Supplementary Materials of Perceptual Variousness Motion Deblurring with Light Global Context Refinement

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Abstract

Deep learning algorithms have made significant progress in dynamic scene deblurring. However, several challenges are still unsettled: 1) The degree and scale of blur in different regions of a blurred image can have a considerable variation in a large range. However, the traditional input pyramid or downscaling-upscaling, is designed to have limited and inflexible perceptual variousness to cope with large blur scale variation. 2) The nonlocal block is proved to be effective in the image enhancement tasks, but it requires high computation and memory cost. In this paper, we are the first to propose a light-weight globally-analyzing module into the image deblurring field, named Light Global Context Refinement (LGCR) module. With exponentially lower cost, it achieves even better performance than the nonlocal unit. Moreover, we propose the Perceptual Variousness Block (PVB) and PVB-piling strategy. By placing PVB repeatedly, the whole method possesses abundant reception field spectrum to be aware of the blur with various degrees and scales. Comprehensive experimental results from the different benchmarks and assessment metrics show that our method achieves excellent performance to set a new state-of-the-art in motion deblurring.

Due to the limitation of the paper's length, many visualization results are not fully demonstrated. Therefore, in this supplemental document, we present more results of the following experiments:

1. Quantitative Evaluation on the benchmarks (Sec. 1);
2. Ablation Study (Sec. 2);

1. Quantitative Evaluation on the benchmarks

Please refer to Figure 2.

2. Ablation Study

Please refer to Figure 1.

References

[1] Hongyun Gao, Xin Tao, Xiaoyong Shen, and Jiaya Jia. Dynamic scene deblurring with parameter selective sharing and nested skip connections. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3848–3856, 2019.

[2] Orest Kupyn, Tetiana Martyniuk, Junru Wu, and Zhangyang Wang. Deblurgan-v2: Deblurring (orders-of-magnitude) faster and better. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 8878–8887, 2019.

[3] Xin Tao, Hongyun Gao, Xiaoyong Shen, Jue Wang, and Jiaya Jia. Scale-recurrent network for deep image deblurring. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 8174–8182, 2018.

[4] Hongguang Zhang, Yuchao Dai, Hongdong Li, and Piotr Koniusz. Deep stacked hierarchical multi-patch network for image deblurring. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5978–5986, 2019.

Figure 1: Visualization of ablation study. The "Bs2" is short for "Baseline 2".

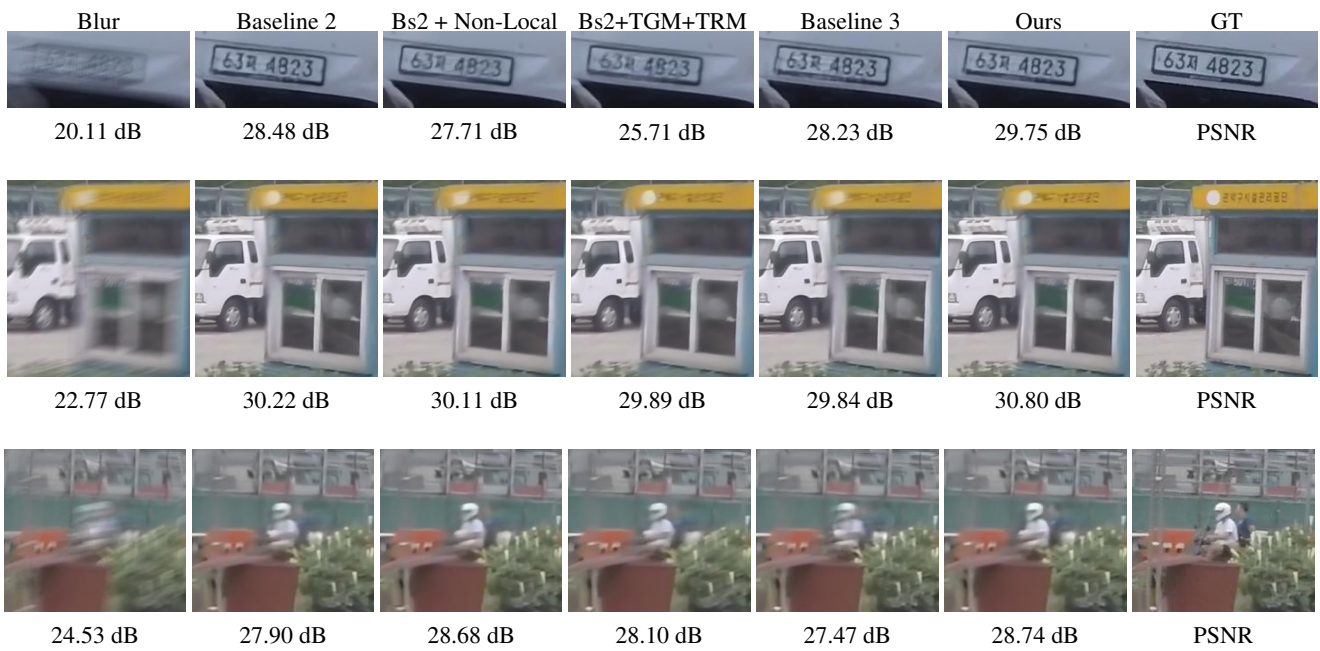| Blur	Baseline 2	Bs2 + Non-Local	Bs2+TGM+TRM	Baseline 3	Ours	GT
20.11 dB	28.48 dB	27.71 dB	25.71 dB	28.23 dB	29.75 dB	PSNR
22.77 dB	30.22 dB	30.11 dB	29.89 dB	29.84 dB	30.80 dB	PSNR
24.53 dB	27.90 dB	28.68 dB	28.10 dB	27.47 dB	28.74 dB	PSNR

Figure 2: Visual results. The first 3 rows are results from GoPro, the next two rows are from RealBlur-J, the last two rows are from RWBI. Please zoom in for detail.

Tao *et al.* [3]	Gao *et al.* [1]	Zhang *et al.* [4]	Kupyn *et al.* [2]	Ours	GT (Input for RWBI)
29.36 dB/0.9297	29.97 dB/0.9328	29.64 dB/0.9326	28.68 dB/0.9125	**30.77 dB/ 0.9404**	PSNR/SSIM ↑
24.45 dB/0.8182	25.70 dB/0.8567	25.33 dB/0.8520	22.96 dB/0.7692	**26.82 dB/0.8855**	PSNR/SSIM ↑
24.63 dB/0.7974	25.17 dB/0.8232	23.81 dB/0.7723	25.13 dB/0.8086	**26.84 dB/0.8685**	PSNR/SSIM ↑
22.95 dB/0.8319	22.85 dB/0.8280	21.15 dB/ 0.8016	22.75 dB/0.8280	**23.98 dB/0.8600**	PSNR/SSIM ↑
-6.268479	-6.310171	-6.683047	-6.449615	**-5.975607**	Deblur-IQA score ↑
-6.932014	-6.676577	-7.308846	-6.674401	**-5.763113**	Deblur-IQA score↑