Non-Coaxial Event-guided Motion Deblurring with Spatial Alignment

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Due to the limitation of space in the main paper, we provide a more detailed analysis of the proposed NED-Net and present more experimental results in this supplementary material. Specifically, in Sec. 1, we describe the details of the datasets. In Sec. 2 and 3, we provide more qualitative results. In Sec. 4, we provide the video demo. Lastly, in Sec. 5, we provide additional experiments and discussion.

Figure 1: Illustration of the camera setup. It consists of a DVXplorer event camera and a FLIR BlackFly S RGB camera.

1. Non-Coaxial Events and RGB dataset

The proposed NCER dataset was acquired with a separate high-resolution event camera and a high-frame-rate RGB camera. As shown in Fig. 1, the two cameras are placed side by side, with a baseline of 3 cm. The details of the NCER dataset are in Table 2 and 3, and some samples are provided in Fig. 2 and 3.

2. More Qualitative Results

We provide more qualitative results here. The qualitative results on the NCER dataset are in Fig. 4, 5, 6, and 7.

3. Real Blur Experiments

We further analyze whether the network trained on the NCER dataset can work on real blur images. As shown in Fig. 8, we provide comparison results of networks on the real blur images generated by moving the camera during the exposure time. Therefore, only qualitative evaluation is possible because ground truth does not exist. The networks using events generalize better for real blur than the only image method. Instead, existing event-based networks still do not handle alignment, so they often provide ghosting effects and cannot restore objects sharply. On the other hand, our NED-Net has the best generalization to real blur and sharply restores the texture considering the alignment, even in real blur.

Table 1: Comparison of PSNR (dB) and SSIM from other methods and our approach. We train networks on both the NCER and NCER-E datasets, and evaluate networks on both datasets. The best score is **highlighted**. The second-best scores are <u>underlined</u>.

Train	NCER-F + NCER-E			
Test	NCER-F		NCER-E	
Method	PSNR↑	SSIM↑	PSNR↑	SSIM↑
Frame				
HINet [1]	27.45	0.8144	31.72	0.8829
MPRNet [5]	27.68	0.8261	<u>32.24</u>	<u>0.8961</u>
Frame + Event				
EFNet [3]	26.66	0.7970	31.35	0.8788
RED-Net [4]	27.79	0.8334	31.54	0.8837
UEVD [2]	<u>27.91</u>	<u>0.8341</u>	31.63	0.8835
NED-Net	**28.40**	**0.8417**	**33.07**	**0.9048**

4. Video Demonstration

To show that the results of our network perform well compared to other methods in the overall sequence, not cherry-picking for specific scenes, we provide a video file. Please pause in the middle of the video and watch it for a better visual comparison.

5. Additional Experiments

Can a unitary network learn two different distributions of datasets at once? Table 1 reports the results of training and evaluation in both NCER-F and NCER-E datasets. If a network trained on both datasets learns all distributions well, it should achieve high performance on both test sets. When comparing existing frame-based and event-based methods, event-based methods are generally dominant in the NCER-F dataset. In the NCER-F dataset, misalignment is insignificant; thus, existing event-based methods show better performance than frame-based methods by aligning two modalities. Conversely, frame-based methods are prevalent in the NCER-E dataset. In the NCER-E dataset, misalignment is quite significant, making it difficult to align in event-based methods. Although trained on both datasets, the performance of existing event-based methods is biased towards the NCER-F dataset and underperforms on the NCER-E dataset. Also, this performance is relatively poor compared to training and testing only in the NCER-E dataset (Table 2 in the main paper). These results demonstrate that previous event-based methods cannot handle the different distributions of misalignment within a single network, even trained on both datasets. On the other hand, our NED-Net achieves the best performance in both the NCER-F and the NCER-E datasets by a large margin compared with previous event-based and only frame-based methods. In addition, the performance in the NCER-E dataset is comparable to the results of Table 2 in the main paper. These results validate that our NED-Net can handle the misalignment of various distributions even with one single network.

References

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Table 2: Overview of the proposed NCER-F dataset. We adjust the number of averaged frames to vary the intensity of the blur.

