Event-based Blurry Frame Interpolation under Blind Exposure
Supplementary Material

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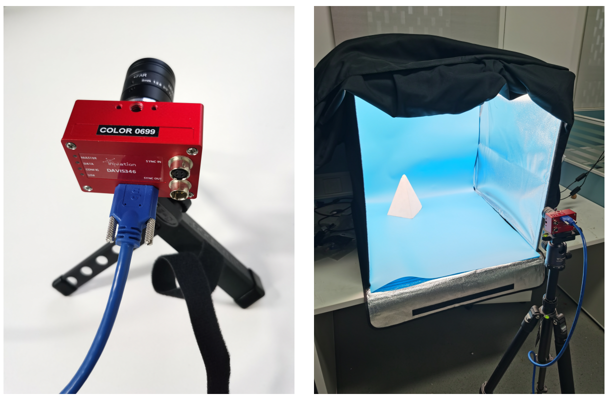

(a) (b)

Figure 1. (a) The DAVIS346 color event camera. (b) The black box for indoor capturing.

1. Video Demonstration

We provide a supplement video at https://drive.google.com/file/d/1-R8DrGMx1HUWGSRdr3ToUWWypgSCN_cY/view?usp=sharing. We strongly recommend referring to it for the qualitative comparison.

2. Details of the Self-collected Dataset

In order to evaluate our method on the real-world system, we make a real-world dataset called RealBlur-DAVIS, which contains real blurry frames and spatially aligned real events. We use a DAVIS346 color event cameras to capture this dataset, as shown in Fig. 1(a). The self-collected RealBlur-DAVIS contains diverse light conditions and motion speeds. For the different exposure assumptions, we set the exposure time as $\{30, 60, 90, 120, 150, 180\}$ ms, with a shutter period of 200 ms to generate low frame-rate blurry videos. Each sequence has a period of about 20 seconds. Our dataset contains indoor and outdoor scenes. For the indoor capturing, we also make a black box as shown in Fig. 1(b) to manually control the illumination intensity. This dataset will be available at https://github.com/WarranWeng/EBFI-BE.

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Table 1. Quantitative results with train-test inconsistency on GoPro [5].

Methods	Inputs	GoPro [5] 7-5 PSNR	SSIM	9-3 PSNR	SSIM	11-1 PSNR	SSIM
EDVR [10]+SloMo [1]	RGB	20.809	0.726	21.155	0.739	21.476	0.752
EDVR [10]+QVI [11]	RGB	20.816	0.724	21.194	0.739	21.534	0.752
EFNet [3]+TLens [9]	RGB+Events	23.589	0.834	23.625	0.836	23.609	0.836
UEVD [8]+TLens [9]	RGB+Events	23.537	0.832	23.600	0.834	23.607	0.834
TNTT [2]	RGB	20.416	0.693	21.066	0.717	21.605	0.738
BIN [7]	RGB	17.305	0.597	17.745	0.608	18.257	0.620
UTI [13]	RGB	20.262	0.696	20.257	0.694	20.203	0.691
EDI [6]	Mono+Events	20.048	0.723	20.139	0.735	20.060	0.737
LEDVDI [4]	RGB+Events	24.537	0.830	24.819	0.841	24.973	0.848
EVDI [12]	RGB+Events	26.798	0.890	26.628	0.888	26.131	0.881
Ours	RGB+Events	**29.166**	**0.928**	**29.167**	**0.930**	**29.066**	**0.928**

3. Additional Experimental Results

Quantitative Results. We provide additional quantitative results with train-test inconsistency on GoPro [5] in Tab. 1. As can be observed, when evaluated on the dataset whose exposure assumption is inconsistent with that of training dataset, we can achieve the best results compared with other competitors, validating the adaptation ability of our method.
Qualitative Results. We show additional qualitative results on RealSharp-DAVIS [8] in Fig. 2 and Fig. 3, and on the self-collected RealBlur-DAVIS in Fig. 4, Fig. 5, Fig. 6 and Fig. 7. It can be clearly observed that we can achieve satisfactory results with fine details and sharp edges in comparison to other competitors, demonstrating the strong ability of generalization and robustness of our method.

