From Events to Clarity: The Event-Guided Diffusion Framework for Dehazing

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Abstract

In this supplementary material, we include (1) more information regarding our collected dataset, (2) additional illustrations and details about our method's experimental results. The collected real-world dataset, the corresponding simulated dataset, and our code will be released on https://evdehaze.github.io/.

1. More information regarding our collected dataset

1.1. Real-world Hazy RGB-Event Dataset

In our UAV-captured real-world haze-event dataset, we collected a total of 6,674 .npy files, each representing an event segment. Alongside these, the dataset includes 61,173 corresponding haze-degraded RGB images, as shown in Fig. 1. To the best of our knowledge, this constitutes the largest real-world hazy image dataset with aligned event data available to date, providing a valuable resource for studying event-guided dehazing in complex outdoor environments.

1.2. Synthetic RGB-Event Datasets

Fig. 2 illustrates simulated event streams corresponding to the RESIDE dataset, which is currently the largest benchmark dataset for haze removal with paired hazy and clear RGB images. To enrich this dataset with temporal cues, we synthetically generated corresponding event data under three typical motion patterns: radial, rotational, and translational. This augmentation results in the largest synthetic RGB-Hazy/Clear-Event dataset to date, providing a valuable benchmark for learning-based event-guided dehazing methods.

2. Additional Experimental Results

Fig. 3 and Fig. 4 are the visualization results on the SOTS dataset (indoor scene). Fig. 5 is the visualization of the event feature x_e with heatmaps.

3. Additional Real-world Results

Beyond the quantitative evaluation on synthetic benchmarks, we further verify the effectiveness of our method on challenging real-world hazy scenes. Fig. 6 and Fig. 7 shows representative qualitative results on images captured by our UAV-mounted RGB-event rig under diverse outdoor conditions, including varying haze densities, long viewing distances, and complex backgrounds (e.g., vegetation, buildings, and sky regions). Our approach is able to recover clearer structures and more natural colors compared with the hazy inputs, while avoiding over-amplifying artifacts in severely degraded areas.

4. Event-only Visualization Videos

To better illustrate what information is actually captured by the event camera, we further include several *event-only visualization videos*. These clips render only the raw event stream without any RGB images: we provide both grayscale visualizations and red/blue polarities. Positive and negative events are highlighted with different colors, revealing sharp motion boundaries, building edges, road markings, and fine textures even under dense haze. These event-only videos are different from the dehazing demo: they are intended to give an intuitive understanding of the rich spatiotemporal cues available in the event domain, which our model exploits as additional guidance for robust dehazing. We hope this can also serve as a reference for future work on event-based restoration under adverse weather conditions.

