Supplementary Materials for "Contrastive Learning for Compact Single Image Dehazing"

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1. Datasets

For synthetic scenes, we select the ITS and SOTS indoor in RESIDE [3], which consist of 13,990 and 500 samples, respectively. Their sizes are the same, *i.e*. 620×460.

For real-world scenes, we adopt Dense-Haze [1] and NH-HAZE [2]. Dense-Haze is the NTIRE2019 challenge dataset in the single image dehazing task, which consists of dense and homogeneous hazy scenes. The hazy scenes have been recorded by introducing real haze generated by professional haze machines. It consists of 45 training images, 5 validation images and 5 test images. As the ground-truth test images are not public, we use validation images as test set in our work. NH-HAZE is the NTIRE2020 challenge dataset in the single image dehazing task, which also consists of 45 training images, 5 validation images and 5 test images. As both the ground-truth of validation images and test images are not public, we divide training images into training set and test set which consist of 40 images and 5 images respectively. Different from other datasets, the hazy on NH-HAZE is nonhomogeneous. The sizes both in Dense-Haze and Dense-Haze are 1,600×1,200.

2. Supplementary Experiments

In this section, we provide more experiments on our AECR-Net, such as ablation study on the deploying position of DFE module and additional visualization of restored images by different SOTA methods and ours.

2.1. Ablation Study

We consider the effect of DFE positions before and after 6 FA blocks. We select two different models (*i.e*. base+DFE and Ours) from Table 2 in our main paper as baselines, which both deploy DFE *after* 6 FA blocks. For better comparisons, we design the corresponding models by deploying the DFE module before 6 FA blocks, which denote "DFE+6FA" and "AECR-Net (DFE+6FA)". These models are trained by the same training setting. The results are summarized in Table 1. Obviously, DFE deployed after the deep layer achieves better performance than the shallow layers. For example, 6FA+DFE without CR achieves 0.52dB PSNR gain over DFE+6FA. (The supplementary is for the line 786 of the main paper.)

Table 1. Comparison of different positions of DFE.

Methods	CR	PSNR	SSIM
DFE+6FA	-	34.98	0.9836
6FA+DFE (*i.e*. base+DFE)	-	35.50	0.9853
AECR-Net (DFE+6FA)	√	35.72	0.9887
Ours (6FA+DFE)	√	37.17	0.9901

2.2. Additional Visual Results

We also provide additional visual results on synthetic dataset (*i.e*. SOTS [3]) and real-world dataset (*e.g*. NH-HAZE [2]), and the visual effect with and without the proposed contrastive regularization (CR) on SOTA methods and our ACER-Net. Specifically, Figs. 1 and 2 are visual comparisons on SOTS dataset. The visual comparison on real-world datasets are shown in Fig. 3 (The supplementary is for the lines 634 and 700 of main paper). The visual effects with and without CR on different dehazing methods are presented in Fig. 4-8 (The supplementary is for the line 820 of main paper).

For SOTS dataset, we can observe that the restored images of GridDehazeNet, FFA-Net, MSBDN and KDDN are better than DCP, DehazeNet and AOD-Net. However, they still has black artifacts (see Fig. 1(e)-1(h) and Fig. 2(e)-

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2(h)). In contrast, our AECR-Net can restore more natural haze-free images, which achieves the similar patterns to the ground-truth.

For real-world dataset, previous works perform poorly due to the complex haze distribution. Compared with DCP, DehazeNet, AOD-Net and GridDehazeNet, our AECR-Net can avoid the serious color distortion (see Fig. 3(b)-3(e). Moreover, our AECR-Net can remove serious artifacts effectively, compare to FFA-Net and KDDN (see stone walkway in Fig. 3(f) and Fig. 3(h)).

