Motion Deblurring with Real Events

Fang Xu[1], Lei Yu[1]*, Bishan Wang[1], Wen Yang[1]*, Gui-Song Xia[2], Xu Jia[3]*, Zhendong Qiao[4], Jianzhuang Liu[4]
[1]School of Electronic Information, Wuhan University
[2]School of Computer Science, Wuhan University
[3]School of Artificial Intelligence, Dalian University of Technology
[4]Noah's Ark Lab, Huawei Technologies
{xufang, ly.wd, bswang, yangwen, guisong.xia}@whu.edu.cn, xjia@dlut.edu.cn, {qiaozhendong, liu.jianzhuang}@huawei.com

1. Dataset Details

GoPro (synthesized events and blurry images), HQF (real-world events and synthesized blurry images) and RBE (real-world events and real-world motion blurs) are provided for training and evaluating. The details of the datasets are shown in Table 3, where the number of diverse scene sequences *#seq.*, image size *size*, number of blurry images *#blurry* and average number of events within the exposure time of the corresponding blurry image *#AVG* are presented. Note that images from the GoPro dataset are down-sampled to a small size to match the real event cameras. And implicitly, *#AVG* in some extent reflects the degree of blur, where larger ratio of $\frac{\#AVG}{size}$ indicates more blurs and vice versa. This ratio ranges roughly from 1.5 to 3 over the whole datasets.

Table 3. The details of GoPro, HQF, and RBE datasets, where RBE (test) is only used for qualitative analysis.

Dataset	*#seq.*	*size*	*#blurry*	*#AVG*
GoPro (train)	240	180×320	3120	174562
GoPro (test)	30	180×320	390	166236
HQF (train)	9	180×240	1303	68902
HQF (test)	5	180×240	250	74984
RBE (train)	7	260×346	2330	159760
RBE (test)	8	260×346	800	189585

2. More Implementation Details

In this section, we will give more implementation details about the two basic sub-networks, *i.e.*, OF-Net and Deblur-Net, of the proposed RED-Net as shown in Fig. 2. We exploit Residual Dense Network [2] for the Deblur-Net targeting at reconstructing a sequence of sharp clear intensity frames from a blurry image. The Deblur-Net receives both the blurry image $\mathbf{B}$ and the corresponding event stream $\mathbf{E}_T$, and outputs M consecutive intensity frames. Correspondingly, the OF-Net is composed of $M-1$ EvFlowNets [7] with shared parameters. By dividing event stream $\mathbf{E}_T$ into $M-1$ subsets with equal time intervals and feeding them respectively into the $M-1$ EvFlowNets, the OF-Net can output $M-1$ optical flows as the prediction of the inter-frame motions.

Specifically, events are stream-like data which cannot be directly fed into the aforementioned networks. Thus the *event-to-frame* transform procedure is required. In this paper, we adopt a similar approach introduced in [7], where the event stream is transformed into a 4-channel *event image*. The first two channels encode the numbers of events of positive/negative polarity occurring at each pixel, and the last two channels encode the timestamps of latest triggered events of positive/negative polarity occurring at each pixel. For the Deblur-Net, we take the concatenation of blurry image and the $M-1$ *event images* as input. For the OF-Net, it only receives each *event image* as input and outputs optical flow between the consecutive reconstructed frames.

3. Sequence Prediction of Optical Flow

As mentioned above, optical flow for the events during the very short time interval is predicted. Fig. 5 presents the optical flow outputs of RED-RBE and corresponding deblurring results of a real-world motion blurred image. The varying color and its intensity show that the motion of the fast moving magic cube is obviously nonlinear during the exposure time, where a linear motion model will suffer the issue of inaccurate trajectory estimation.

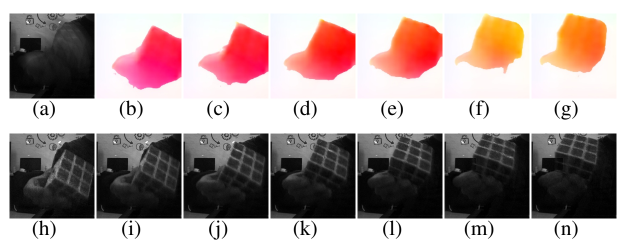

Figure 5. Optical flow output of OF-Net: (a) a motion blurred image, (b)-(g) the optical flow within the exposure time of the motion blurred image, and (h)-(n) the recovered sequence of sharp images.