4. Extreme Interpolation Results

As mentioned in the main paper, the proposed temporal-exposure control component is able to take arbitrary timestamp as input. In other words, it is possible to perform extreme interpolation if the step of timestamp is small enough. We show the results in Fig. 8 and the supplement video. As can be clearly observed, our method is capable of generating the high frame-rate sharp video even up to 640 FPS from the 5 FPS low frame-rate blurry video.

Figure 2. Additional qualitative results on RealSharp-DAVIS [8].

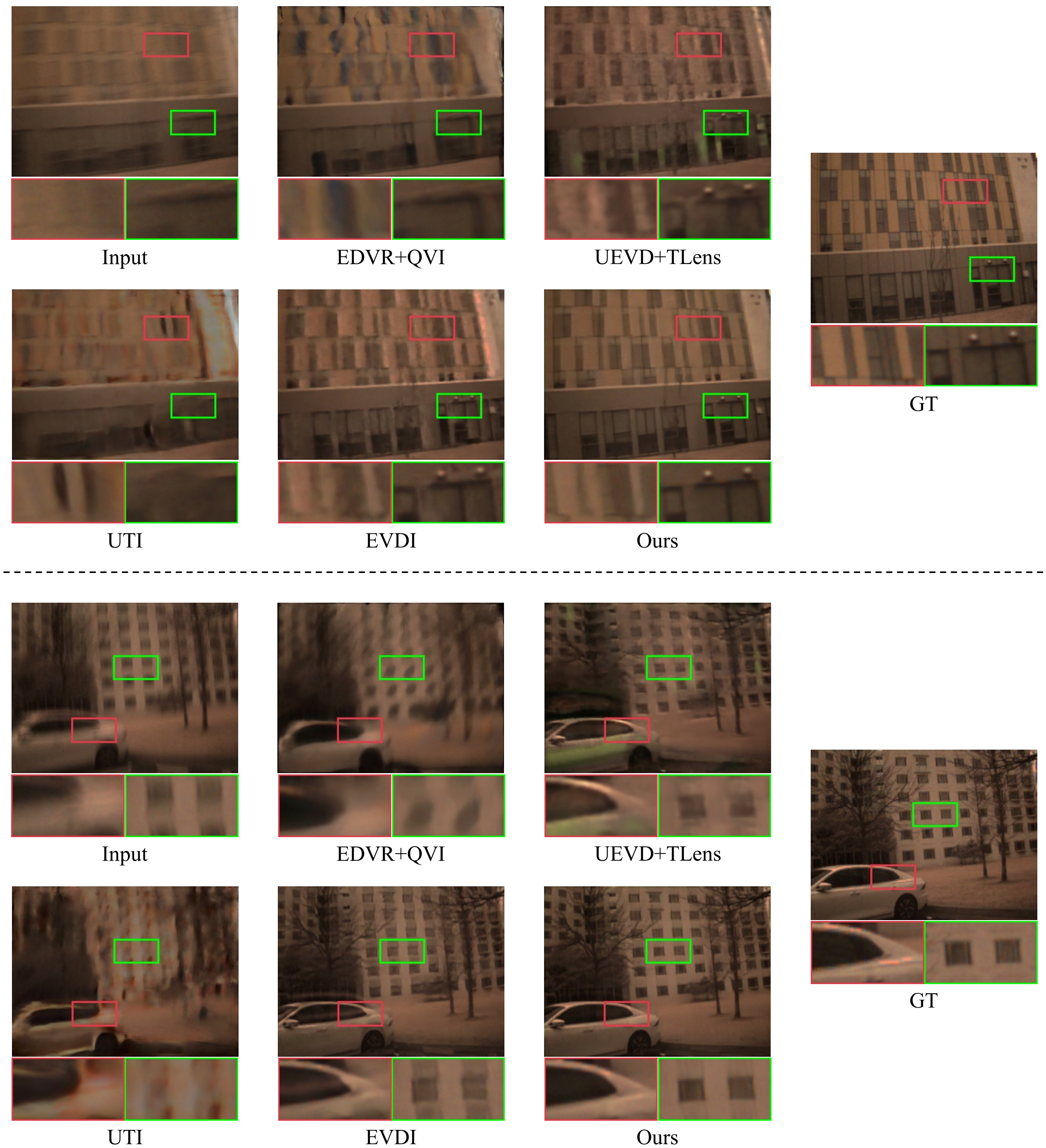

Figure 3. Additional qualitative results on RealSharp-DAVIS [8].