Sequence Name	**No. Frames**	**No. Average**	**Description**
Train Set			
Rooftop far away building 1	1957	15	Outdoor, very far away scene, rotation z-axis
Rooftop far away building 2	1821	27	Outdoor, very far away scene, rotation z-axis, moving objects
Rooftop view first floor	1426	15	Outdoor, close and far away scene, rotation z-axis, fast motion, accelerating object
Traffic sign background trees road	1556	19	Outdoor, close scene, rotation z-axis and x-axis, accelerating object
Flower with traffic sign	346	25	Outdoor, close scene, dynamic motion
Cross walk with traffic sign 1	489	11	Outdoor, close scene, dynamic and fast motion
Gym in the shade	721	15	Outdoor, close scene, rotation z-axis, accelerating object, reflection object
Gym outer wall 1	697	21	Outdoor, close scene, rotation z-axis, reflection, repetitive pattern
Building 1	914	19	Outdoor, close scene, rotation z-axis, text, repetitive pattern
Building 2	868	21	Outdoor, far away scene, random rotation, moving object, repetitive pattern
Building 3	756	25	Outdoor, far away scene, random rotation, repetitive pattern
Building 4	831	17	Outdoor, close scene, rotation y-axis, fast motion, heavily repetitive pattern
Building 5	1089	23	Outdoor, far away scene, rotation z-axis, repetitive pattern
Pond 1	1094	25	Outdoor, close and far away scene, dynamic motion, fast motion, non-linear motion, water
Tree background pond	920	29	Outdoor, close scene, rotation z-axis, water, reflection
Statue 1	606	29	Outdoor, close scene, random rotation, text, repetitive pattern
Bike	827	21	Outdoor, close scene, rotation y-axis, text, repetitive pattern
Parking 1	810	15	Outdoor, close scene, dynamic motion, text, reflection, repetitive pattern
Parking 2	1581	21	Outdoor, close scene, rotation z-axis, text, repetitive pattern
Tree 1	346	25	Outdoor, close scene, random rotation
Tree background building	704	17	Outdoor, far-away scene, rotation z-axis and x-axis
Bus 1	260	19	Outdoor, close and far-away scene, dynamic motion, text, repetitive pattern
Bench 1	641	31	Outdoor, close scene, dynamic motion, fast motion
Flower pots on the stairs 1	999	19	Outdoor, close scene, dynamic motion, repetitive pattern
Multi-floor railing 1	976	23	Indoor, close scene, rotation x-axis and z-axis, reflection, repetitive pattern
Repetitive pattern ceiling 1	519	27	Indoor, far away scene, random rotation, heavily repetitive pattern
Lounge chair	996	23	Indoor, close scene, random rotation

Sequence Name	No. Frames	No. Average	Description
Test Set			
Rooftop far away building 3	1444	25	Outdoor, close and far away scene, rotation z-axis
Rooftop far away building 4	1737	25	Outdoor, very far away scene, rotation z-axis
Pond 2	984	25	Outdoor, close and far away scene, rotation z-axis, reflection, non-linear motion, water
Statue 2	512	29	Outdoor, close scene, rotation y-axis, text, repetitive pattern
Parking 3	955	19	Outdoor, close scene, rotation z-axis, text
Gym outer wall 2	793	25	Outdoor, close scene, random and dynamic rotation, reflection, fast motion, repetitive pattern
Tree 2	426	25	Outdoor, close scene, dynamic motion
Sign and tree	928	15	Outdoor, close scene, random rotation
Building 6	1155	21	Outdoor, close scene, dynamic motion, fast motion, heavily repetitive pattern
Building 7	1167	31	Outdoor, close scene, dynamic motion, fast motion, heavily repetitive pattern
Flower pots on the stairs 2	930	15	Outdoor, close scene, dynamic motion, repetitive pattern
Bench 2	576	19	Outdoor, close scene, dynamic motion, slow motion
Smoking room	888	15	Outdoor, close scene, rotation z-axis and x-axis, fast motion, heavily repetitive pattern
Cross walk with traffic sign 2	615	15	Outdoor, close scene, dynamic and fast motion, accelerating object, text
Repetitive pattern ceiling 2	846	27	Indoor, far away scene, random rotation, heavily repetitive pattern
Multi-floor railing 2	979	27	Indoor, close scene, rotation x-axis and z-axis, reflection, repetitive pattern

Table 3: Overview of the proposed NCER-E dataset. We adjust the number of averaged frames to vary the intensity of the blur.

Sequence Name	**No. Frames**	**No. Average**	**Description**
Train Set			
Tissue 1	724	17	Outdoor, very close scene with faraway objects
Tissue 2	614	13	Outdoor, very close scene with faraway objects
Tissue 3	946	15	Outdoor, very close scene with faraway objects
Book Black 1	689	15	Outdoor, very close scene with faraway objects
Book White 1	886	15	Outdoor, very close scene with faraway objects
Book White 2	961	13	Outdoor, very close scene with faraway objects
Snack Box	426	15	Outdoor, very close scene with faraway objects
Fan 1	815	15	Outdoor, very close scene with faraway objects
Fan 2	329	13	Outdoor, very close scene with faraway objects
GPU Box 1	636	11	Outdoor, very close scene with faraway objects
Lion Doll 1	712	15	Outdoor, very close scene with faraway objects
Lion Doll 2	759	13	Outdoor, very close scene with faraway objects
Lion Doll 3	806	15	Outdoor, very close scene with faraway objects
Lion Doll 4	871	11	Outdoor, very close scene with faraway objects
Cup 1	656	11	Outdoor, very close scene with faraway objects, fast motion with strong blur
Cup 2	404	11	Outdoor, very close scene with faraway objects, fast motion with strong blur
Square Doll 1	571	7	Outdoor, very close scene with faraway objects, fast motion with strong blur
Square Doll 2	325	9	Outdoor, very close scene with faraway objects, fast motion with strong blur
Keyboard 1	505	5	Outdoor, very close scene with faraway objects, fast motion with strong blur
Keyboard 2	545	9	Outdoor, very close scene with faraway objects, fast motion with strong blur
Lamp 1	247	9	Outdoor, very close scene with faraway objects, fast motion with strong blur
Lamp 2	271	7	Outdoor, very close scene with faraway objects, fast motion with strong blur

