	26.65	0.933	0.093	5.67	25.90	3.90
Proposed	25.67	0.926	0.099	6.01	27.09	3.86
Proposed*	29.77	0.939	0.080	3.79	22.62	3.86

tion of the HES-HDR dataset is depicted in Figure 8, which shows similar conclusions as DSEC [8]. Besides, even with unnatural color-shifted LDR image, our results have a more natural appearance and better fidelity.

4.3. Ablation Study

Our ablation study includes two parts, different conditioning processes, and different refinement targets. The quantitative evaluations of different conditioning processes are shown in the upper part of Table 3. “ConCond” and “RestCond” are as described in Section 3.2. “W/o Pyramid” represents removing the pyramid fusion module and adopting the lowest HDR features as conditions. The proposed one (“W/o Refinement”) outperforms others. The qualitative evaluations in Figure 4 show that the proposed one can better utilize events and LDR information to provide faithful and realistic images. The quantitative evaluations of refinement and structure loss are depicted in the lower parts of Table 3. The ablation of removing the refinement module is shown by “W/o Refinement”. Compared with diffusion-only method “W/o Refinement”, the refinement module improves the fidelity in terms of supervised metrics. Employing GT as a supervision target (“W/o structure”) makes the reference metrics a little better than “Proposed”. However,

due to the different supervision targets, directly comparing the proposed method with GT cannot show our structure-preserving capacity. Therefore, we include “Proposed*”, which is calculated with the adjusted GT O_{adj} . The image quality reflected by NIQE of “Proposed” is better than “W/o structure”. As shown by Figure 5, more natural and higher-quality images without distortion can be generated with the proposed refinement module.

5. Conclusion

In this paper, we present a fidelity-preserving HDR reconstruction method based on diffusion models. Our method consists of two parts, event-guided conditioning generation and fine-grained detail refinement. We utilize an event-image encoder and a pyramid fusion module to efficiently and effectively fuse events and images, providing HDR conditions to guide the diffusion process and generate missing information. A refinement module with histogram-based structure loss is proposed to tackle distortion without changing the brightness and contrast. Experiments on both synthetic and real data demonstrate the generation and fidelity preservation ability of our method.

Limitations. Since diffusion models have uncertainty in the generation process, it is difficult to apply our method for video generation, for the challenge of maintaining consistency over consecutive frames.

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Event-guided HDR Reconstruction with Diffusion Priors

Supplementary Material

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In the supplementary material, we provide more implementation details and comparison results. The details of different conditioning settings are described in Section 6. More details about our networks are provided in Section 7. The dataset extraction strategy of DSEC [8] is illustrated in Section 8. The training details are shown in Section 9. We provide more qualitative comparisons of ablation studies in Section 10. We show the diverse diffusion results in Section 11 to support the proposed structure loss as described in Section 3.3. We include human study to further support our results in Section 12. Efficiency comparison of existing methods is illustrated in Section 13. More results on synthetic and real data are provided in Section 14 and Section 15. Finally, we provide the consecutive results of our method to show its limited performance on video generation in Section 16.

6. Different conditioning settings

In Section 3.2, we introduce two other kinds of conditioning settings, concatenating LDR images and events, and adopting restored images as conditions, respectively. In this section, we provide more details about those two settings.

ConCond: concatenating LDR images and events. As described in Section 3.2 by Equation (5), one of the conditioning settings is directly concatenating LDR images and events as the input for embedding module $\mathcal{T}_{\text{ConCond}}$, which is denoted as “ConCond”. The architecture of the embedding module is shown in Figure 9. The input condition channel K is set to $3 + C$, in which 3 is the number of channels of LDR image and C is the number of channels of stacked events voxel described by Equation (4). The embedding module $\mathcal{T}_{\text{ConCond}}$ aligns the shape of the inputs with latent space, which consists of one convolutional layer, three down-sample layers, and a final convolutional layer. Each down-sample block is composed of two convolutional layers with a kernel size of 3×3 , where the stride is 1 and 2, respectively. The results of embedding module $\mathcal{T}_{\text{ConCond}}$ are provided to the control module $\mathcal{C}$ to control the diffusion process as described in Equation (5) and Equation (9).

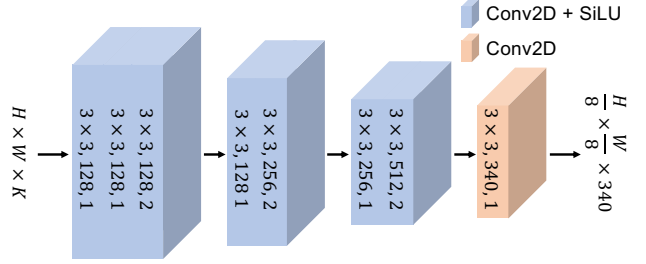


Figure 9. Architecture of embedding module $\mathcal{T}_{\text{ConCond}}$ ($K = 3 + C$) and $\mathcal{T}_{\text{RestCond}}$ ($K = 3$). The number in each box is kernel size, output channel, and stride, respectively.

RestCond: adopting restored images As described in Section 3.2 by Equation (7), another conditioning setting is applying restored image provided by HDRv [49] as the input for embedding module $\mathcal{T}_{\text{RestCond}}$, denoted as “RestCond”. The embedding module $\mathcal{T}_{\text{RestCond}}$ for “RestCond” is modified from embedding module $\mathcal{T}_{\text{ConCond}}$ by setting the input condition channel K to 3, as illustrated in Figure 9, in which 3 is the number of channels of the restored image. The control module $\mathcal{C}$ takes embedding results $\mathcal{E}_{\text{RestCond}}$ in Equation (7) as input to control the denoising process as illustrated by Equation (9).