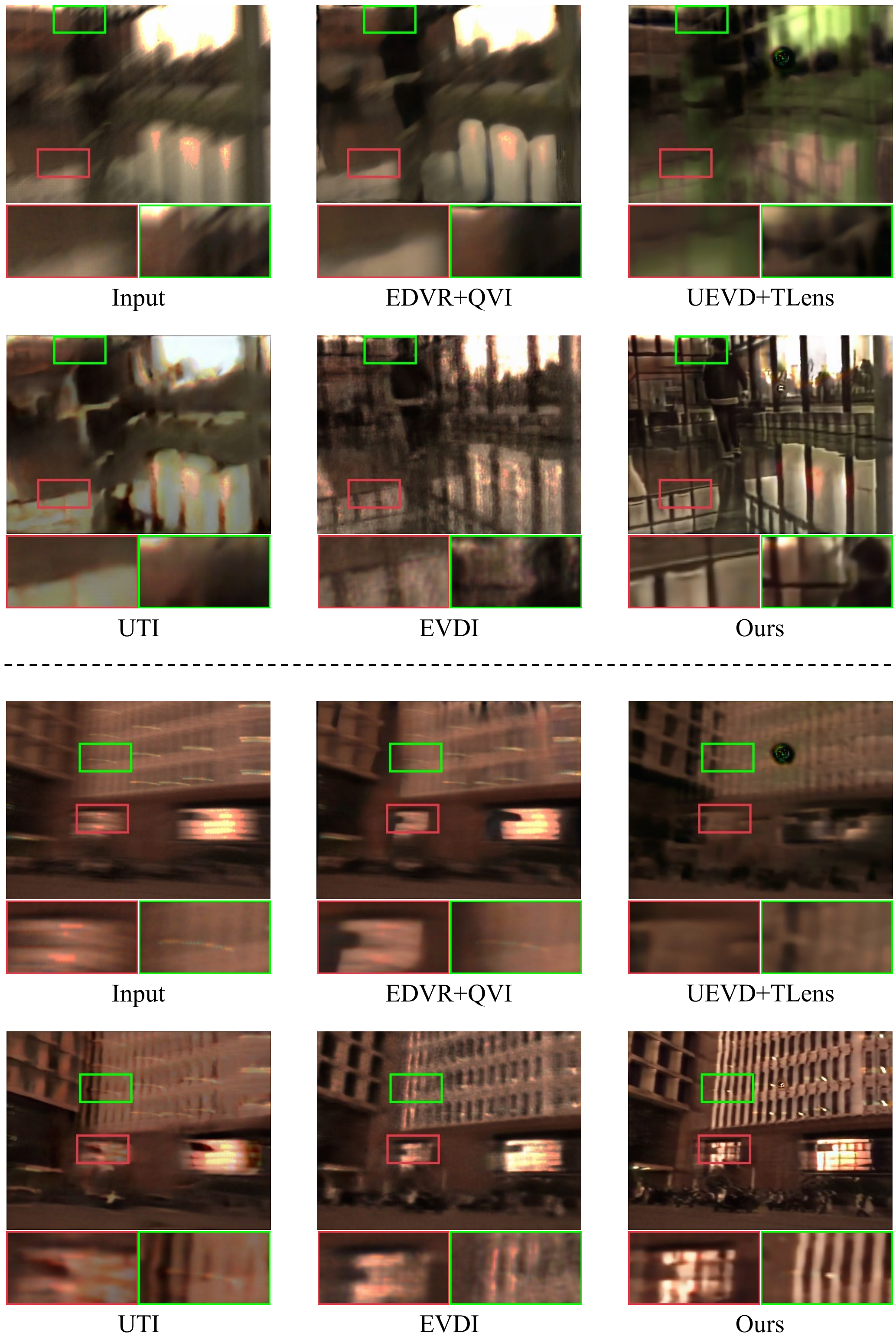

Figure 4. Additional qualitative results on the self-collected real-world blurry video dataset RealBlur-DAVIS.