Sequence Name	**No. Frames**	**No. Average**	**Description**
Test Set			
Tissue 4	703	11	Outdoor, very close scene with faraway objects
Tissue 5	1053	13	Outdoor, very close scene with faraway objects
Book Black 2	1082	13	Outdoor, very close scene with faraway objects
Book Black 3	813	11	Outdoor, very close scene with faraway objects
Book White 3	961	9	Outdoor, very close scene with faraway objects
Fan 3	1175	15	Outdoor, very close scene with faraway objects
Fan 4	699	13	Outdoor, very close scene with faraway objects
GPU Box 2	1028	11	Outdoor, very close scene with faraway objects
Lion Doll 5	507	15	Outdoor, very close scene with faraway objects
Lion Doll 6	871	11	Outdoor, very close scene with faraway objects
Square Doll 3	529	7	Outdoor, very close scene with faraway objects, fast motion with strong blur
Square Doll 4	417	7	Outdoor, very close scene with faraway objects, fast motion with strong blur
Keyboard 3	328	7	Outdoor, very close scene with faraway objects, fast motion with strong blur

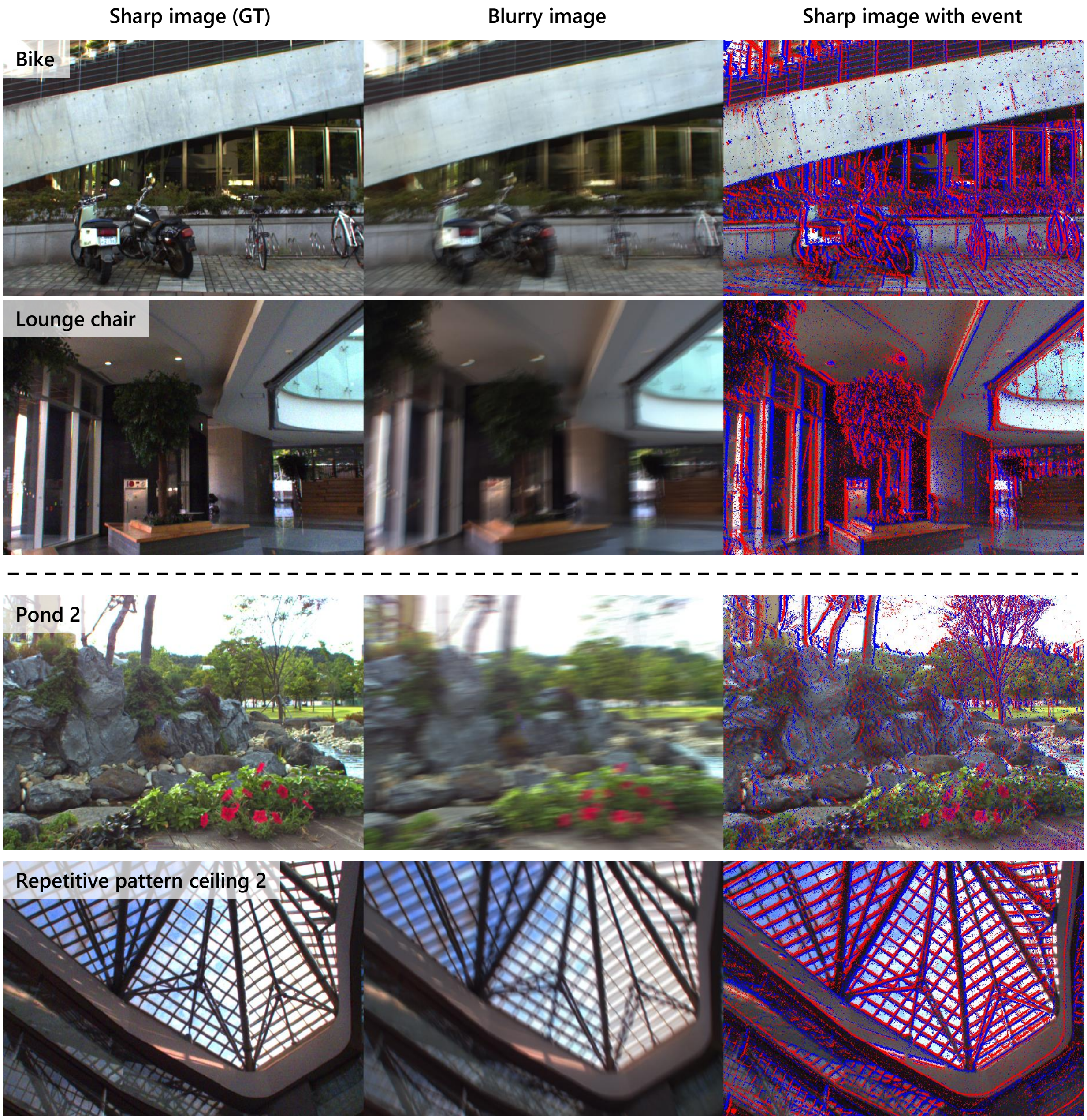

Figure 2: Samples of the proposed NCER-F dataset. **Top:** train, **Bottom:** test sets. Our dataset contains a variety of indoor and outdoor sequences, as well as close and far away scenes. In addition, for general application, the strength of blur varies from sequence to sequence. The third column shows the sharp image and the corresponding events are not spatially aligned.

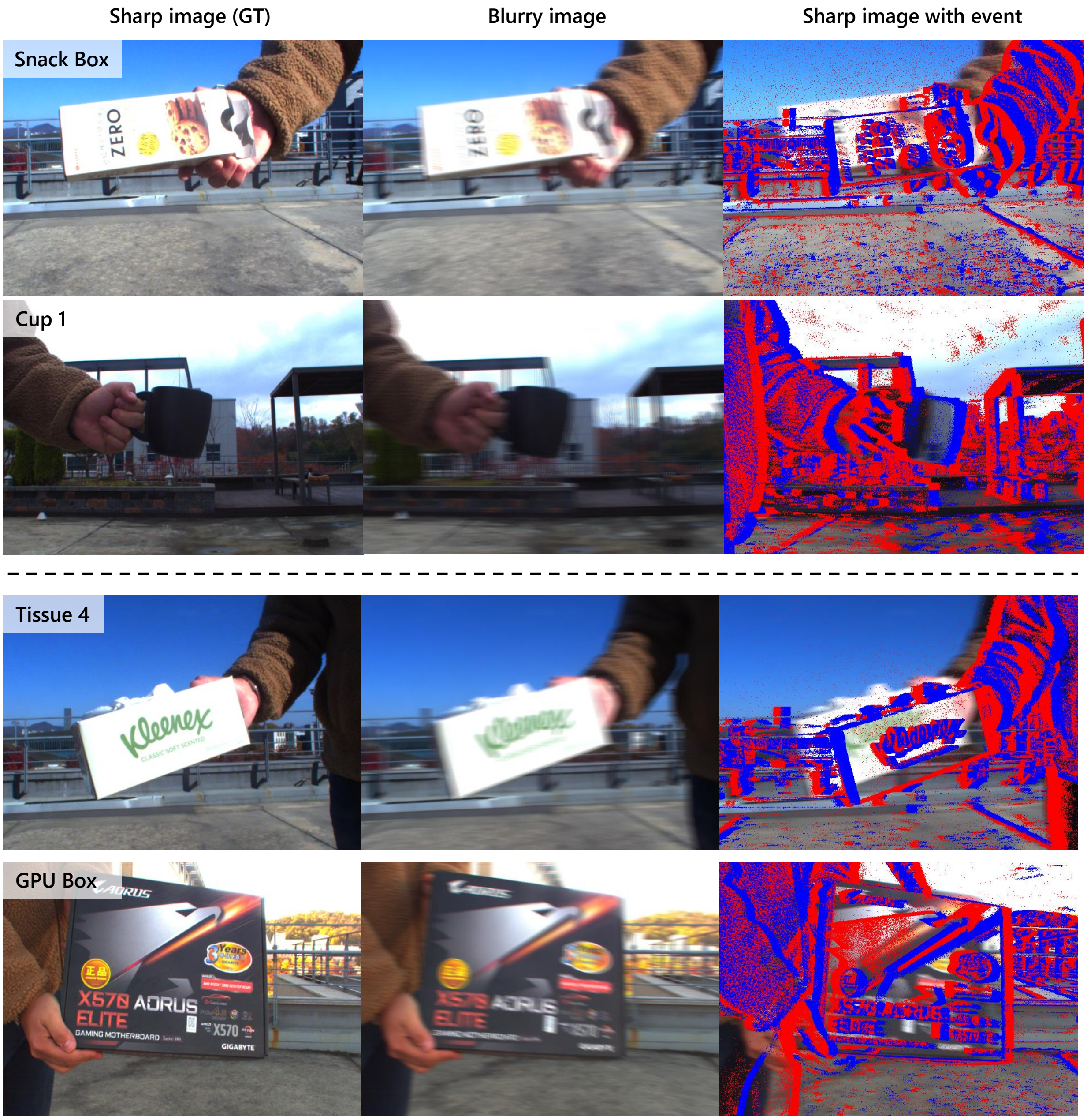

Figure 3: Samples of the proposed NCER-E dataset. **Top:** train, **Bottom:** test sets. It is challenging to precisely align the two modalities using globally explicit alignment because the NCER-E dataset consists of objects that are both close and far away simultaneously.