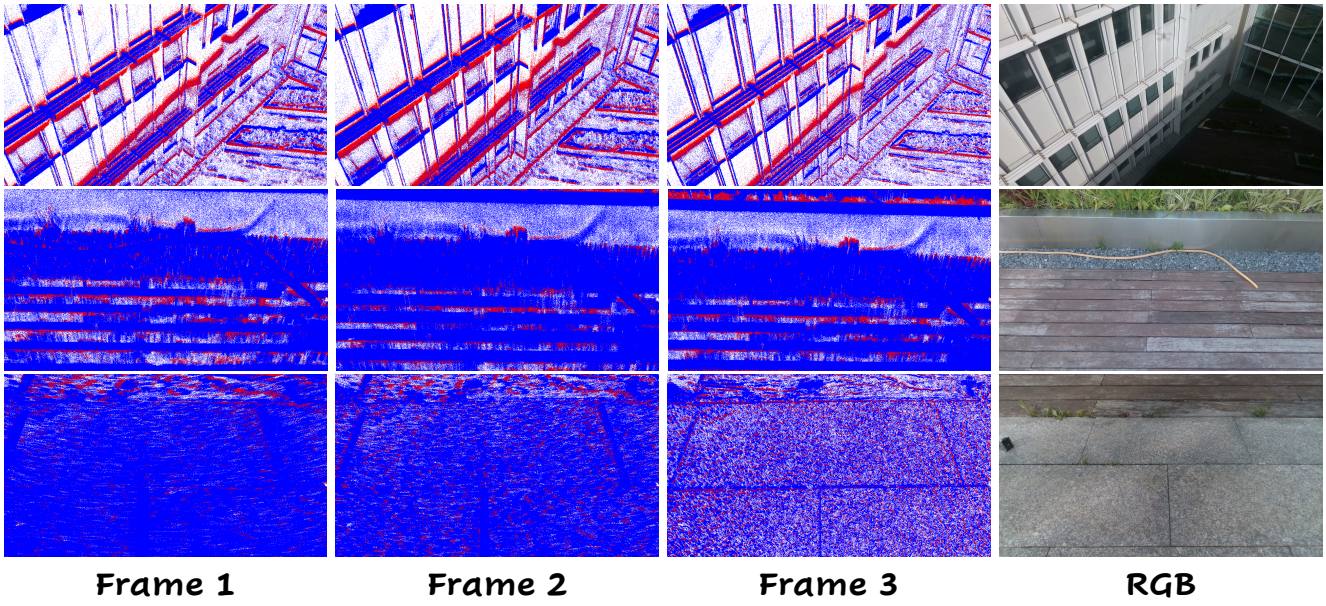

Figure 1. Visualization of real-world event data captured by our UAV-mounted event camera in hazy outdoor environments. Each row shows three consecutive event slices (Frame 1–3) followed by the corresponding RGB image. The event frames visualize the spatiotemporal dynamics of scene changes with positive and negative polarities highlighted in red and blue, respectively. These rich temporal cues can guide robust dehazing under severe degradation. Our dataset contains 6,674 such event segments and 61,173 aligned RGB images, making it the largest real-world hazy event dataset to date.

