Single Image Reflection Removal with Edge Guidance, Reflection Classifier, and Recurrent Decomposition
Supplementary Materials

Ya-Chu Chang* Chia-Ni Lu* Chia-Chi Cheng Wei-Chen Chiu
National Chiao Tung University, Taiwan

1. Training Details

Our implementation is based on Pytorch with Nvidia Geforce GTX 2080 Ti GPU. The proposed networks are trained with Adam optimizer [2], with the learning rate of edge extractor E and reflection classifier C set to 10^{-5} and 5×10^{-6} respectively. The learning rate of our full model is set to 10^{-3}.

2. Computation Time and Memory Usage

In this section, we demonstrate the computation time and memory usage under two real-world benchmark datasets, in comparison with several baselines. Since some baselines take up a lot of memory, we adjust the size of the input image to 256×256 in order to run the process on only one GPU. As shown in Table 1 and Table 2, we can see that our proposed method is 3.3 times faster than the state-of-the-art IBCLN [3] with comparable memory usage.

3. More Qualitative Results

Here we provide more examples of our qualitative results as well as the comparison with respect to other baselines in Figure 1, 2, and 3.

4. Edge Estimator Results

Here we provide some results of the edge estimator in Figure 4. The edge estimator can distinguish the edges of transmission layer correctly, which helps our full model to emphasize the contour of the transmission layer and generate more exquisite results.

References

[1] Qingnan Fan, Jiaolong Yang, Gang Hua, Baoquan Chen, and David Wipf. A generic deep architecture for single image reflection removal and image smoothing. In *IEEE International Conference on Computer Vision (ICCV)*, 2017.

[2] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *International Conference on Learning Representations (ICLR)*, 2015.

[3] Chao Li, Yixiao Yang, Kun He, Stephen Lin, and John E Hopcroft. Single image reflection removal through cascaded refinement. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3565–3574, 2020.

[4] Renjie Wan, Boxin Shi, Ling-Yu Duan, Ah-Hwee Tan, and Alex C Kot. Benchmarking single-image reflection removal algorithms. In *IEEE International Conference on Computer Vision (ICCV)*, 2017.

[5] Kaixuan Wei, Jiaolong Yang, Ying Fu, Wipf David, and Hua Huang. Single image reflection removal exploiting misaligned training data and network enhancements. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.

[6] Qiang Wen, Yinjie Tan, Jing Qin, Wenxi Liu, Guoqiang Han, and Shengfeng He. Single image reflection removal beyond linearity. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.

[7] Jie Yang, Dong Gong, Lingqiao Liu, and Qinfeng Shi. Seeing deeply and bidirectionally: A deep learning approach for single image reflection removal. In *European Conference on Computer Vision (ECCV)*, 2018.

[8] Xuaner Zhang, Ren Ng, and Qifeng Chen. Single image reflection separation with perceptual losses. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.

*Both authors contributed equally to the paper

Method	SIR^2 [4]			Zhang [8]	Average
	Postcard	Solid Objects	Wild Scenes		
Zhang *et al*. [8]	55.313	54.867	118.263	248.564	70.616
BDN [7]	16.397	13.692	21.016	42.949	16.913
Wen *et al*. [6]	16.641	16.635	26.758	44.030	18.973
ERRNet [5]	312.252	303.473	351.476	476.289	320.037
IBCLN [3]	81.363	82.493	96.496	130.052	85.659
Ours	28.121	21.929	26.938	43.256	26.005

Table 1: Computation time with respect to two real-world benchmark datasets (Unit: ms per image).

Method	SIR^2 [4]						Zhang [8]	
	Postcard		Solid Objects		Wild Scenes			
	CPU	GPU	CPU	GPU	CPU	GPU	CPU	GPU
Zhang *et al*. [8]	7,073	10,873	7,111	10,873	7,071	10,873	7,065	10,873
BDN [7]	2,447	1,363	2,447	1,363	2,447	1,363	2,448	1,365
Wen *et al*. [6]	2,678	1,137	2,675	1,137	2,677	1,137	2,683	1,363
ERRNet [5]	2,606	9,323	2,604	9,485	2,609	9,359	2,608	9,485
IBCLN [3]	2,615	1,173	2,586	1,173	2,580	1,173	2,574	1,173
Ours	2,500	1,573	2,499	1,573	2,498	1,573	2,526	1,573

Table 2: Memory usage on CPU and GPU under two real-world benchmark datasets (Unit: MiB).