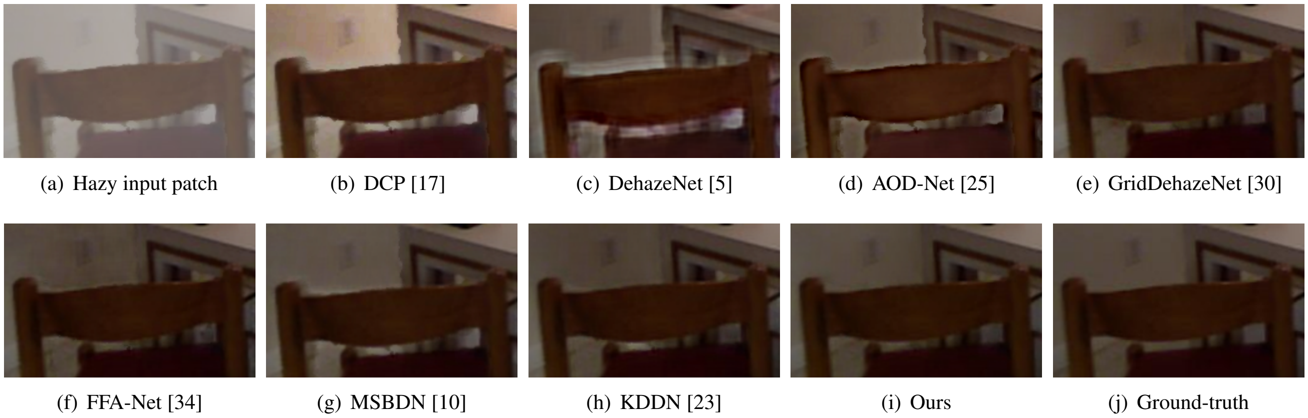
For the effect of CR, adding our CR can effectively improve image quality to restore more clear images, which are shown Fig. 4-8. For example, as shown in Fig. 6, the restored image by GridDehazeNet still has yellow spots or artifacts in the wall. In contrast, GridDehazeNet+CR removes the artifacts effectively for better visualization. Therefore, as a regularization, CR is model-agnostic and universal to further help various image dehazing methods to improve the visual quality.

References

[1] Codruta O. Ancuti, Cosmin Ancuti, Mateu Sbert, and Radu Timofte. Dense haze: A benchmark for image dehazing with dense-haze and haze-free images. In *ICIP*, 2019. 1

[2] C. O. Ancuti, C. Ancuti, and R. Timofte. NH-HAZE: An image dehazing benchmark with nonhomogeneous hazy and haze-free images. *CVPRW*, 2020. 1

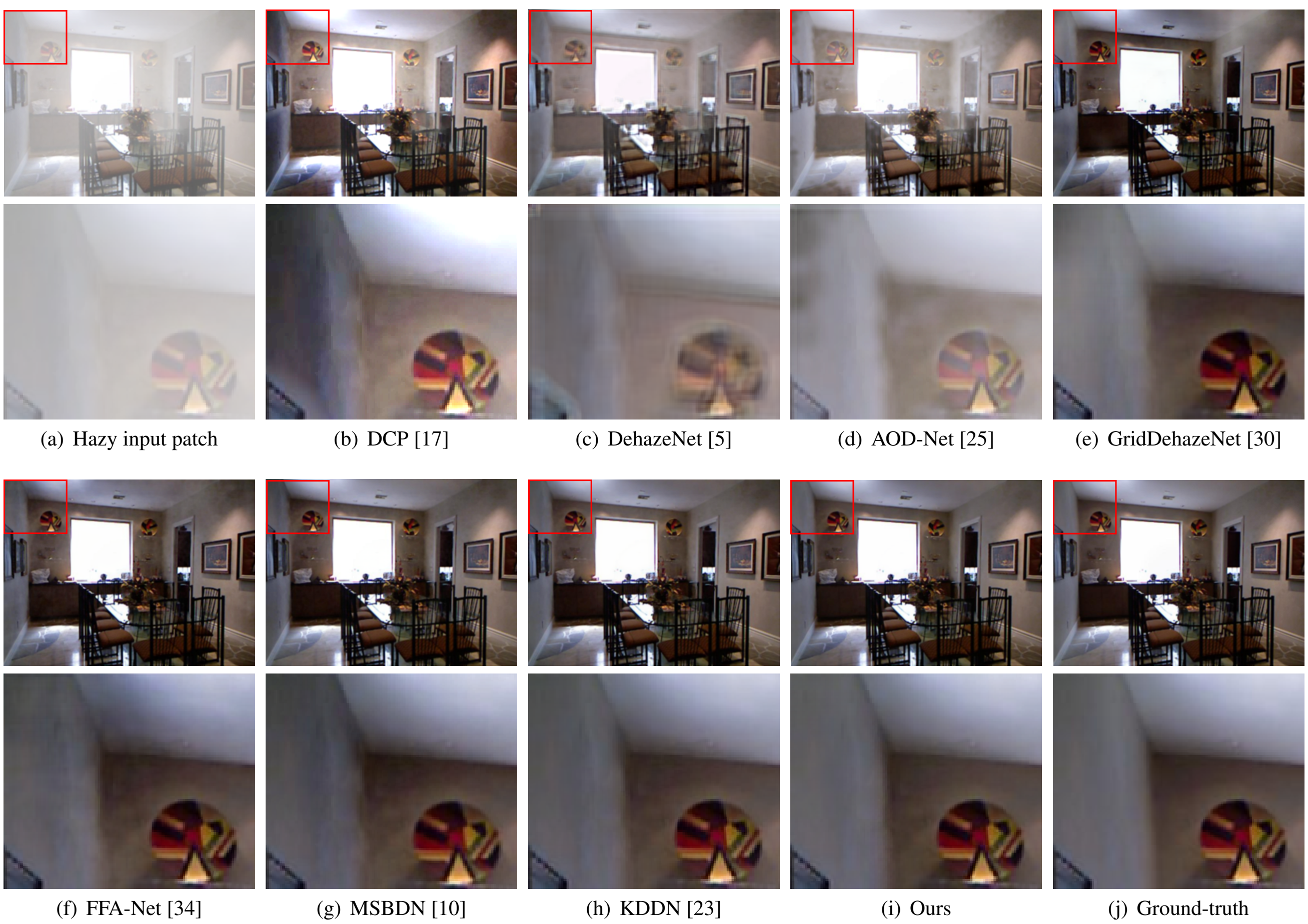
[3] Boyi Li, Wenqi Ren, Dengpan Fu, Dacheng Tao, Dan Feng, Wenjun Zeng, and Zhangyang Wang. Benchmarking single-image dehazing and beyond. *TIP*, 28(1):492–505, 2019. 1, 3



