MULTI-CONTEXT AND ENHANCED RECONSTRUCTION NETWORK FOR SINGLE IMAGE SUPER RESOLUTION

— Supplementary Material —

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1. OVERVIEW

In this supplemental material, we first provide additional two sets of experiments to prove the effectiveness of our proposed MCB and MCIBs, *i.e.*, using MCB for other low-level computer vision task and analyzing effectiveness with different numbers of MCIBs. Then, more visual comparisons to the current state-of-the-art light-weighted methods with $< 6M$ parameters are provided in Figure 3-11. Note that all the testing images are from Set5 [1], Set14 [2], BSDS100 [3], and Urban100 [4]. As we can observe, all the visualization results are consistent with our claims in the main paper.

2. ADDITIONAL EXPERIMENTS

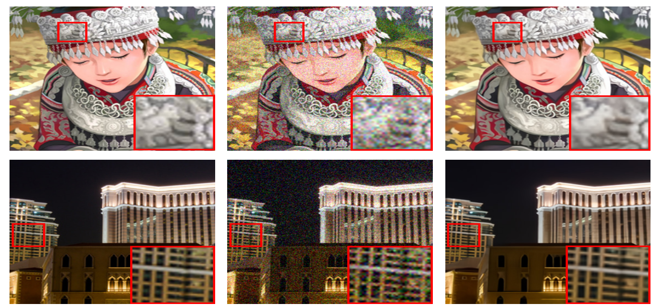
2.1. Effectiveness of MCB on Other Vision Task

In order to further verify the validity of our proposed MCB structure, we use our network at stage 1 to other low-level computer vision tasks. We provide the results of image denoising in Figure 1. Apparently, our proposed MCERN produces a good result on image denoising because our MCB structure is able to extract abundant hierarchical and contextual features for image reconstruction. More qualitative results of color image denoising are shown in Figure 2.

The above experiment further demonstrates that our proposed MCB is an effective structure which can distill features with different contextual characteristics by two branches and extract features in different receptive fields by two cascaded convolution layers of each branch. And multiple MCBs are combined into an MCIB that is able to integrate contextual features of different adaptively from MCBs.

2.2. Effectiveness with Different Number of MCIBs

We set different numbers of MCIBs in our proposed MCERN and evaluate the performances on three datasets. As shown in Table 1, the values of both PSNR and SSIM for our network get better as the number of MCIBs increases. Such an observation is consistent with what we expect, since the generalization ability will also increase when the number of parameters of our network will go up when we grow the number of MCIBs. As a trade-off between the performance and the complexity of the network, we determine to use three MCIBs, which provides strong reconstruction ability and requires only a few parameters and Multi-Adds.



(a) Original (b) Noisy (c) MCERN

Fig. 1. Qualitative comparisons of color image denoising. The second column shows the noisy images with noise level 25. MCERN recovers fine local details, which is mainly contributed by the abundant hierarchical and contextual features extracted by our proposed MCB. Best viewed in zoom in.

Table 1. MCIBs number analysis. By varying the number of MCIBs in MCERN, we can produce a slightly different overall network and explore their performance.

number of MCIBs	Set14 [2] PSNR	Set14 [2] SSIM	BSDS100 [3] PSNR	BSDS100 [3] SSIM	Urban100 [4] PSNR	Urban100 [4] SSIM
2	33.68	0.9179	32.23	0.9005	32.34	0.9305
3	33.83	0.9196	32.27	0.9014	32.67	0.9336
4	**33.92**	**0.9214**	**32.35**	**0.9021**	**32.77**	**0.9341**

*This work was co-supervised by Chengjiang Long and Xin Yang. The corresponding author is Xin Yang.

3. ADDITIONAL QUALITATIVE RESULTS

In Figure 3-11(Figure 3, 4 and 5 with scale factor $\times 2$; Figure 6, 7, and 8 with scale factor $\times 3$; and Figure 9, 10 and 11 with scale factor $\times 4$), we provide additional results on different datasets and different upsampling scales to clearly show the effectiveness of our proposed network. The comparisons focus to compare between seven current state-of-the-art lightweight networks which are SRCNN [5], VDSR [6], LapSRN [7], CARN [8], SRMDNF [9], NLRN [10], and MSRN [11]. The complete results on all datasets will be published in our website.