7. Networks details

Event-image Encoder $\mathcal{H}$ The architecture of the event-image encoder $\mathcal{H}$ in our implementation is derived from the original implementation of HDRv [49] as shown in Figure 3. The modality-specific encoders of events and LDR images follow the original implementation, and the parameters are loaded from the released files. For the modality fusion module, we remove the handcrafted confidence map in the original implementation to avoid filtering useful information. The architecture remains the same as the original, and all the parameters are initialized from released files.

Control Module $\mathcal{C}$ The architecture of control module $\mathcal{C}$ follows the architecture of the denoiser encoder by replacing input latent z_t with the summation of z_t and condition $\mathcal{E}(I_{\text{LDR}}, E)$. To simplify training, we initialize

[†]This work is done during Yixin’s internship at SenseTime.

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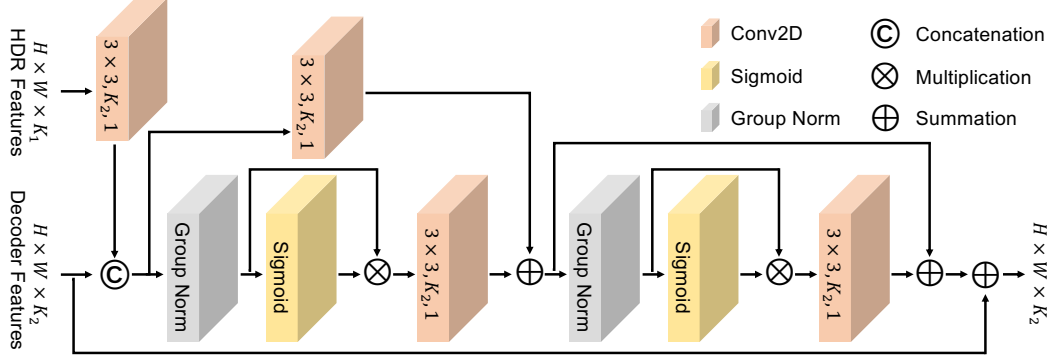


Figure 10. Architecture of feature fusion layer in refinement module $\mathcal{D}$. A fusion layer is applied before each up-sample layer in the original VAE.

the parameters of our control module C using the “control_v11e_sd15_ip2p” version of ControlNet [51].

Refinement module $\mathcal{D}$ The refinement module $\mathcal{D}$ decodes the estimate latent z_0 to undistorted HDR image H with the HDR features from the event-image encoder. Therefore, we modify the original VAE decoder implementation to add HDR features into its decoding process. Specifically, we add a feature fusion layer to each up-sampler layer of the VAE decoder, which fuses the HDR feature with the original VAE decode feature by the convolutional layers and residual layers as shown in Figure 10. K_1 and K_2 are the dimensions of input HDR features and decoder features from the original VAE implementation, respectively. Only the added fusion layers and convolutional output layers are trained in our experiments.

Noise scheduling For the noise scheduler, we adopt DDIM scheduler as described in Section 3.4 and set the number of training timesteps to 1000. The noise is added using a scaled linear beta schedule ranging from 0.00085 to 0.012. The model predicts pure noise (epsilon) during denoising, following the standard DDPM approach ^{β_1}

8. DSEC [8] dataset

DESC [8] is a dataset for driving scenarios, which contains paired events and LDR images in different light conditions. We specifically choose 6 HDR scenes from its test dataset as our test dataset: “interlaken_00_a”, “interlaken_00_b”, “interlaken_01_a”, “zurich_city_13_a”, “zurich_city_13_b”, “zurich_city_15_a”, respectively. For “zurich_city_15_a”, we only choose the 960th frame to the 1059th frame since it is not a typical HDR scene.

9. Training details

Dataset preparation We generate the synthetic dataset for training and testing as described in Section 3.4. After obtaining the generated HDR images and events, we generate LDR images from HDR images with the image formulation pipeline, which consists of exposing, dynamic range clipping, and quantization. We randomly generate exposure time t to let $x\%$ pixel to be over-/under-exposed, and x is uniformly sampled in $[0.2, 0.5]$. In dynamic range clipping, the values larger than 1 are clipped to 1. For quantization, we quantize the original float values into 8 bit integer in $[0, 255]$ and remap them to $[0, 1]$ as the final input. In this way, we obtain the LDR image L from HDR image O by:

$$L = \lfloor \text{Clip}(O \cdot t, \max = 1) * 255 \rfloor / 255 \quad (15)$$

Histogram matching To refine the distortion existing in our diffusion results (shown by “W/o Refinement”), we adopt local histogram matching [46] to reduce the brightness and color gap between diffusion results and ground truth. To perform local histogram matching [46], we first split the whole image into $2P_h \times 2P_w$ patches, while $P_h = P_w = 8$ in our experiments. For each 2×2 patch, we calculate the adjustment parameters based on original histogram matching, which are q paired pixel values defining the brightness mapping from the original image to the destination image. We directly record the paired pixel value of the original image and destination image as the adjustment parameters. We set $q = 6$ in our experiments. To smooth the parameters of nearby patches, a convolutional layer with 5×5 Gaussian kernels is applied to the adjustment parameters with shape $P_h \times P_w$. The smoothed adjustment parameters are applied to each patch to obtain the final adjusted results. We perform local histogram matching for color images, which is implemented by separately processing each channel.