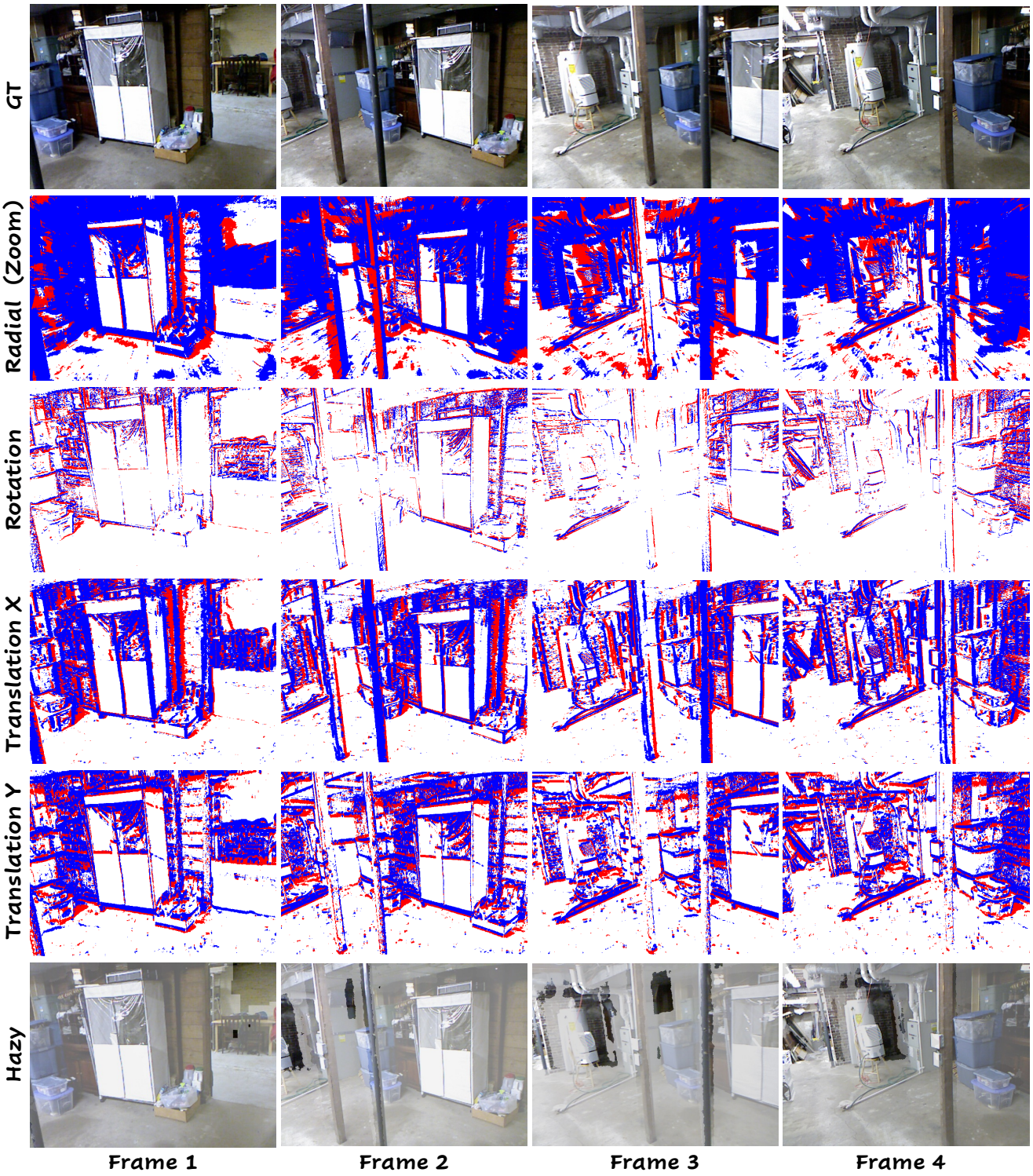

Figure 2. Simulated event data corresponding to the RESIDE dataset under radial, rotational, and translational motions. By augmenting RESIDE, the largest hazy-clear RGB image dataset with corresponding simulated events, we construct the largest synthetic RGB-Hazy/Clear-Event dataset, enabling joint modeling of spatial, temporal, and degradation priors.