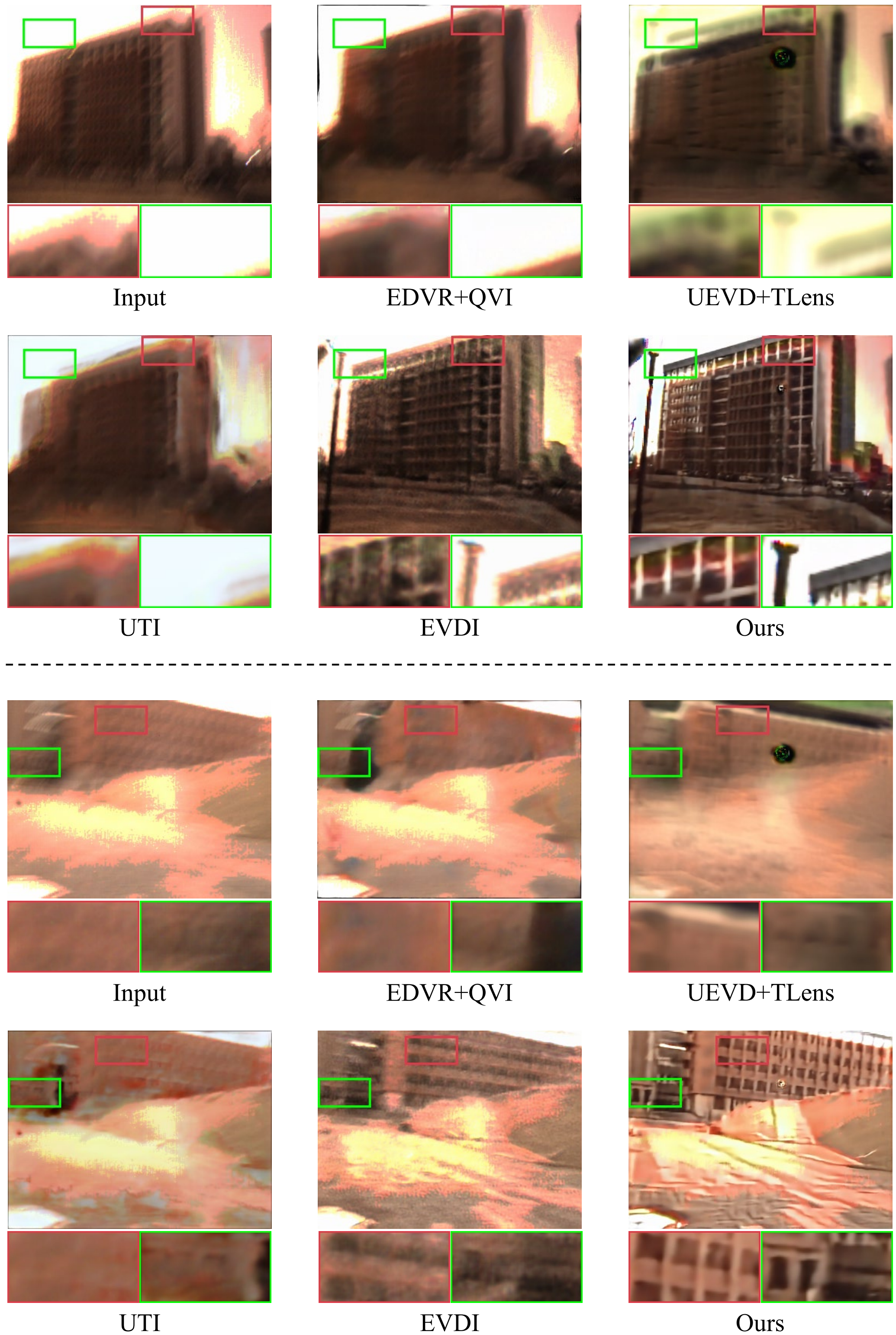

Figure 5. Additional qualitative results on the self-collected real-world blurry video dataset RealBlur-DAVIS.