The adjusted examples are shown in Figure 11. The pur-

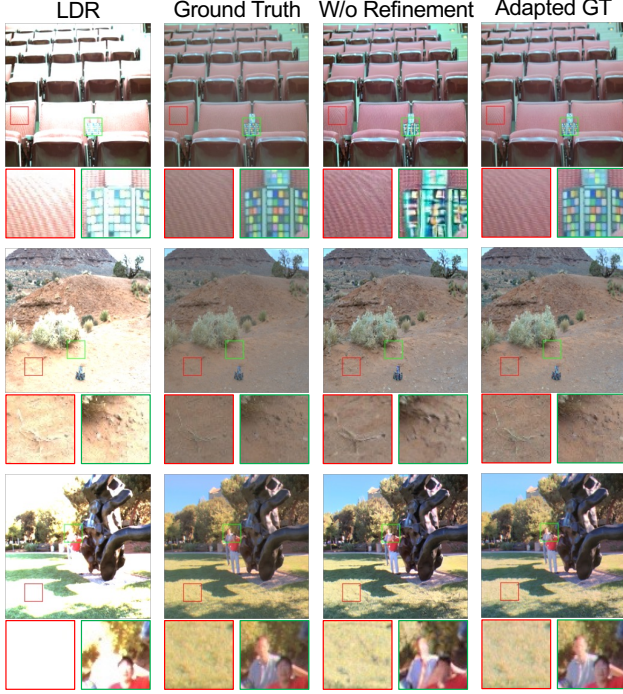


Figure 11. Adapted GT results on training data. Although our diffusion results (shown by “W/o Refinement”) suffer from distortion as shown in the green box, it can serve as a good guidance to adjust the original ground truth. Adjusting the color and brightness with the histogram also improves the contrast and color as shown in the red box.

pose of our histogram matching is to reduce the color and brightness gap between the supervision target and diffusion results, which is already achieved as shown in Figure 11. Besides, the original ground truth suffers from color shifting in the first and third row, and low contrast by tone mapping in the second row. Benefiting from diffusion priors embedded in our diffusion results (shown by “W/o Refinement”), the adapted GT images have better contrast and color, which can improve the visual quality of the final refined results.

10. Ablation study

Quantitative comparison on iteration steps The impacts of different iteration steps are shown in Table 4. Balancing performance and inference speed, we finally select 9 iterations.

Quantitative comparison on loss hyperparameter The hyperparameter experiment for Equation (14) with $\alpha = 0.01, \beta = 10^{-4}$ (Param 1) and $\alpha = 0.01, \beta = 0.01$ (Param 2) are shown in Table 4.

Table 4. Quantitative comparison on iteration steps

	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	CIEDE $\downarrow$	FID $\downarrow$	NIQE $\downarrow$
Iteration-5	24.96	0.918	0.111	6.39	29.70	3.83
Iteration-9	25.67	0.926	0.099	6.01	27.09	3.86
Iteration-15	25.89	0.928	0.096	5.90	26.43	3.88
Param 1	24.85	0.906	0.128	6.56	34.15	3.93
Param 2	24.76	0.909	0.124	6.61	32.01	3.93

Table 5. Efficiency comparison of ablation studies.

	FLOPs (G)	Params (M)	Time (s)
ConCond	8387.563	1270.09	1.33
RestCond	9207.416	1328.03	1.42
W/o Refinement	9122.417	1320.32	1.40
Ours-complete	10380.843	1349.31	1.41

Qualitative comparison on conditioning The qualitative evaluation of different conditioning and generation processes is illustrated in Figure 12. Directly concatenating events and LDR image, denoted by “ConCond”, cannot well-utilize both LDR image and events to provide accurate and sufficient details as depicted by the first row and the green box of remaining rows in Figure 12. HDRev [49] fuses LDR image and events to provide better details as shown by “Restored” in Figure 12, while severe artifacts exist. And it is difficult to reconstruction faithful details in high-frequency and significantly over-exposed areas, *e.g.*, the red box of the first row in Figure 12. Employing restored results as condition, adopting restored image as condition, indicated by “RestCond”, suffers from information lost exists in “Restored” as highlighted in the red box of the first row and the green box of the third row in Figure 12. Also, the artifacts in “Restored” also influence “RestCond” to provide unfaithful results as shown by the green box of the second row in Figure 12. Leveraging the HDR features provided by the event-image encoder as described in Section 3.2, the proposed method recovers faithful and colorful results by making better use of input LDR image and events with the proposed conditioning and generation method.

Qualitative comparison on structure loss The qualitative evaluation of structure loss is depicted in Figure 13. Our diffusion results (shown by “W/o Refinement”) may exist distortion as shown by the green box in Figure 13. To refine the distortion and provide natural results, we perform fine-grained detail refinement with the structure loss. With the proposed structure loss, images with higher contrast and more details can be generated, as indicated by the green box of the first row, and the red box in the second and third row of Figure 13. Besides, introducing structure loss reduces