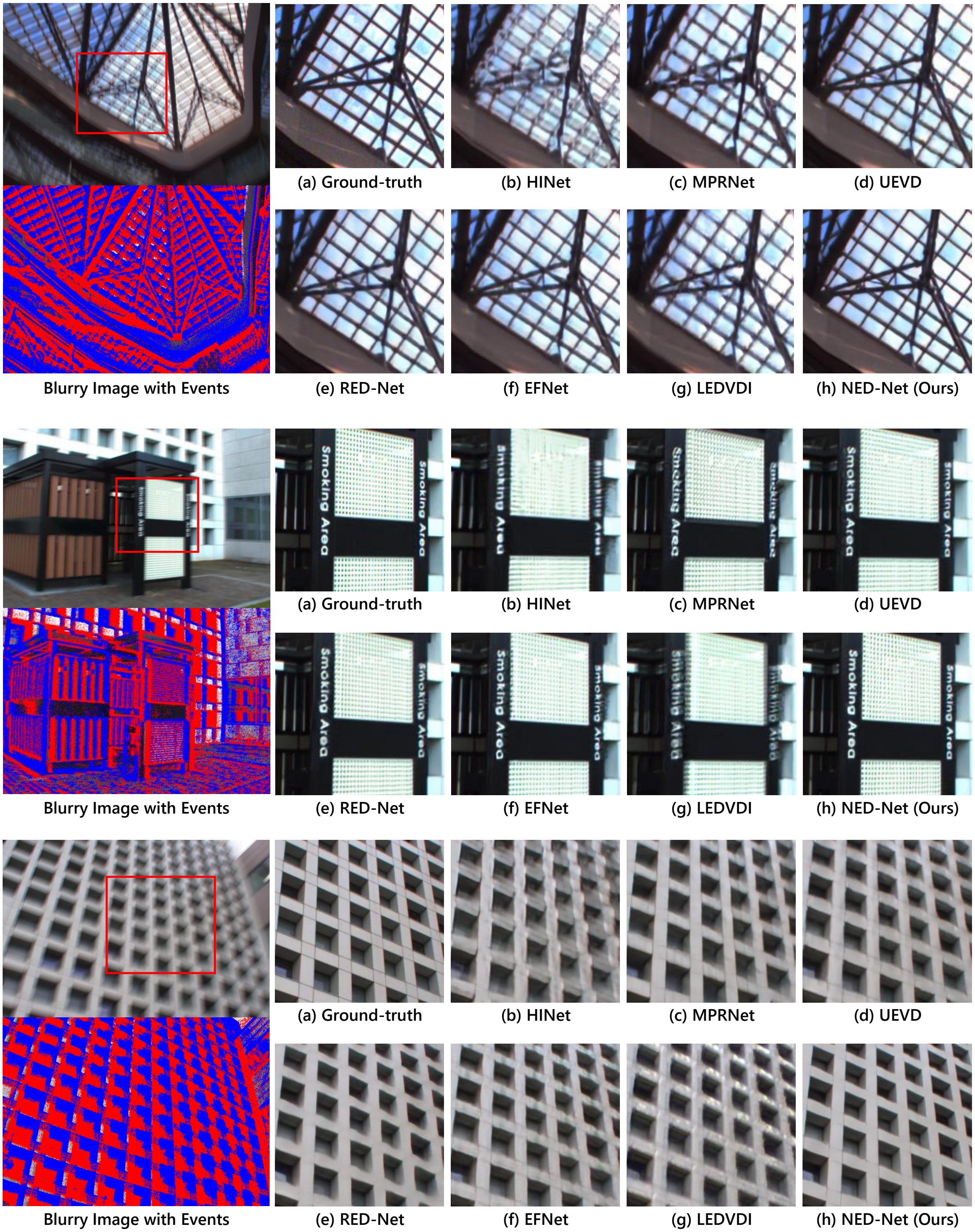

Figure 4: Qualitative comparison for the proposed method with other methods on the NCER-F dataset.