4. REFERENCES

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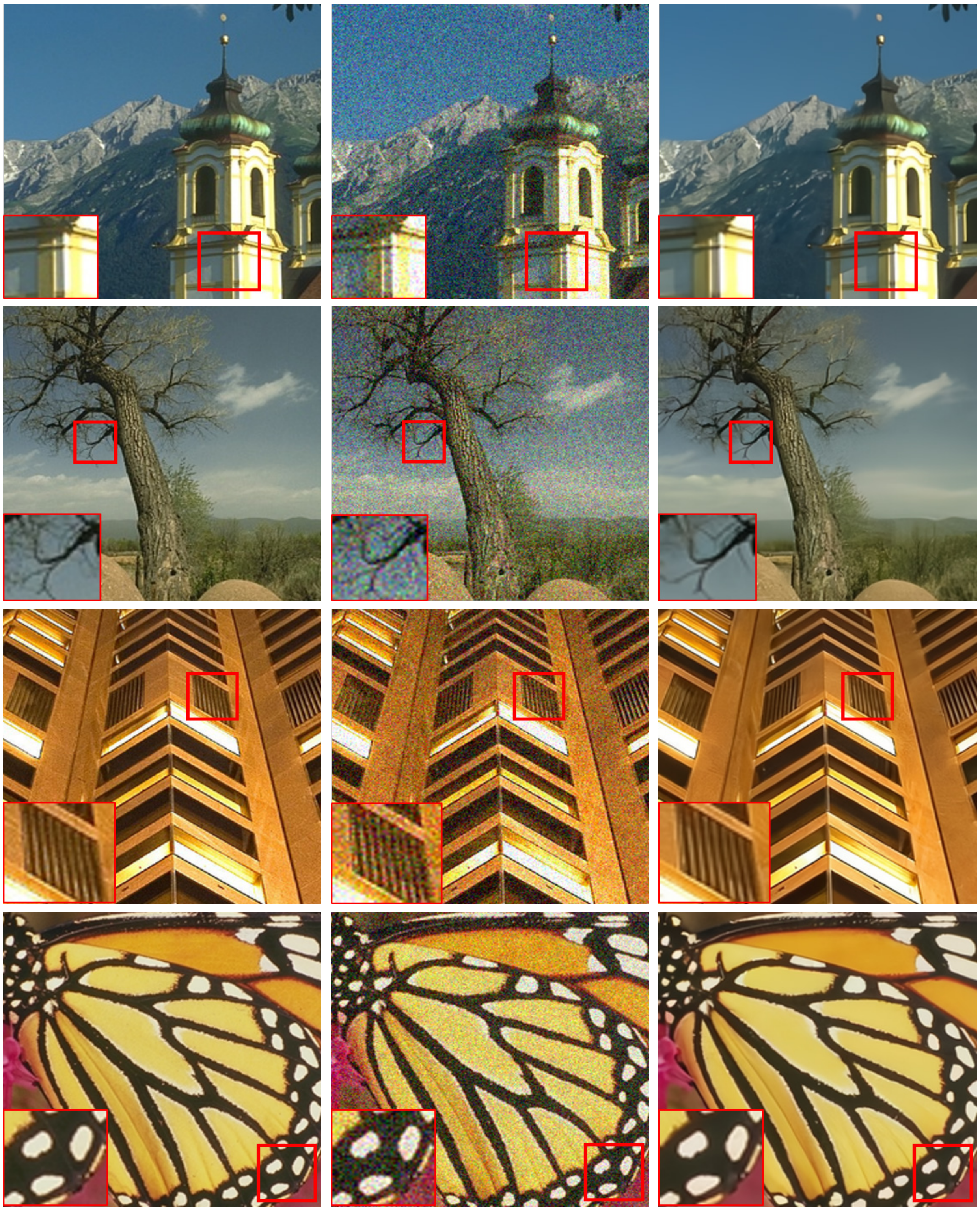

(a) Original (b) Noisy (c) MCERN

Fig. 2. Qualitative comparisons of color image denoising. The second column shows the noisy images with noise level 25. MCERN recovers fine local details, which is mainly contributed by the abundant hierarchical and contextual features extracted by our proposed MCB.

Fig. 3. Visual comparison between different algorithms on *ppt3* from Set14 [2] with scale factor $\times 2$.