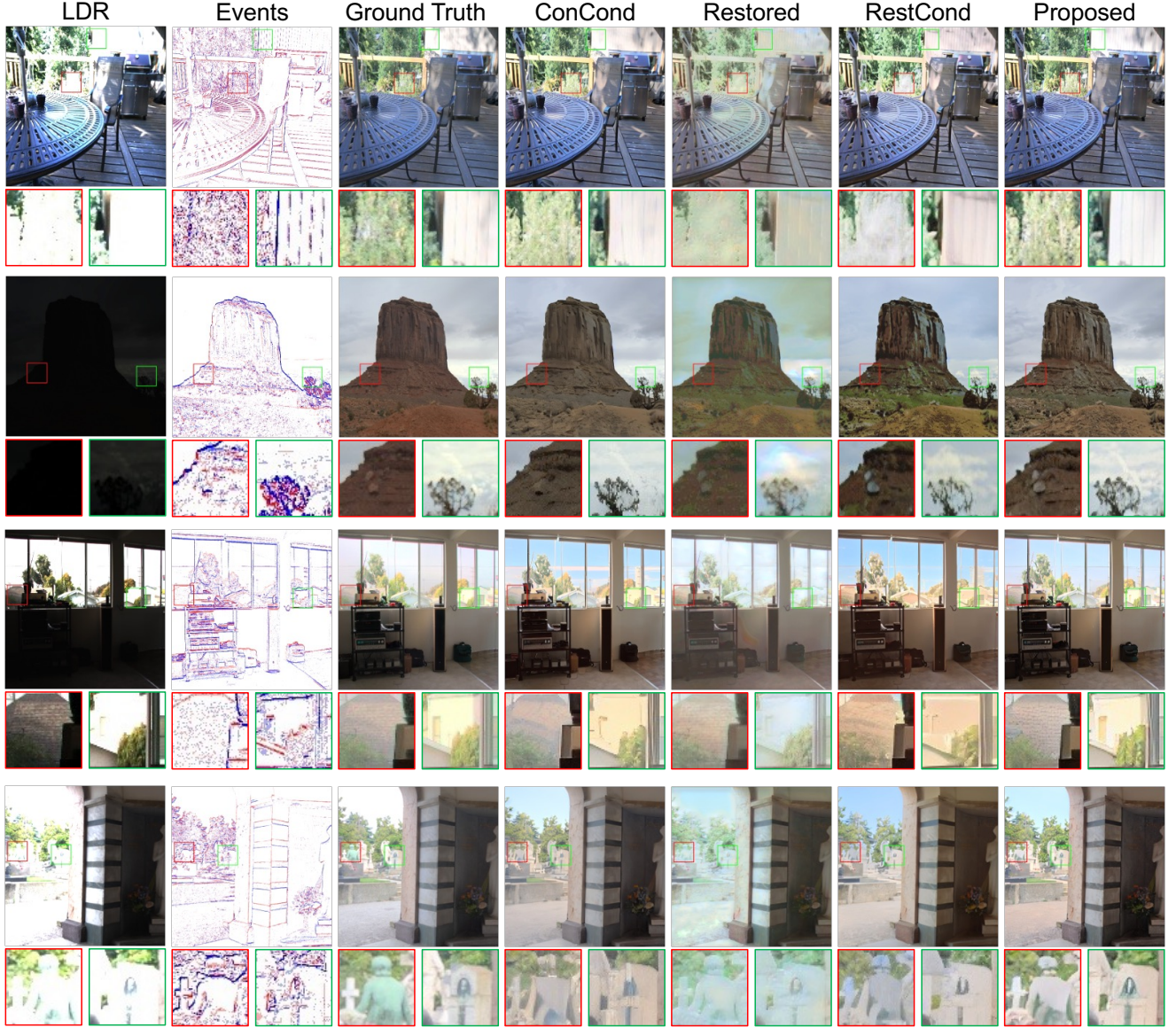


Figure 12. Qualitative comparisons on different conditioning and generation processes as described in Section 3.2. It is hard for “ConCond” to integrate events and LDR image to provide faithful results. “Restored” [49] effectively extracts details by fusing events and LDR image, while its results exist some artifacts. It also struggles with compensating for large over-exposed areas. “RestCond” provides better details than “ConCond” in nearly well-exposed areas, but it is misled by “Restored” to provide unsatisfactory results in large over-/under-exposed areas. The proposed method exploits the information in events and LDR image to provide faithful and colorful recovery results.

the difficulty of color prediction, as discussed in Section 11, which may lead to unnatural color transition as shown in the green box of the second row and red box of the fourth row in Figure 13. Introducing structure loss not only reduces the difficulty of learning but also provides pleasant visual results with natural contrast.

Efficiency comparison We calculate the Floating Point Operations Per Second (FLOPs), the total parameters

(Params), and the running time of all ablation studies, as shown in Table 5. The ablation studies of structure loss share the same pipeline, which is the same as our complete model. The proposed conditioning and generation method is more efficient than “RestCond”, which indicates that removing redundant decoder-encoder modules improves the efficiency of leveraging events and LDR image information.