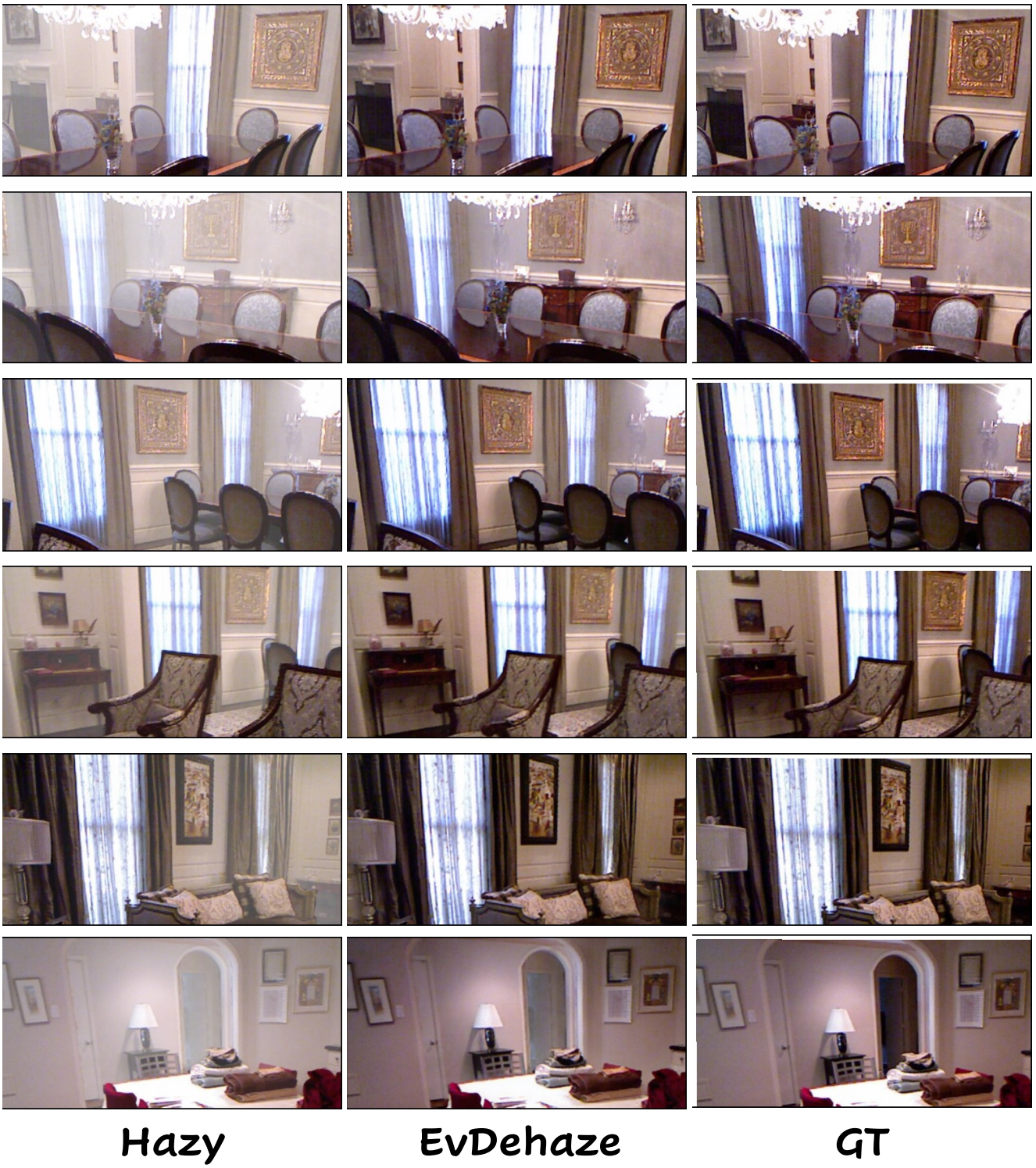

Figure 3. Part 1 of visualization results on the SOTS dataset (indoor scene).