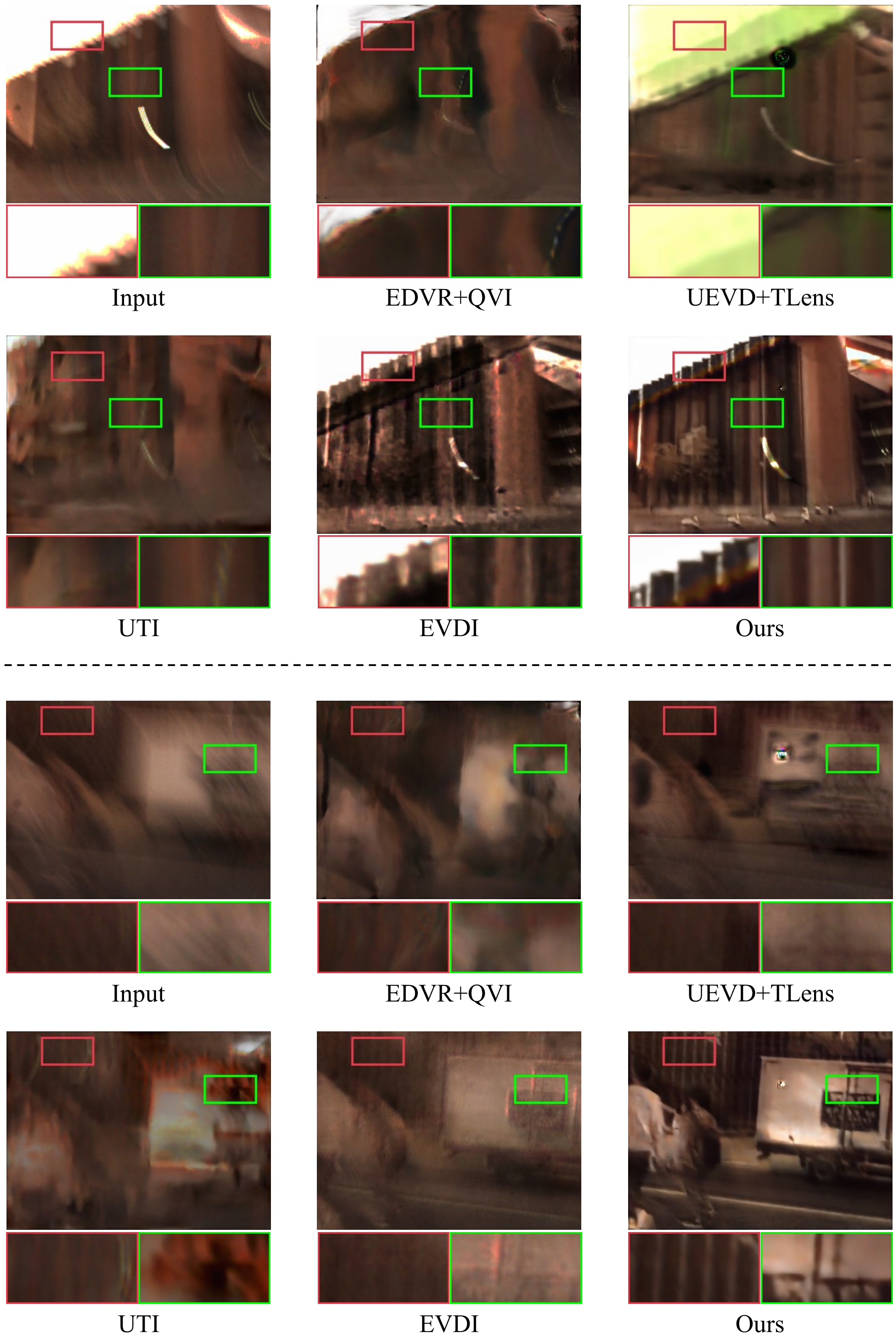

Figure 6. Additional qualitative results on the self-collected real-world blurry video dataset RealBlur-DAVIS.