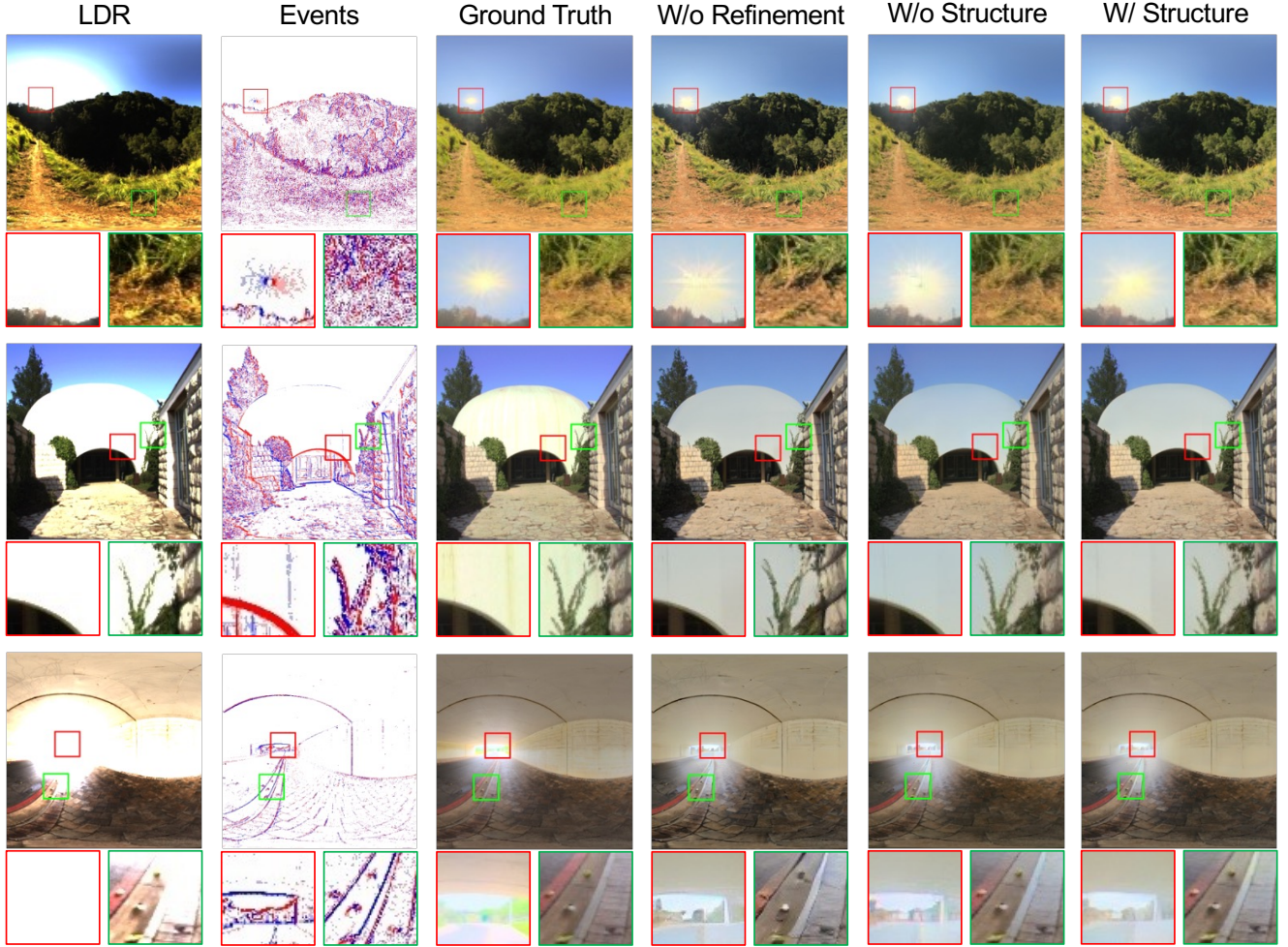


Figure 13. Qualitative comparisons on structure loss as described in Section 3.3. More natural images with higher contrast and better color appearance can be reconstructed with the proposed structure loss.

Table 6. Efficiency comparison of existing methods.

	FLOPs (G)	Params (M)	Time (s)
Liu <i>et al.</i> [25]	451.004	29.03	0.03
EventHDR [54]	1229.133	3.14	0.17
NeurImg [14]	301.385	37.39	0.08
HDRev [49]	821.551	57.94	0.79
Sagiri [22]	29327.032	1328.23	5.52
Ours	10380.843	1349.31	1.41

11. Diverse diffusion results

To demonstrate the uncertainty of our diffusion process, we randomly sample different results with the same input events and LDR image but different initial noise. The results are shown in Figure 14. Even with the sample input, the generation results by the diffusion process have large color differences even in training datasets. Directly training

the refinement module with ground truth brings color uncertainty, resulting in unsatisfactory color adjustment as illustrated in Figure 5 and Figure 13. As demonstrated in Figure 11, the adapted ground truth, denoted by “Adapted GT”, has a similar color appearance as diffusion results. Applying adapted ground truth as supervision targets makes the refinement module focus on detail refinement and retains the generation properties of diffusion models.

12. Human study

We conduct a human study on the real data (DSEC [8]) containing over-/normal-/under-exposed images for perceptual evaluation. We pick up 97 samples at equal intervals to construct our human perceptual dataset¹ to evaluate high-illuminance, low-illuminance, and overall quality by a sur-

¹Please refer to our [Github](https://github.com/YixinYang-00/HDRev-Diff): github.com/YixinYang-00/HDRev-Diff.