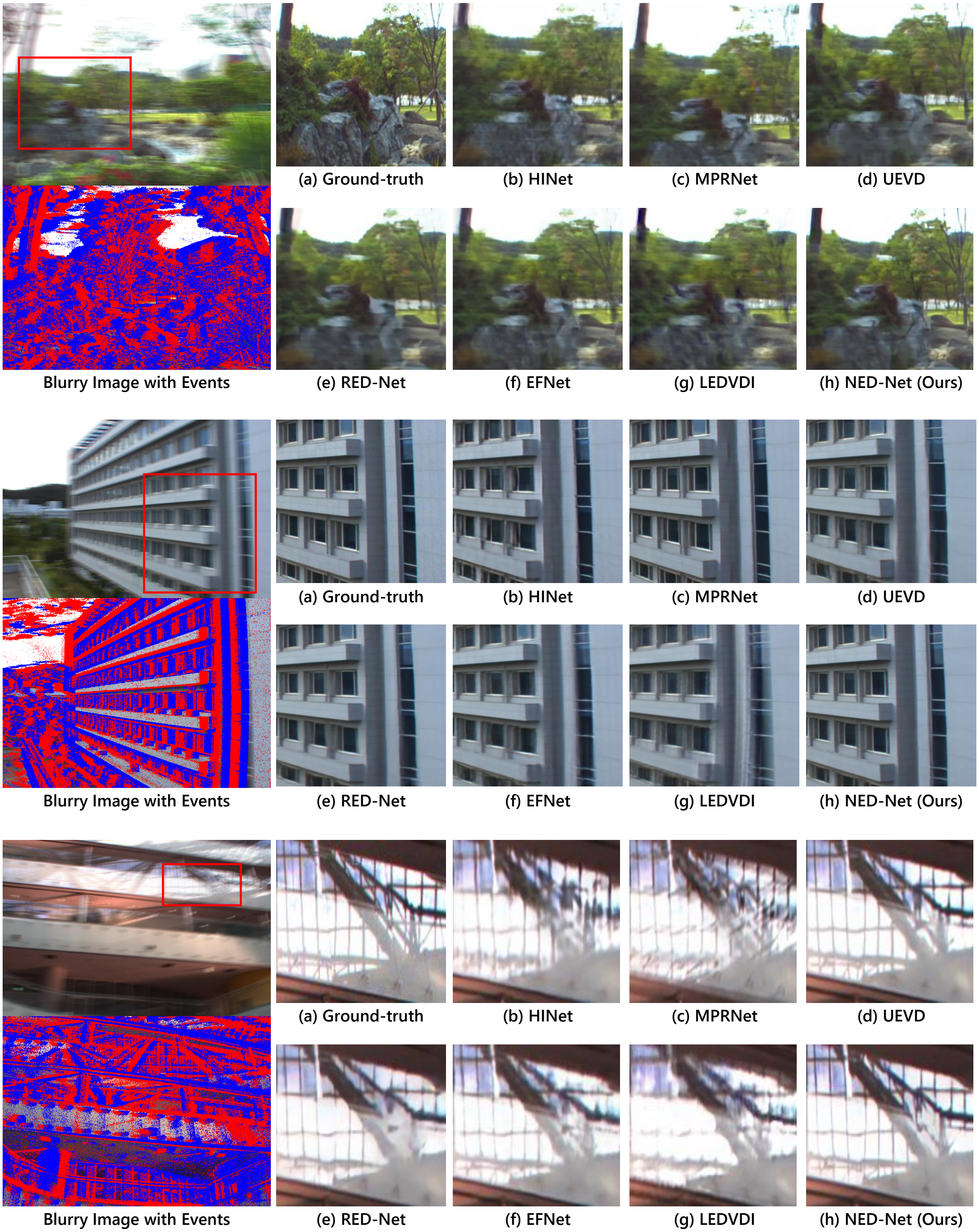

Figure 5: Qualitative comparison for the proposed method with other methods on the NCER-F dataset.