4. Qualitative Ablation Study

In our manuscript, we have carried out an ablation study to discuss the importance of synthesized events (SynEv), blurring with LM (LM), blurring with PLM (PLM) and real-world events (ReEv). Quantitative results over the HQF dataset have been presented in Tab. 2. It is shown that both

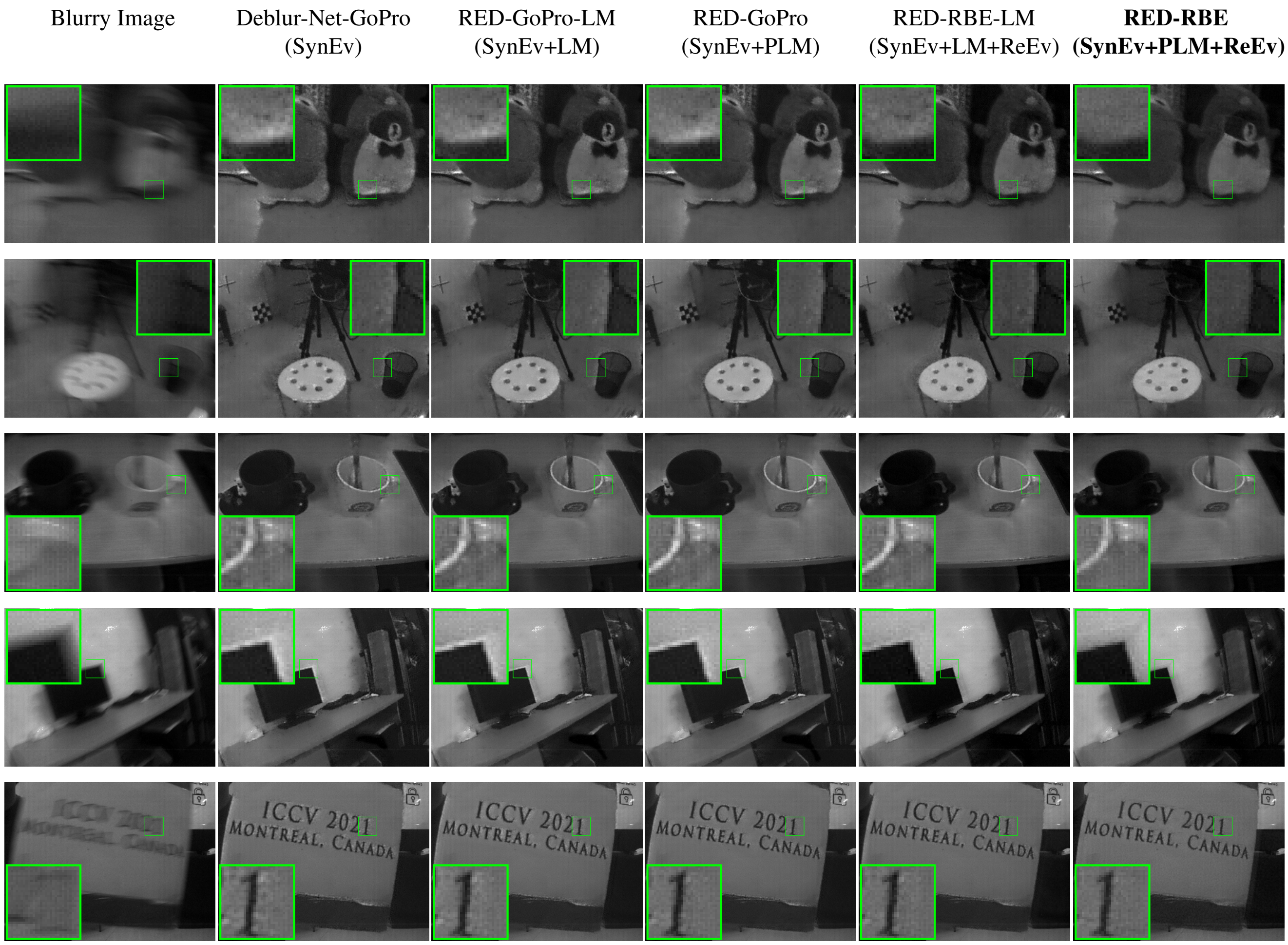

Figure 6. Qualitative ablation study with 5 blurry scenes by different RED-Nets. For each scene, from left to right are respectively the blurry image and its deblurred results by Deblur-Net-GoPro (SynEv), RED-GoPro-LM (SynEv+LM), RED-GoPro (SynEv+PLM), RED-RBE-LM (SynEv+LM+ReEv) and RED-RBE (SynEv+PLM+ReEv). And the results are corresponding to the Tab. 2 in our manuscript.