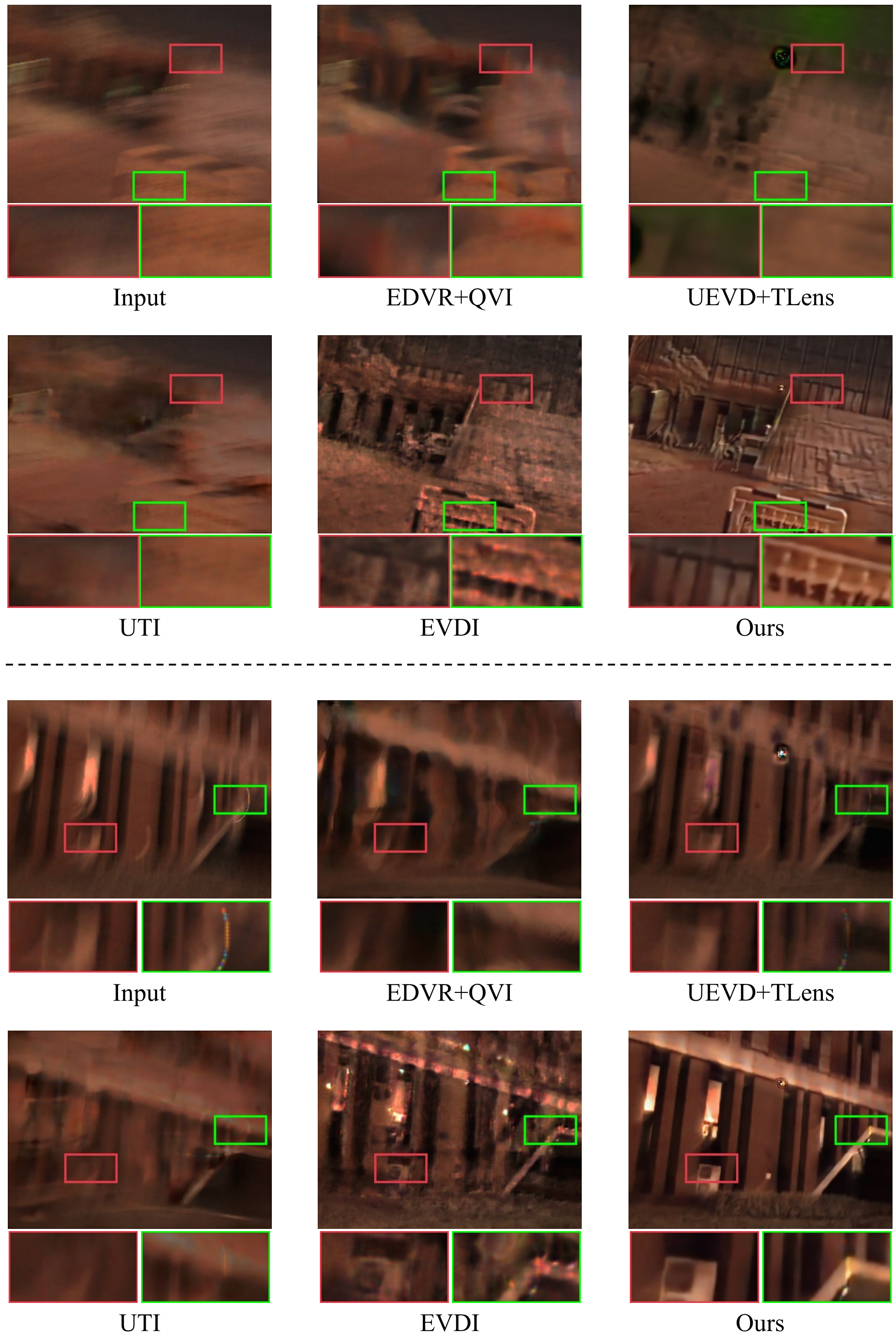

Figure 7. Additional qualitative results on the self-collected real-world blurry video dataset RealBlur-DAVIS.