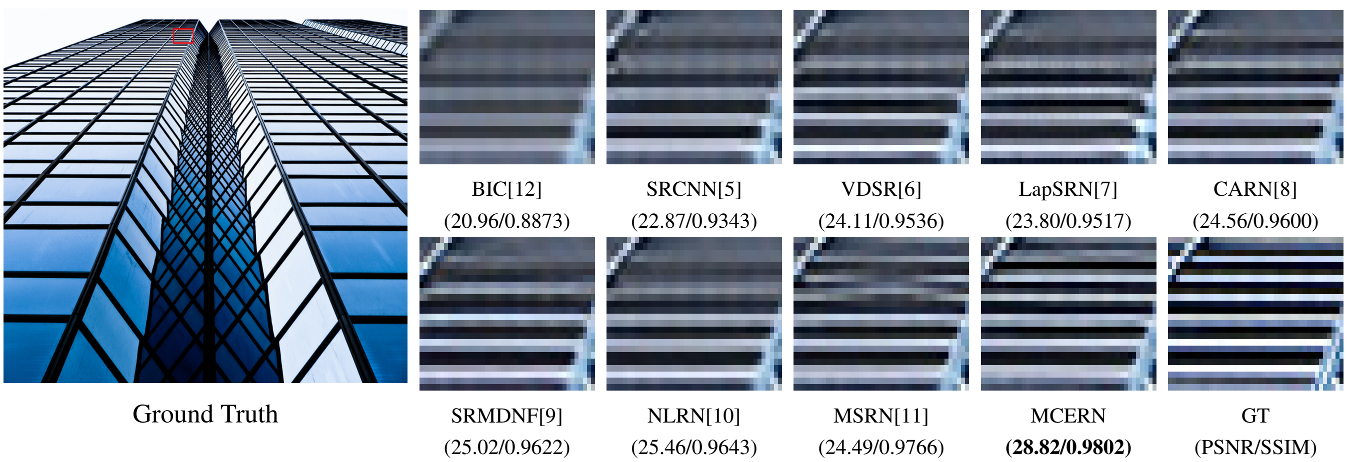

Fig. 4. Visual comparison between different algorithms on *img067* from Urban100 [4] with scale factor $\times 2$.

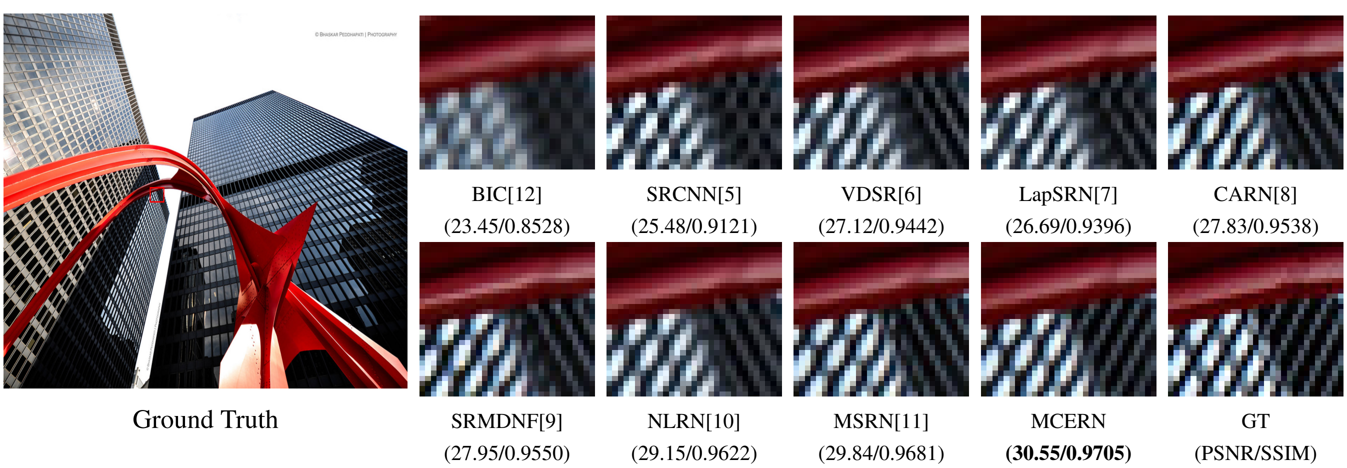

Fig. 5. Visual comparison between different algorithms on *img062* from Urban100 [4] with scale factor $\times 2$.