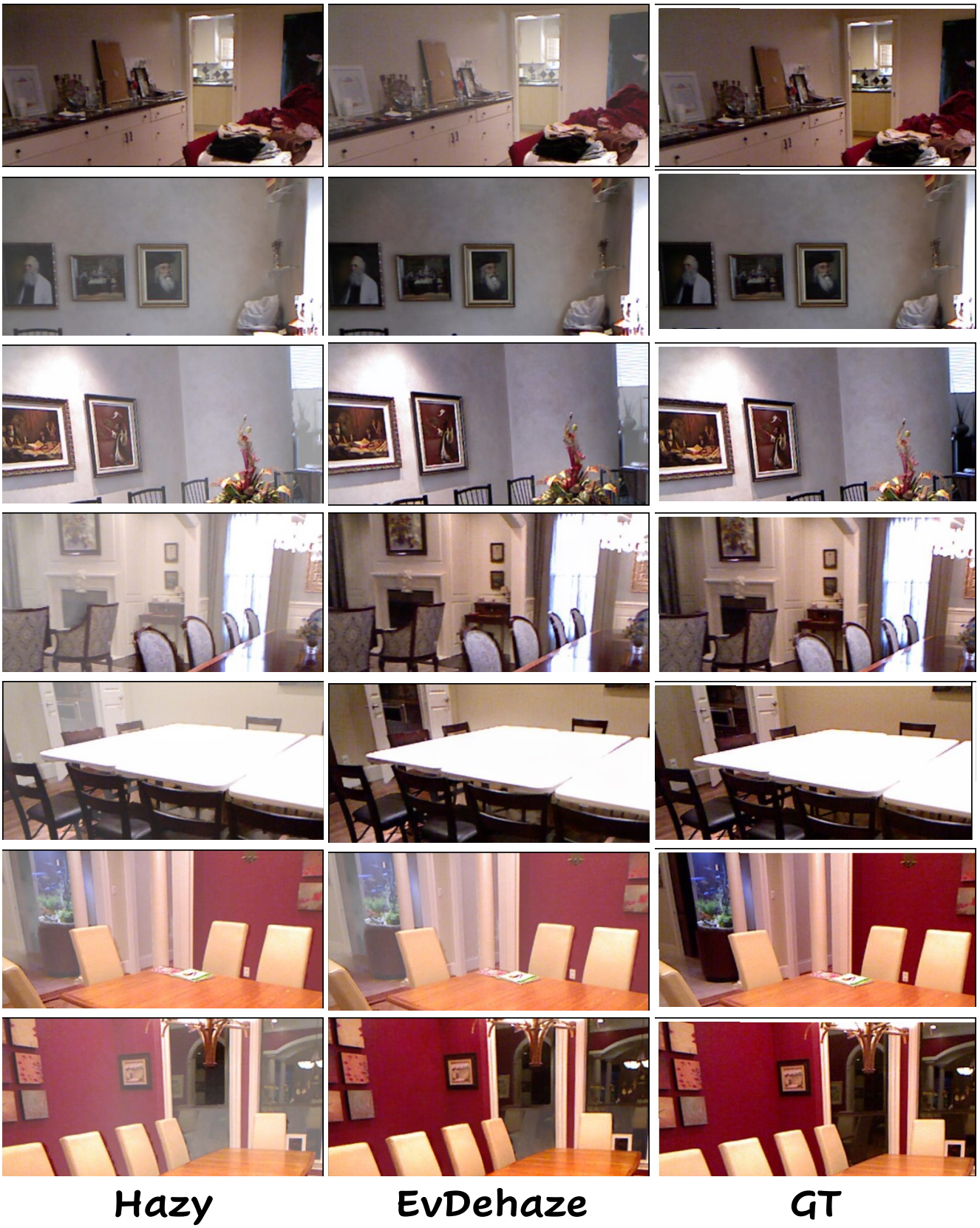

Figure 4. Part 2 of visualization results on the SOTS dataset (indoor scene).

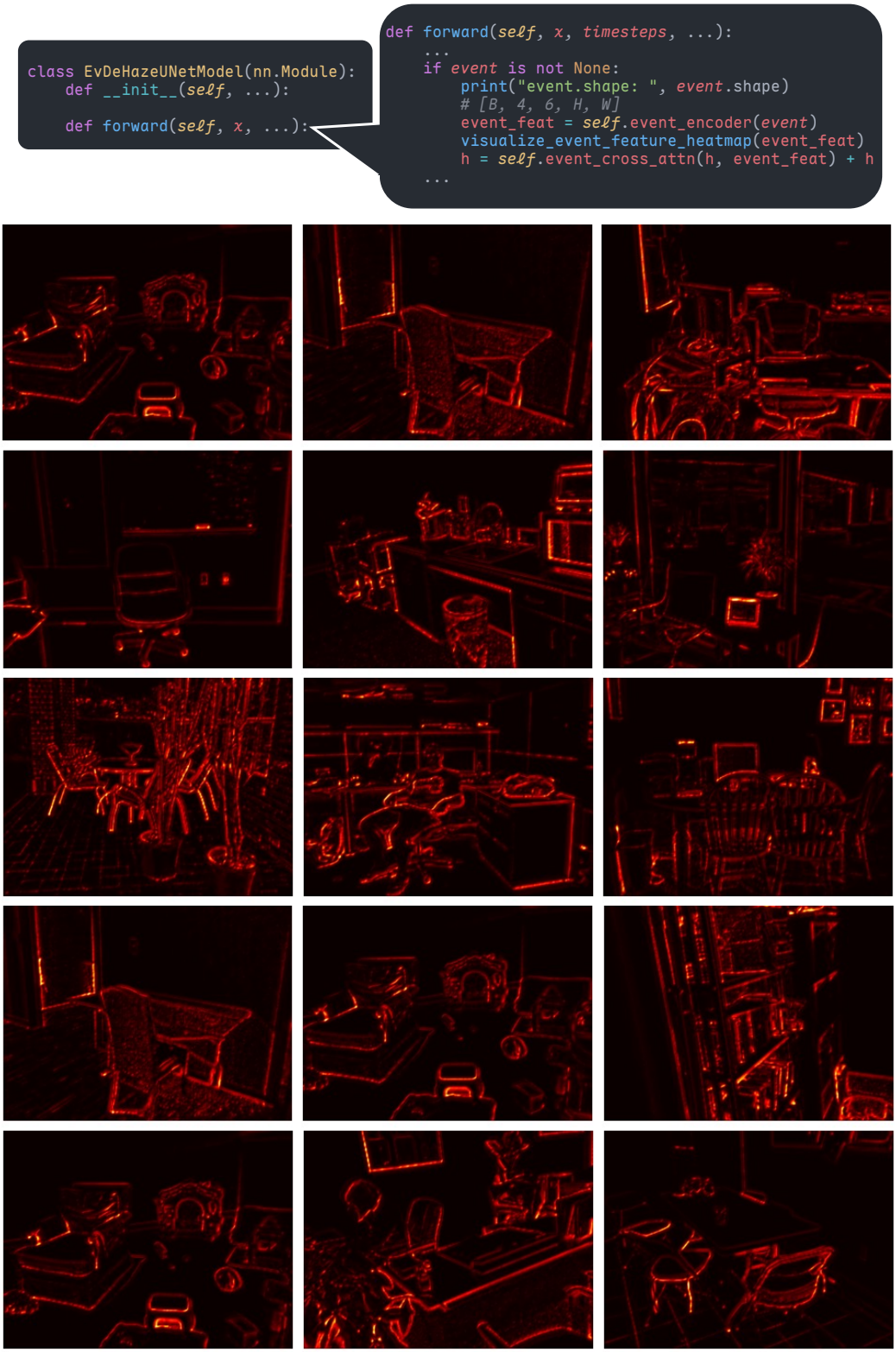

Figure 5. Visualization of the event feature x_e with heatmaps.