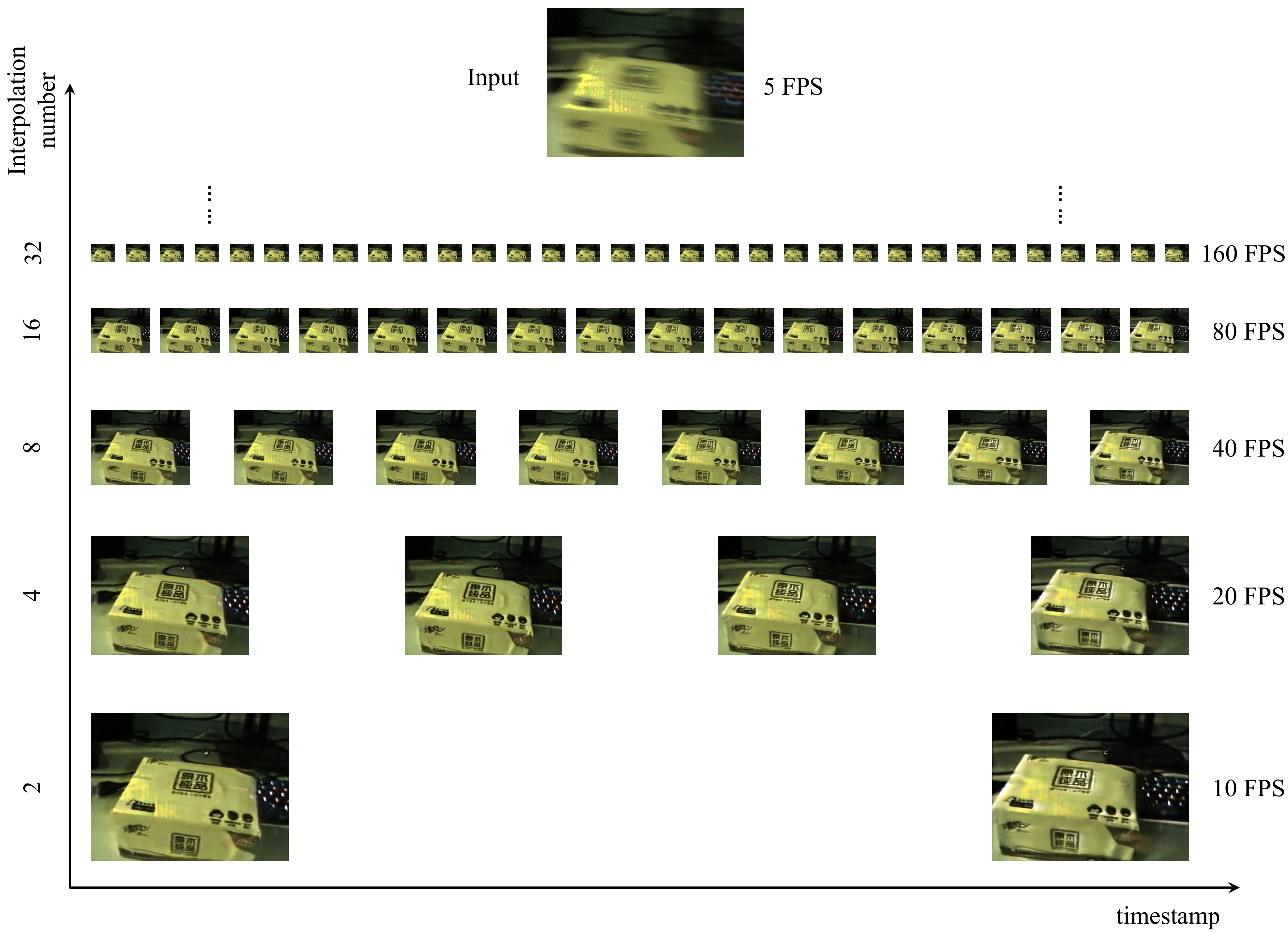

Figure 8. Extreme interpolation results on the self-collected real blurry video dataset RealBlur-DAVIS. Given a 5 FPS blurry video, we can generate the sharp video even up to 640 FPS (*i.e*., the interpolation number is 128). **Please refer to the supplement video for a better visual experience**.

References

[1] Huaizu Jiang, Deqing Sun, Varun Jampani, Ming-Hsuan Yang, Erik Learned-Miller, and Jan Kautz. Super slomo: High quality estimation of multiple intermediate frames for video interpolation. In *CVPR*, 2018. 1

[2] Meiguang Jin, Zhe Hu, and Paolo Favaro. Learning to extract flawless slow motion from blurry videos. In *CVPR*, 2019. 1

[3] Sun Lei, Sakaridis Christos, Liang Jingyun, Jiang Qi, Yang Kailun, Sun Peng, Ye Yaozu, Wang Kaiwei, and Gool Luc Van. Event-based fusion for motion deblurring with cross-modal attention. In *ECCV*. Springer, 2022. 1

[4] Songnan Lin, Jiawei Zhang, Jinshan Pan, Zhe Jiang, Dongqing Zou, Yongtian Wang, Jing Chen, and Jimmy Ren. Learning event-driven video deblurring and interpolation. In *ECCV*. Springer, 2020. 1

[5] Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee. Deep multi-scale convolutional neural network for dynamic scene deblurring. In *CVPR*, 2017. 1