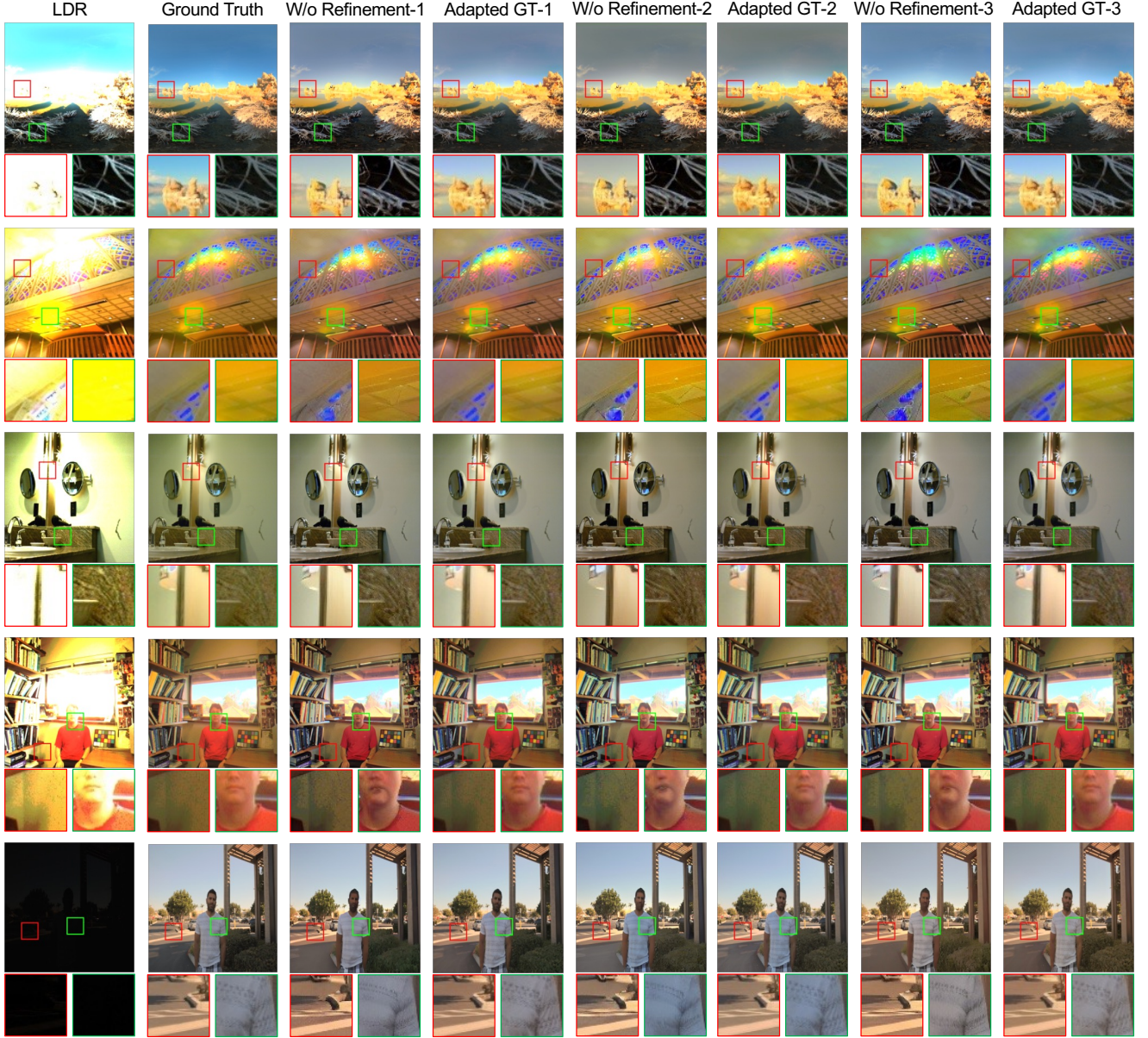


Figure 14. Diversity results with different initial noise. The adapted ground truth has similar color properties as diffusion results, which makes the refinement module focus on details refinement. Areas with obviously different colors are pointed out by red boxes.

vey link². All methods are shuffled to avoid bias. Reports from 40 participants on all the samples, as shown in Table 7, the proposed method achieves highest preference among those three aspects.

13. Efficiency comparison of existing methods

The efficiency comparison is shown in Table 6. Regression-based methods [14, 25, 49, 54] have lower FLOPs, parameters, and running time. With a similar diffusion model back-

Table 7. Quantitative evaluation of human study, which is evaluated in three aspects: High-illuminance, Low-illuminance, and Overall preference ratio.

	High	Low	Overall
Liu <i>et al.</i> [25]	23.00%	17.60%	17.78%
NeurImg [14]	2.58%	1.80%	0.90%
HDRev [49]	2.77%	7.80%	2.96%
Sagiri [22]	5.03%	1.74%	1.10%
Ours	66.62%	71.06%	77.26%

²Survey link: <https://www.wjx.cn/vm/QzCmzw2.aspx#>

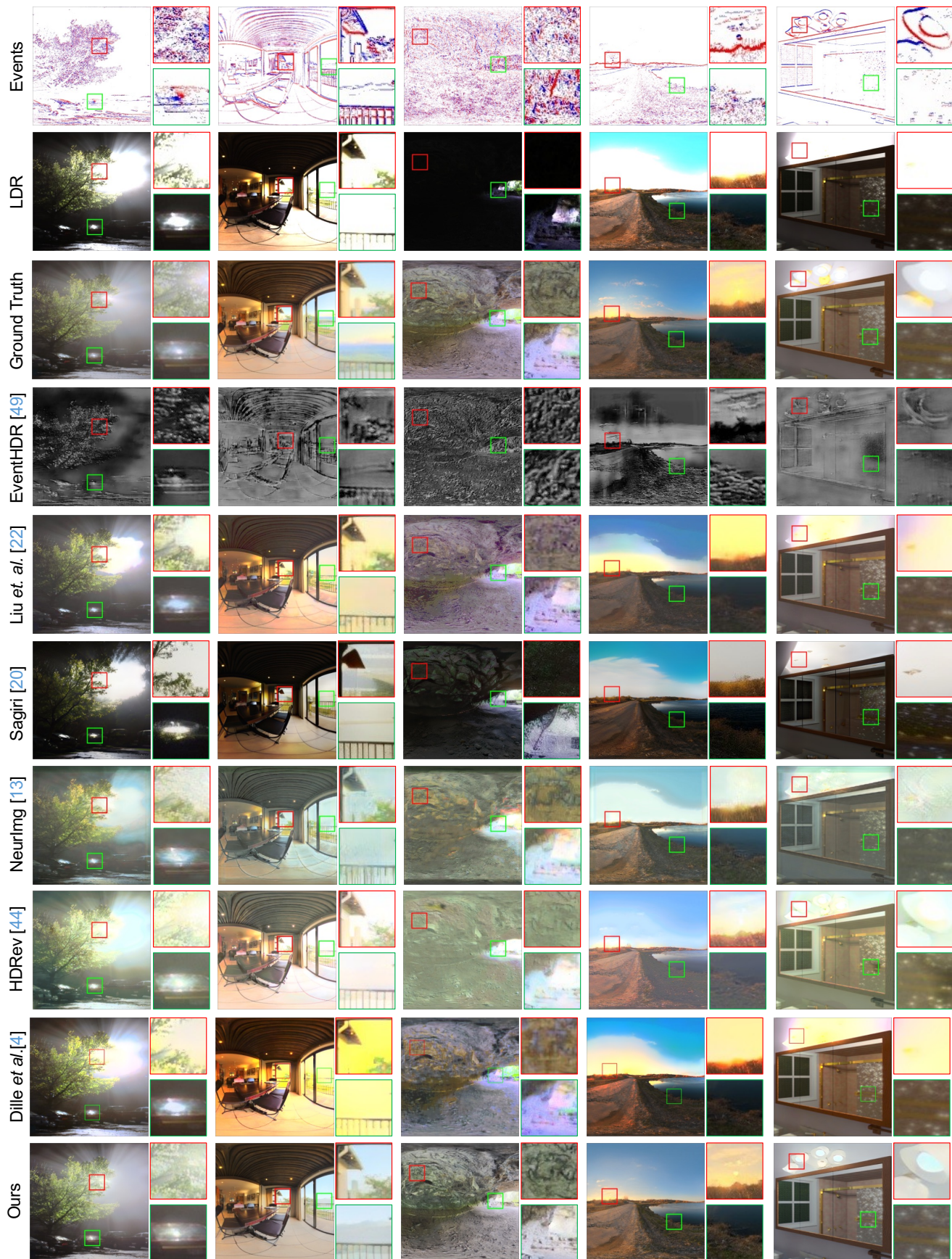


Figure 15. Qualitative evaluation of synthetic data on dataset collected by Yang *et al.* [49].