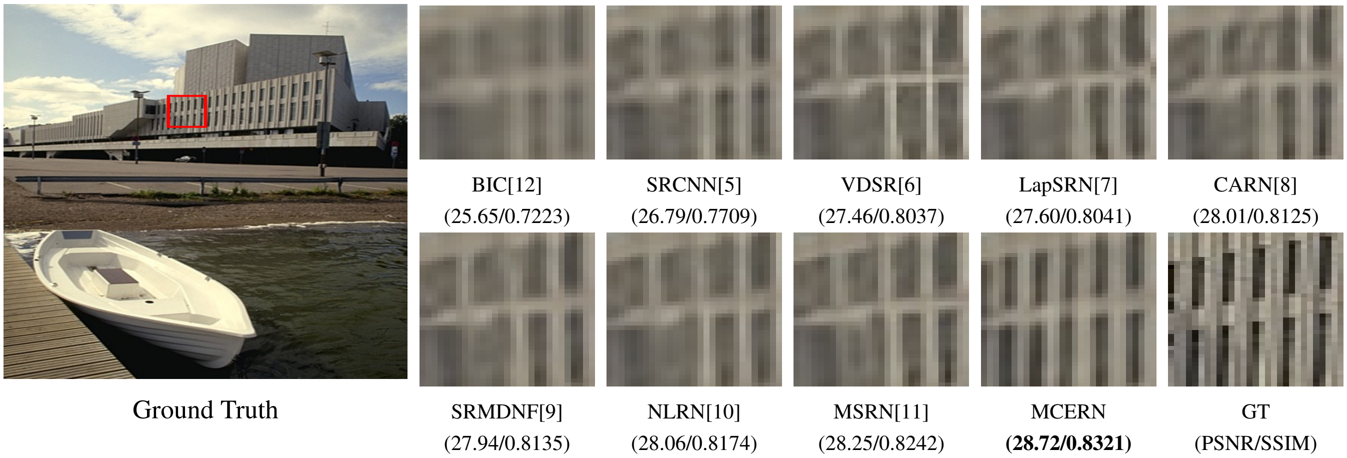

Fig. 6. Visual comparison between different algorithms on *78004* from BSDS100 [3] with scale factor $\times 3$.

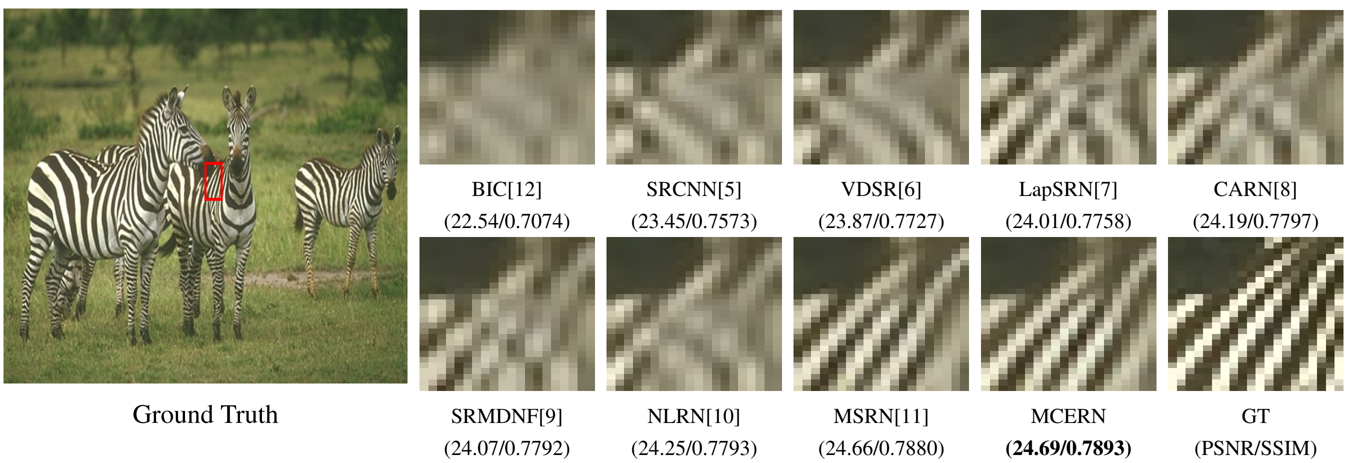

Fig. 7. Visual comparison between different algorithms on *253027* from BSDS100 [3] with scale factor $\times 3$.