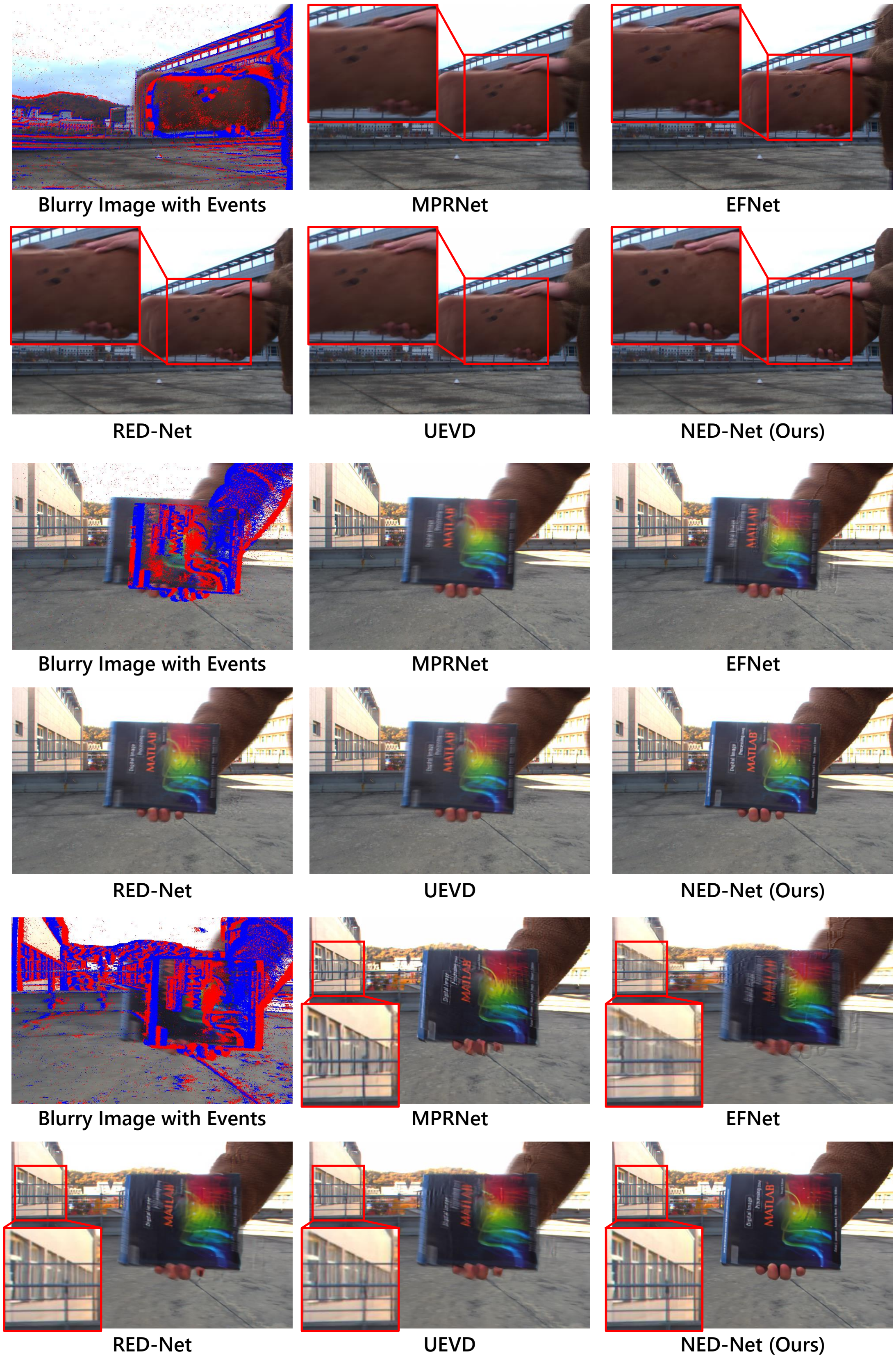

Figure 6: Qualitative comparison on the NCER-E dataset without fine-tuning. Please zoom for better view.