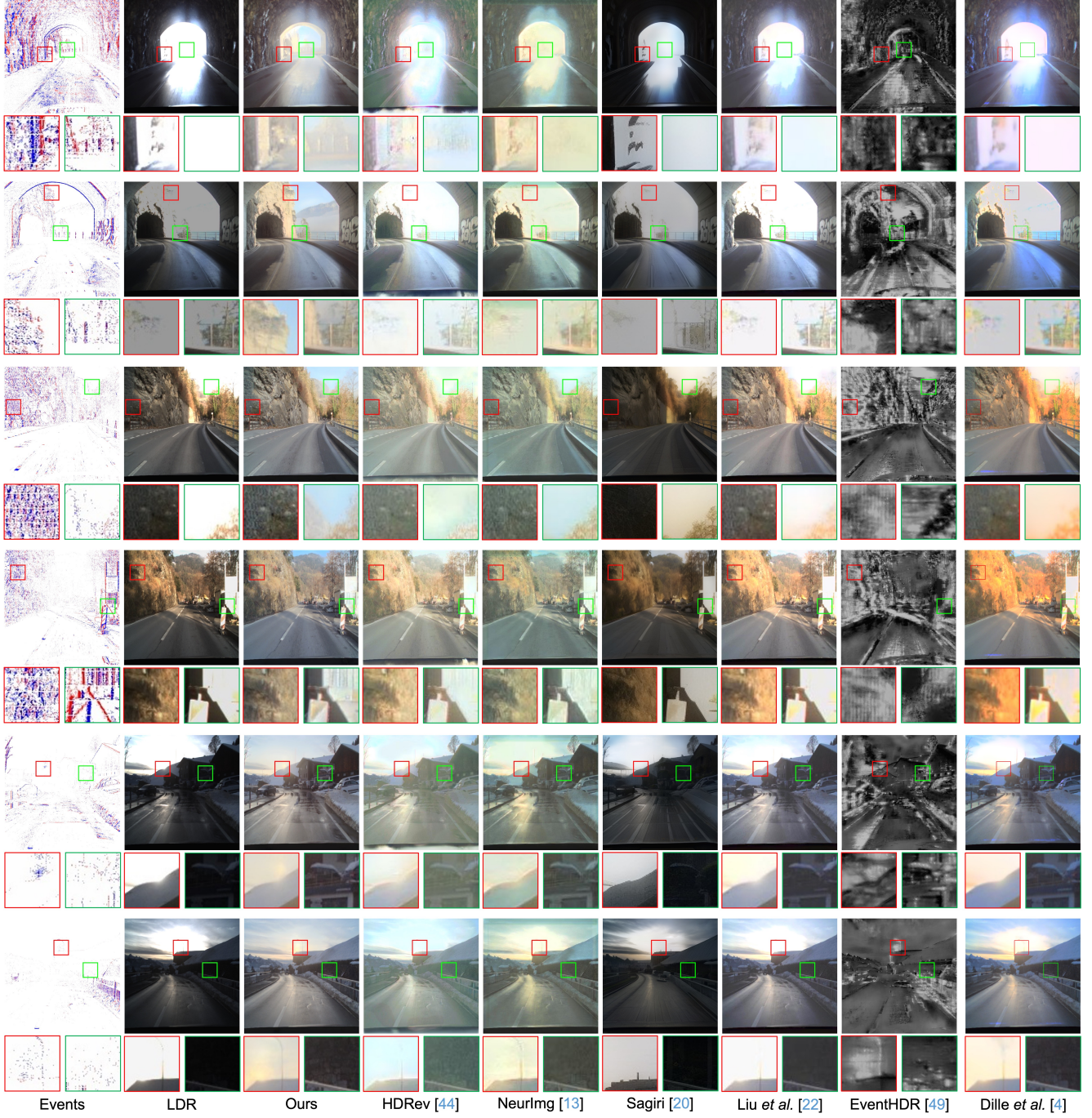


Figure 16. Qualitative comparisons of real data on DSEC [8].

bone, the proposed method has lower FLOPs (G) and faster running time than Sagiri [22]. Only with a slight parameter increase, we achieve better performance compared to Sagiri [22] as shown by Table 1.

14. More results on synthetic data

More quantitative comparisons are shown in Table 8. We add five metrics laid in two categories to further support

our results. More qualitative comparisons are shown in Figure 15. EventHDR [54] only reconstructs HDR intensity. Liu *et al.* [25] cannot reconstruct HDR scenes only with a single LDR image as input. Besides, the details in dark regions are wiped as indicated by the green box of the fourth column in Figure 15. Sagiri [22] has difficulty maintaining consistency with LDR images and predicting missing information in over-/under-exposed areas. However, compared



Figure 17. Qualitative comparisons of real data on HES-HDR [14].

with Liu *et al.* [25], Sagiri [22] can predict the handrail with diffusion priors as depicted in the second column of Figure 15. Although with events as input, NeuImg [14] and HDRev [49] are challenged to leverage the HDR information in events to reconstruct plausible results. Meanwhile, HDRev [49], which fuses events and images in the feature domain, shows better results than NeuImg [14], which

fuses intensity images reconstructed from events with LDR images in the image domain. The better performance inspires us to extract conditions in the feature domain, instead of reconstructed HDR image at first. The proposed method reconstructs colorful and plausible results consistent with LDR images and events.