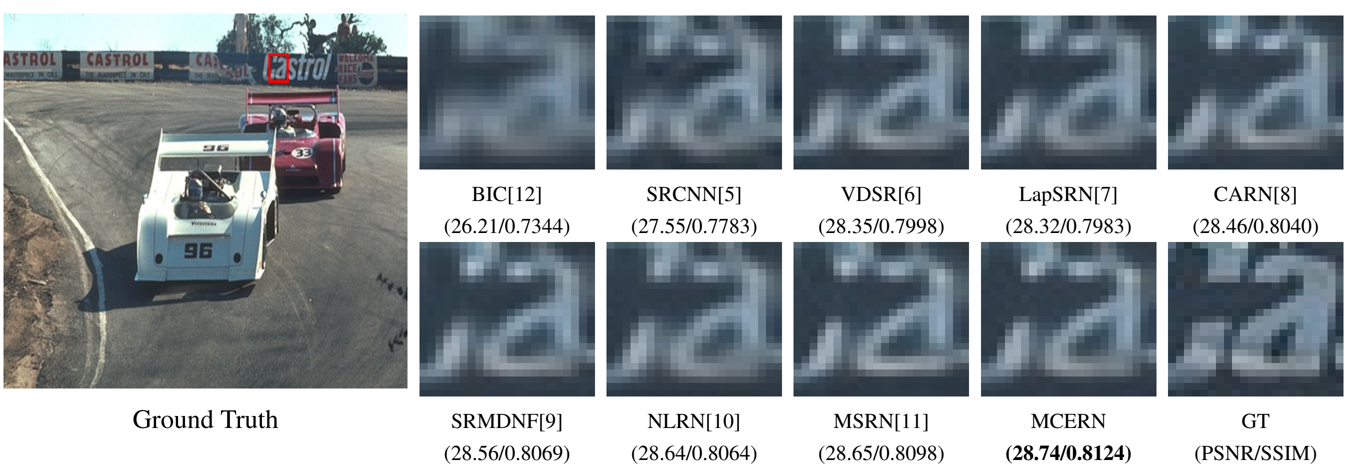

Fig. 8. Visual comparison between different algorithms on *21077* from BSDS100 [3] with scale factor $\times 3$.

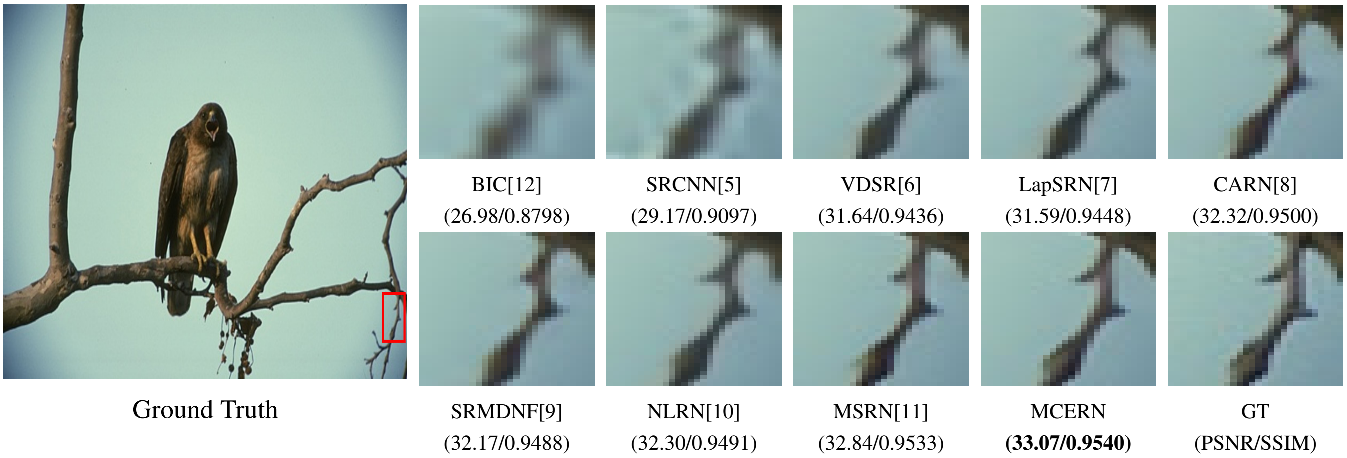

Fig. 9. Visual comparison between different algorithms on *42049* from BSDS100 [3] with scale factor $\times 4$.