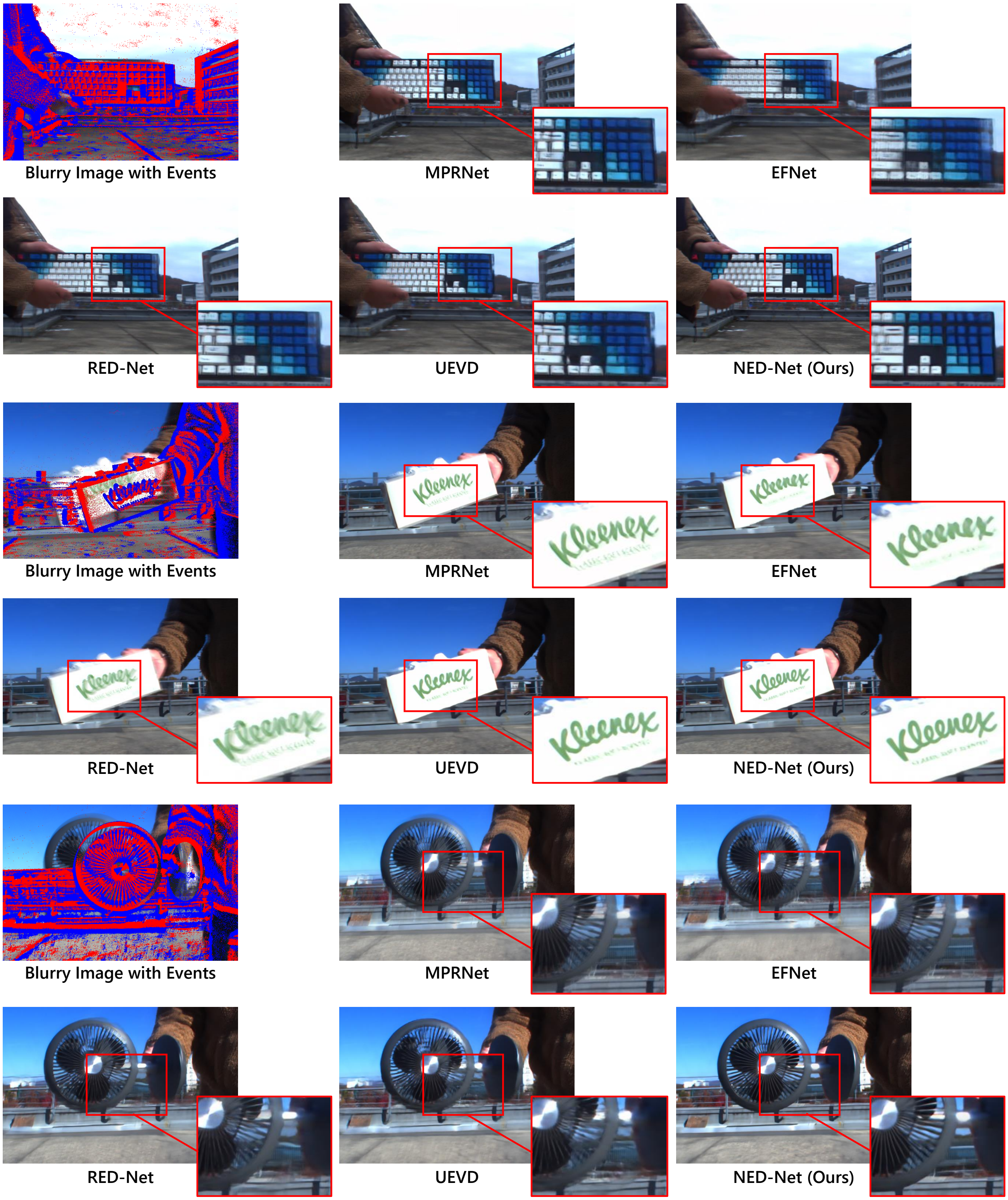

Figure 7: Qualitative comparison on the NCER-E dataset with fine-tuning. Please zoom for better view.

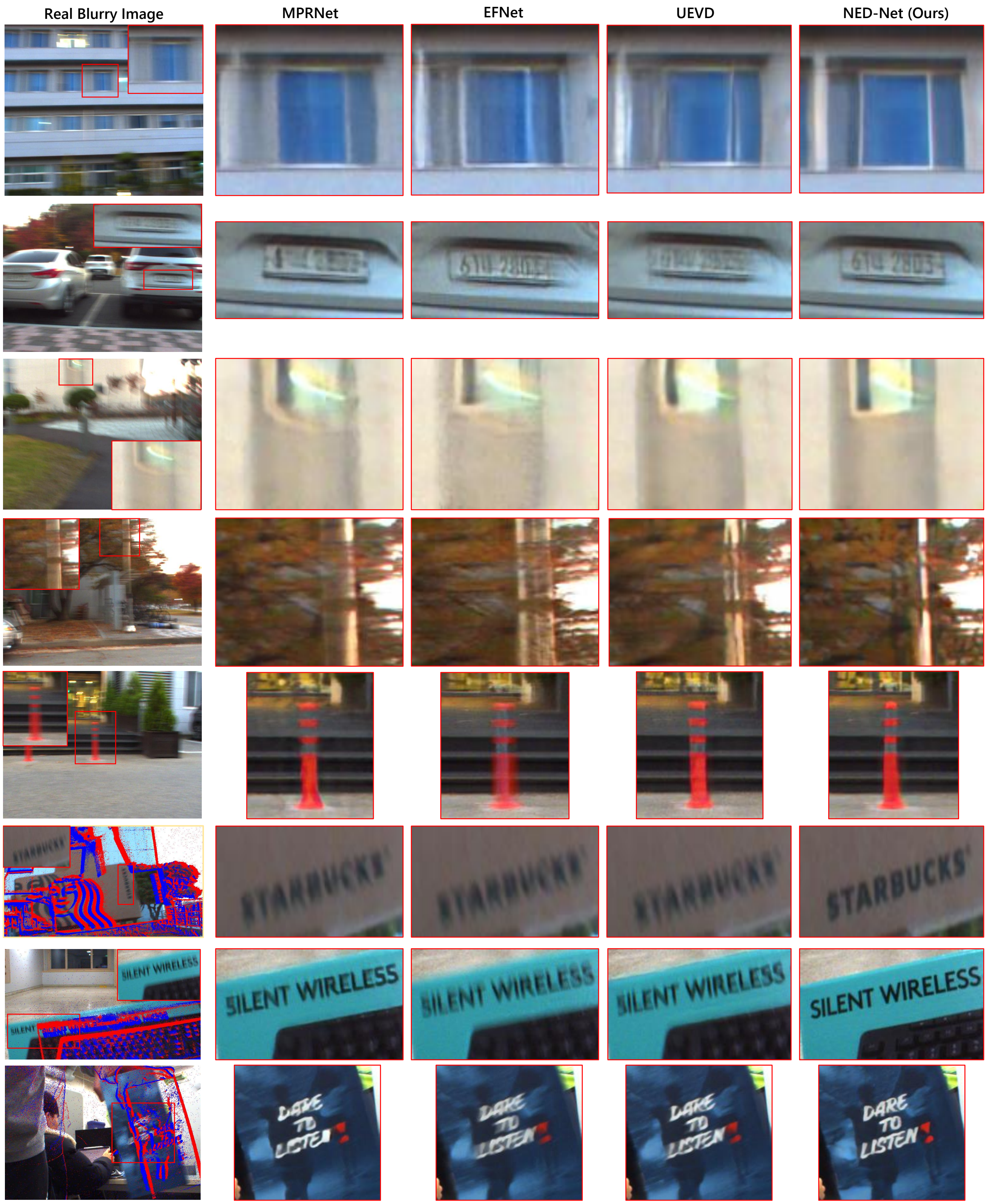

Figure 8: Qualitative comparison on the real blurry samples.