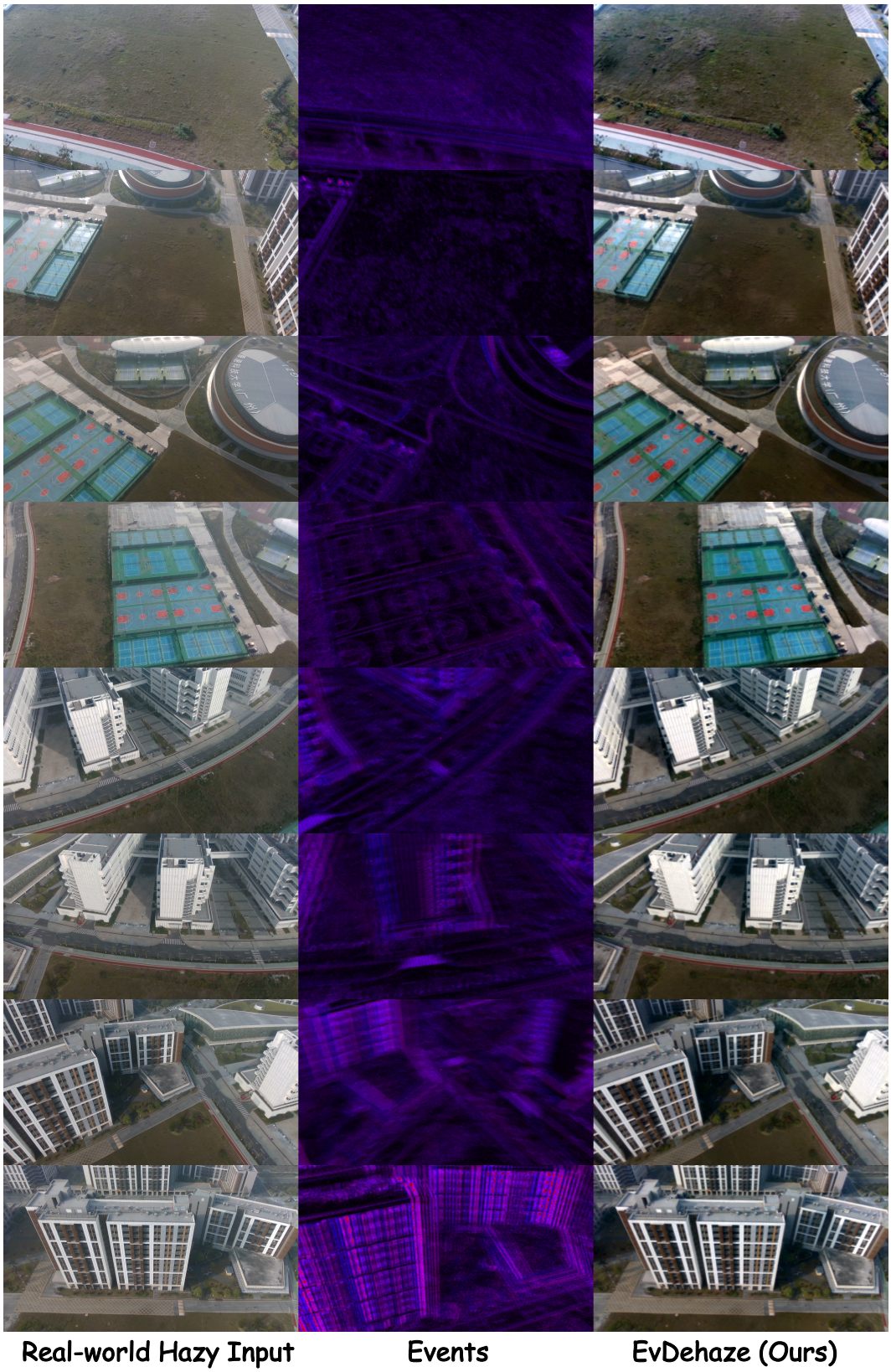

Figure 6. Visualization of real-world results on our proposed method.