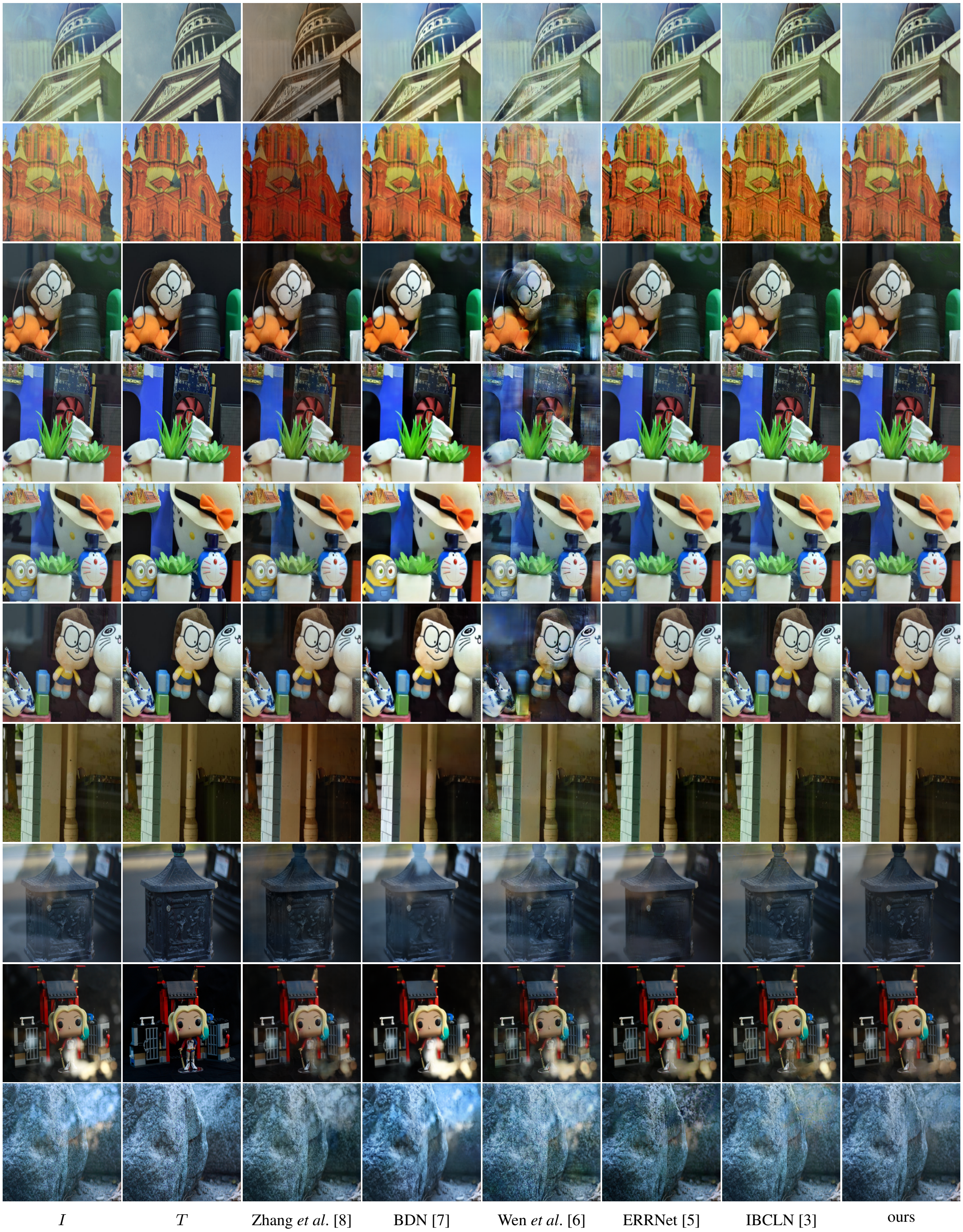