PLM and ReEv play important roles for event-based motion deblurring over the real-world scenarios. In this section, we implement a qualitative ablation study to further validate this point, as shown in Fig. 6

5. More Qualitative Results

We present additional qualitative experimental results in Fig. 7 comparing to the state-of-the-art deblurring methods including blur2mflow [1] and LEVS [3], and event-based motion deblurring methods including EDI [5], eSL-Net [6] and LEDVDI [4]. As seen from the results, our proposed RED-RBF training with real-world events and real-world motion blurs achieves the best visualization performance by avoiding the *halo artifacts*.

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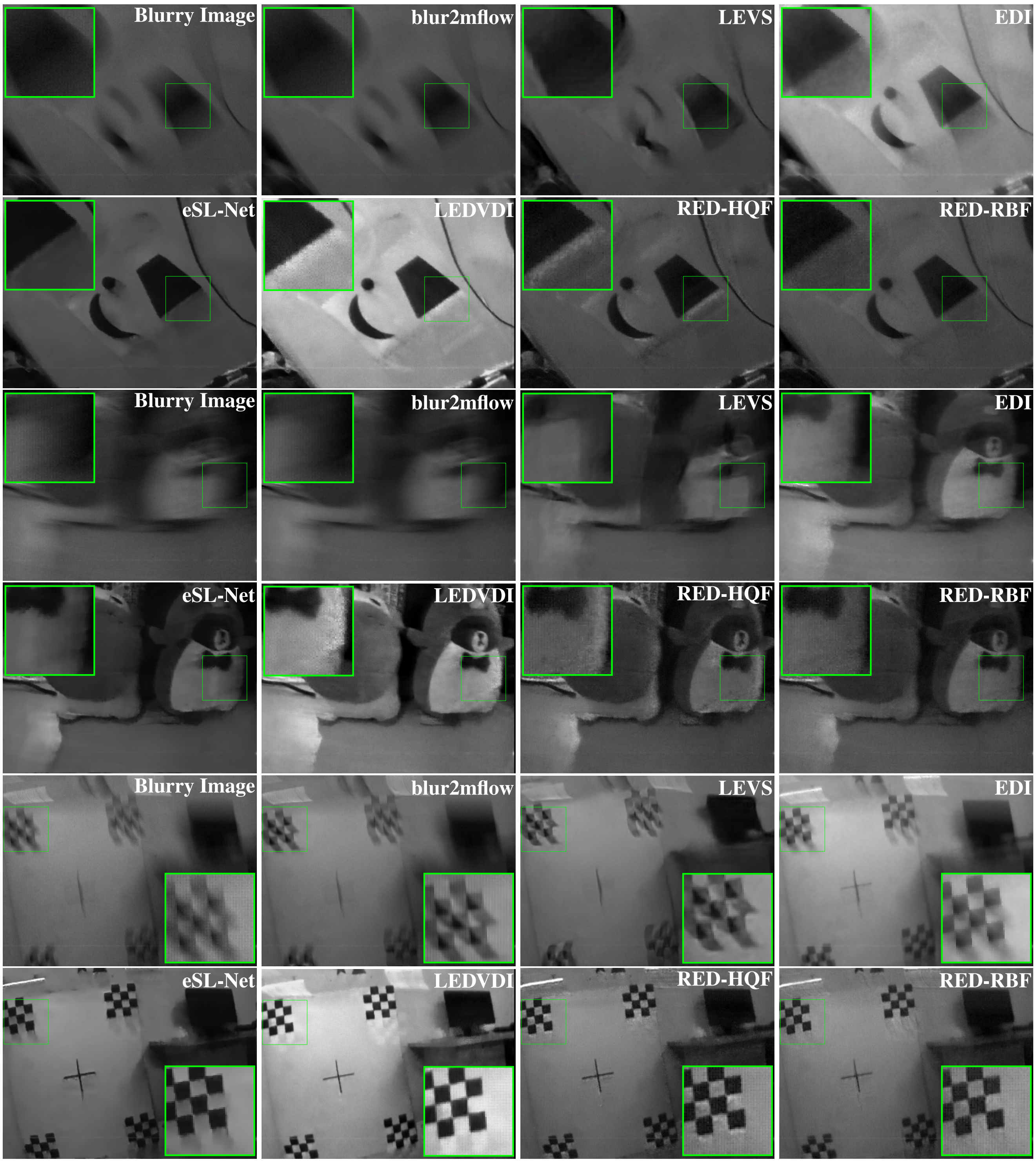

Figure 7. Qualitative results of motion deblur for 3 blurry scenes by 7 different methods. For each scene, from top-left to bottom-right are respectively the blurry image and its deblurred results by blur2mflow [1], LEVS [3], EDI [5], eSL-Net [6], LEDVDI [4] and our proposed RED-HQF and RED-RBE.