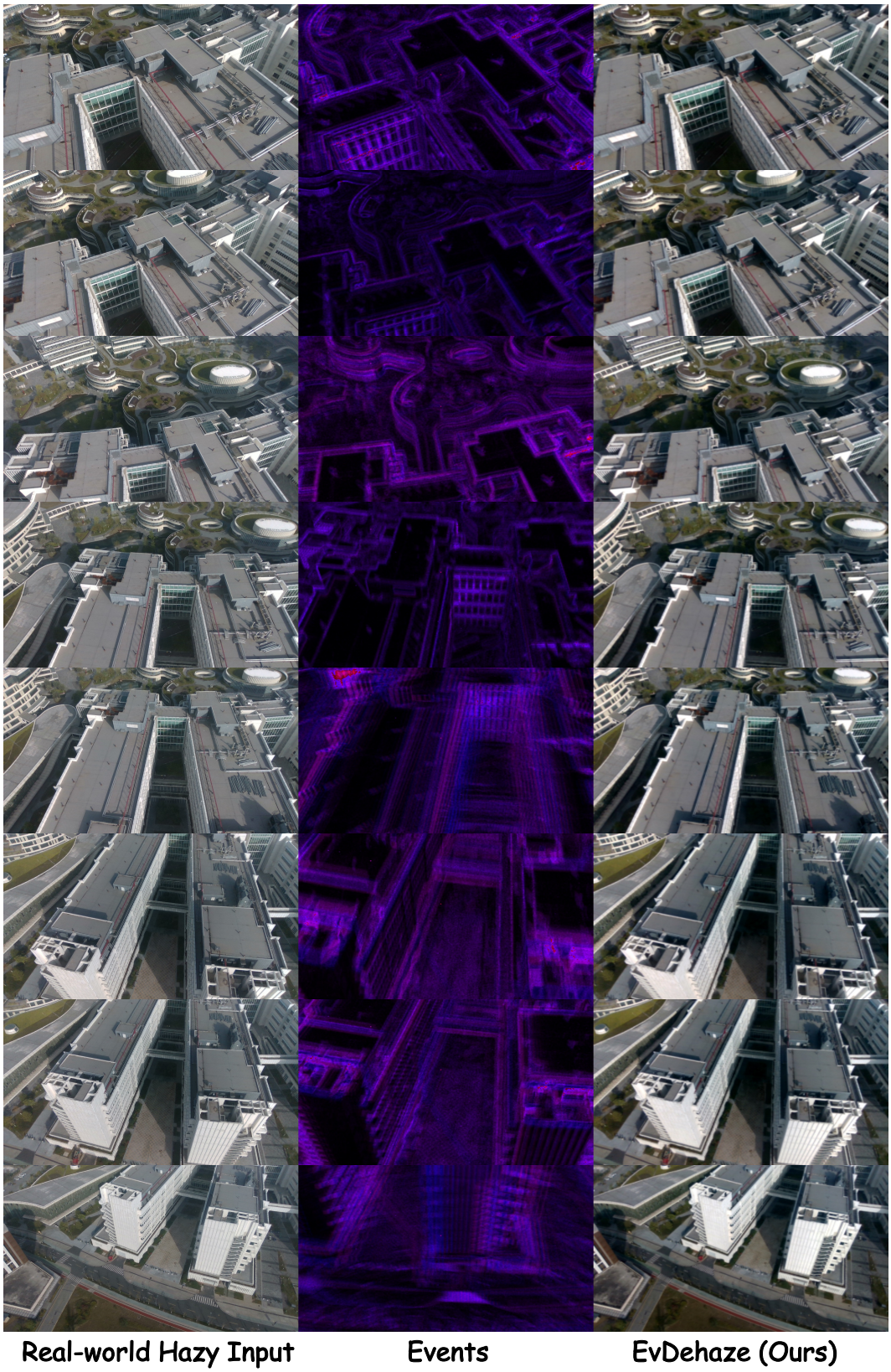

Figure 7. Visualization of real-world results on our proposed method.