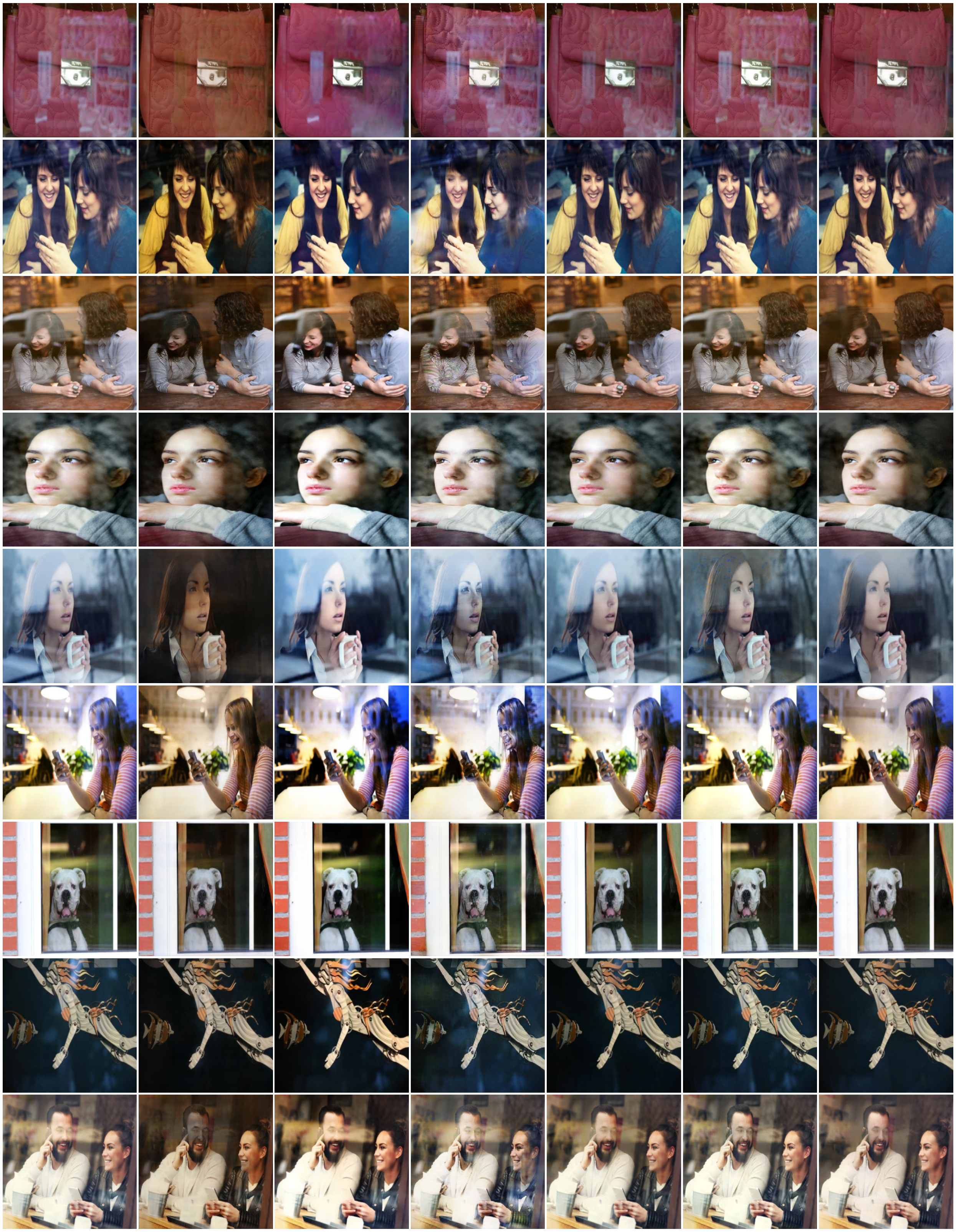