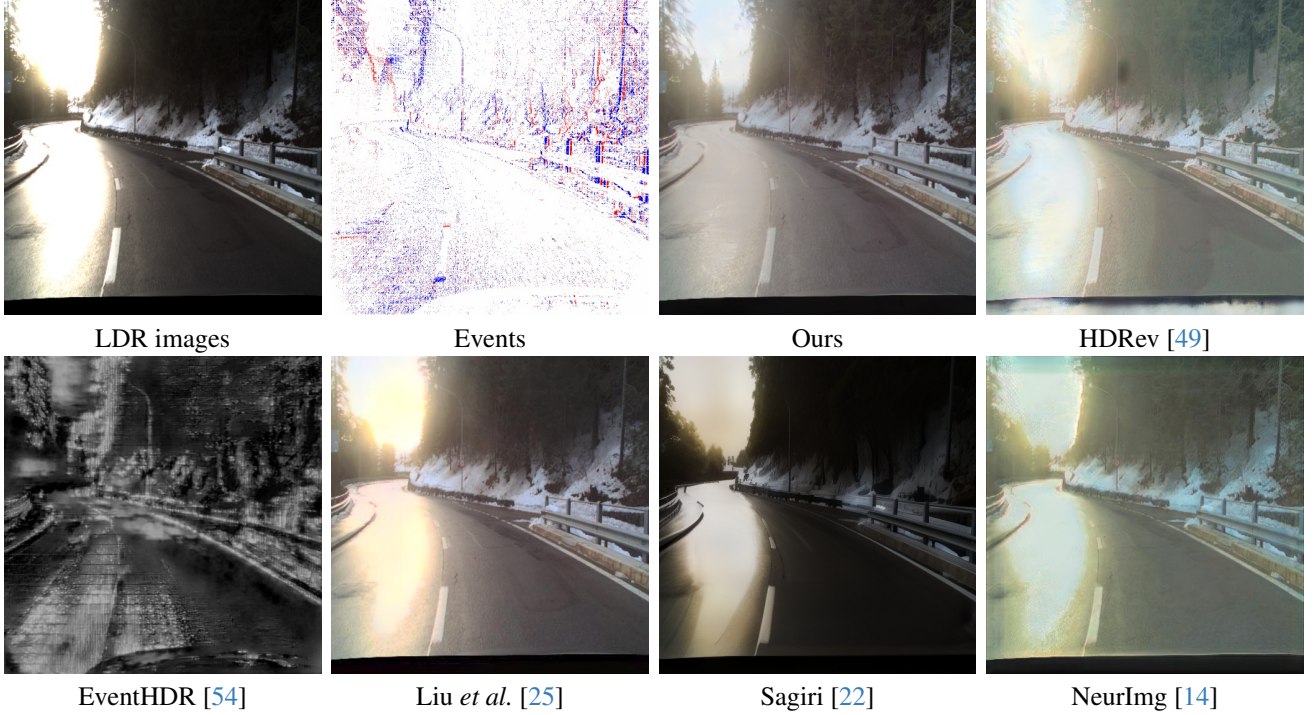


Figure 18. Consecutive results of the proposed method on DSEC [8] dataset. The proposed method shows the natural results with fewer artifacts and proper brightness. GIF animations could be displayed properly when viewed with Adobe Acrobat or KDE Okular.

Table 8. Additional quantitative evaluation of synthetic data.

		Liu <i>et al.</i> [25]	EventHDR [54]	Sagiri [22]	HDRRev [49]	NeurImg [14]	Liang <i>et al.</i> [23]	Dille <i>et al.</i> [4]	Ours
Video Metrics	t-LPIPS ⁵ ↓	0.025	0.112	0.107	0.024	0.021	0.086	0.012	0.018
	HDR-VQM↓	1.052	1.174	1.138	1.010	1.020	0.958	0.745	0.278
HDR Metrics	HDR-VDP-3↑	3.540	3.500	3.334	3.537	3.543	3.160	5.870	7.21
	PU-PSNR↑	24.643	23.432	23.49	23.71	24.73	21.96	32.39	32.20
	PU-SSIM↑	0.451	0.412	0.474	0.460	0.481	0.429	0.800	0.838

15. More results on real data

Comparison on DSEC dataset Additional results on DSEC [8] dataset are shown in Figure 16. It is difficult for EventHDR [54] to reconstruct distinguishable details on real data. Liu *et al.* [25] and Sagiri [22] are challenged in predicting over-exposed areas and retaining details in well-exposed and dark areas. NeurImg [14] is able to predict some of the information in over-exposed areas, while the results are low quality and have obviously artifacts in dark areas. HDRRev [49] better preserves detail in well-exposed areas than NeurImg [14], while it is difficult to leverage the information in events to predict HDR images. The proposed method leverages the advantage of events and diffusion priors, providing natural and high-quality HDR images.

Comparison on HES-HDR dataset Additional results on the HES-HDR [14] dataset are shown in Figure 17. EventHDR [54] is challenged to reconstruct HDR informa-

tion. Sagiri [22] and Liu *et al.* [25] can only hallucinate HDR information, which is difficult for large over-exposed areas, as shown in the third and sixth row in Figure 17. HDRRev [49] and NeurImg [14] are also hard to compensate for over-exposed areas. The proposed method demonstrates superior performance in both compensating missing information for over-/under-exposed areas and preserving details in well-exposed regions as depicted by Figure 17.

16. Failure case in consecutive frames

We provide two results in Figure 18 to show our limitation on video generation. The proposed method does not consider the consecutive connection between adjacent frames. Although the proposed method maintains consistency with input LDR images and events, it cannot restore consecutive details for adjacent frames. Therefore, the over-exposed areas obviously flicker as demonstrated by the sky of Figure 18.