[6] Liyuan Pan, Cedric Scheerlinck, Xin Yu, Richard Hartley, Miaomiao Liu, and Yuchao Dai. Bringing a blurry frame alive at high frame-rate with an event camera. In *CVPR*, 2019. 1

[7] Wang Shen, Wenbo Bao, Guangtao Zhai, Li Chen, Xiongkuo Min, and Zhiyong Gao. Blurry video frame interpolation. In *CVPR*, 2020. 1

[8] Kim Taewoo, Lee Jeongmin, Wang Lin, and Yoon Kuk-Jin. Event-guided deblurring of unknown exposure time videos. In *ECCV*. Springer, 2022. 1, 2, 3

[9] Stepan Tulyakov, Daniel Gehrig, Stamatios Georgoulis, Julius Erbach, Mathias Gehrig, Yuanyou Li, and Davide Scaramuzza. Time lens: Event-based video frame interpolation. In *CVPR*, 2021. 1

[10] Xintao Wang, Kelvin CK Chan, Ke Yu, Chao Dong, and Chen Change Loy. Edvr: Video restoration with enhanced deformable convolutional networks. In *CVPRW*, 2019. 1

[11] Xiangyu Xu, Li Siyao, Wenxiu Sun, Qian Yin, and Ming-Hsuan Yang. Quadratic video interpolation. In *NeurIPS*, 2019. 1

[12] Xiang Zhang and Lei Yu. Unifying motion deblurring and frame interpolation with events. In *CVPR*, 2022. 1

[13] Youjian Zhang, Chaoyue Wang, and Dacheng Tao. Video frame interpolation without temporal priors. In *NeurIPS*, 2020. 1