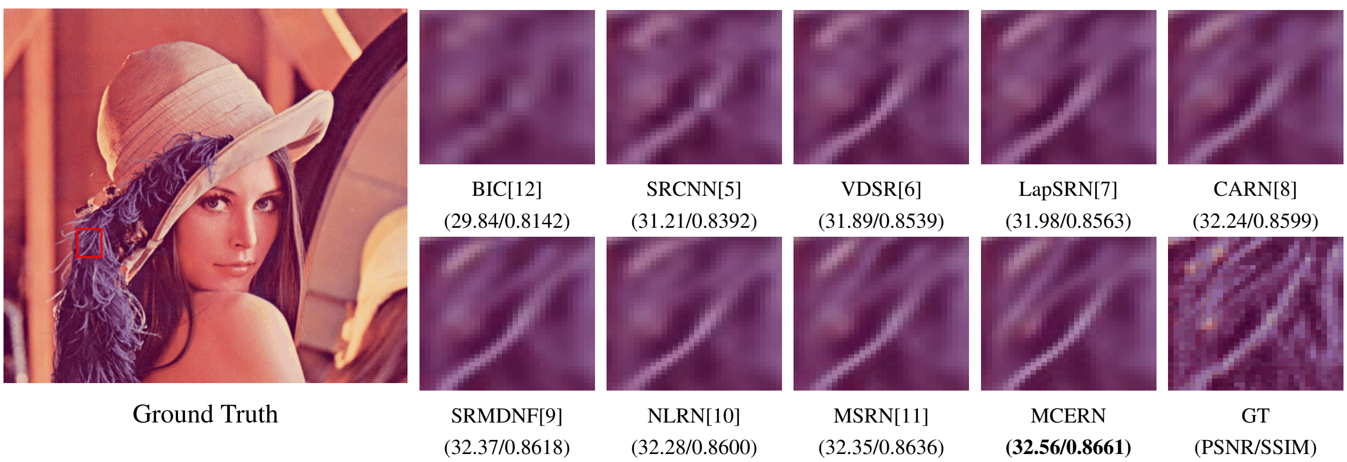

Fig. 10. Visual comparison between different algorithms on *lenna* from Set14 [2] with scale factor $\times 4$.

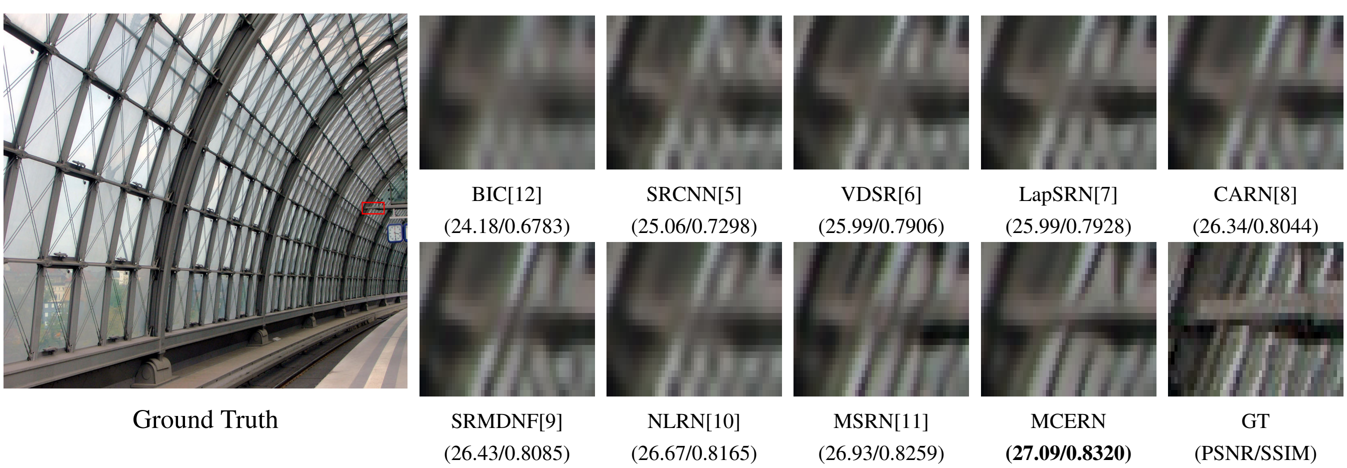

Fig. 11. Visual comparison between different algorithms on *img002* from Urban100 [4] with scale factor $\times 4$.