Figure 1: Qualitative examples on real-world images from SIR^2 [4] (rows 1-7) and Zhang *et al*. [8] (row 8-10).

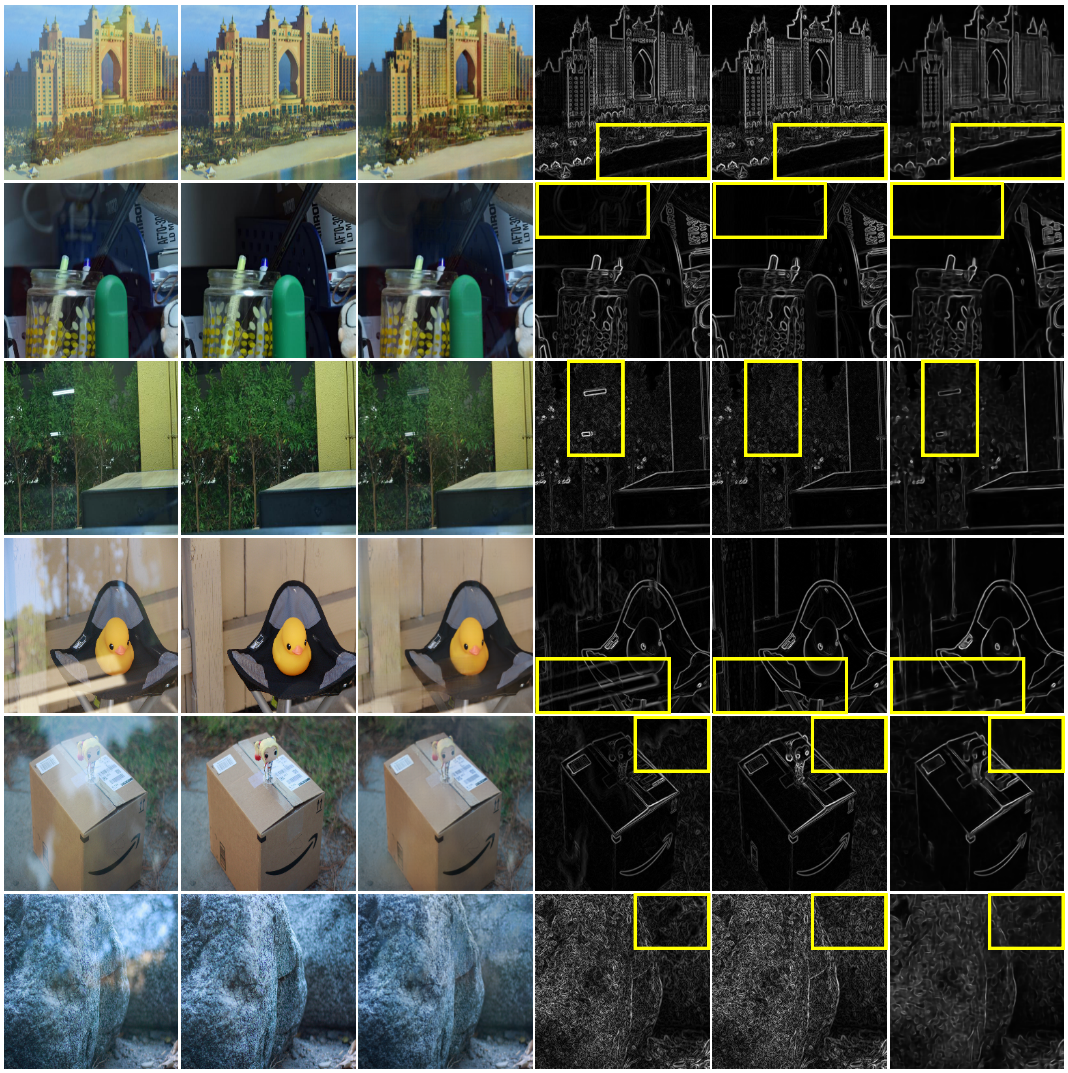
I | Zhang *et al.* [8] | BDN [7] | Wen *et al.* [6] | ERRNet [5] | IBCLN [3] | ours

Figure 2: Qualitative examples on real-world images from SIR^2 [4] Wild Scene sub-dataset (rows 1-7) and our own real-world images (row 8-9).



I | Zhang *et al*. [8] | BDN [7] | Wen *et al*. [6] | ERRNet [5] | IBCLN [3] | ours

Figure 3: Qualitative examples on real-world images from CEILNet [1].



I T ours I_{edge} T_{edge} $\tilde{T}_{edge}$

Figure 4: Edge estimator results on real-world images from SIR^2 [4] (rows 1-3) and Zhang *et al*. [8] (rows 4-6).