(a) Hazy input patch (b) DCP [17] (c) DehazeNet [5] (d) AOD-Net [25] (e) GridDehazeNet [30]

(f) FFA-Net [34] (g) MSBDN [10] (h) KDDN [23] (i) Ours (j) Ground-truth

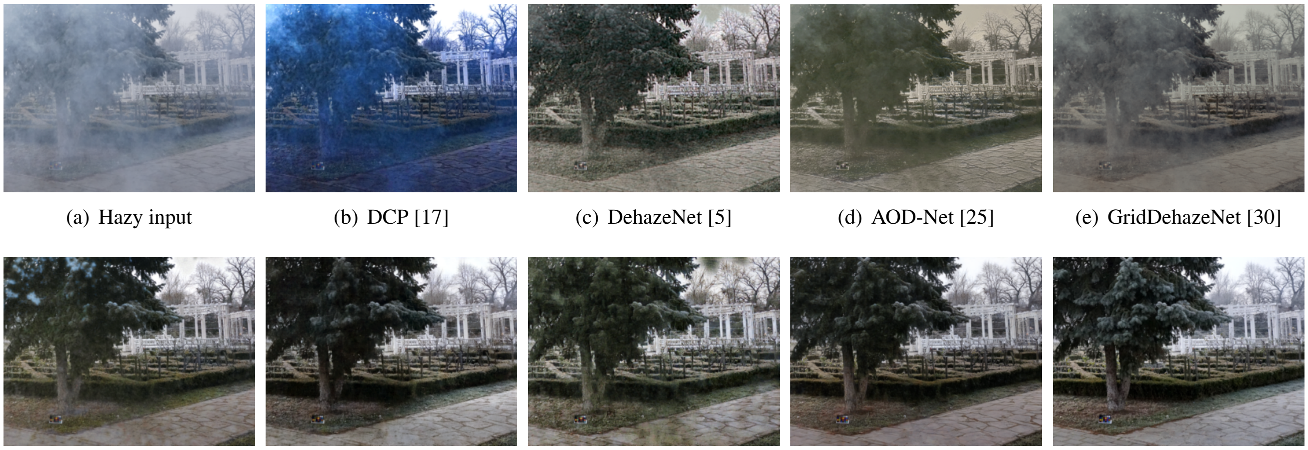
Figure 1. Visual comparison on the patch of 1415_10.png (SOTS).



(a) Hazy input patch (b) DCP [17] (c) DehazeNet [5] (d) AOD-Net [25] (e) GridDehazeNet [30]

(f) FFA-Net [34] (g) MSBDN [10] (h) KDDN [23] (i) Ours (j) Ground-truth

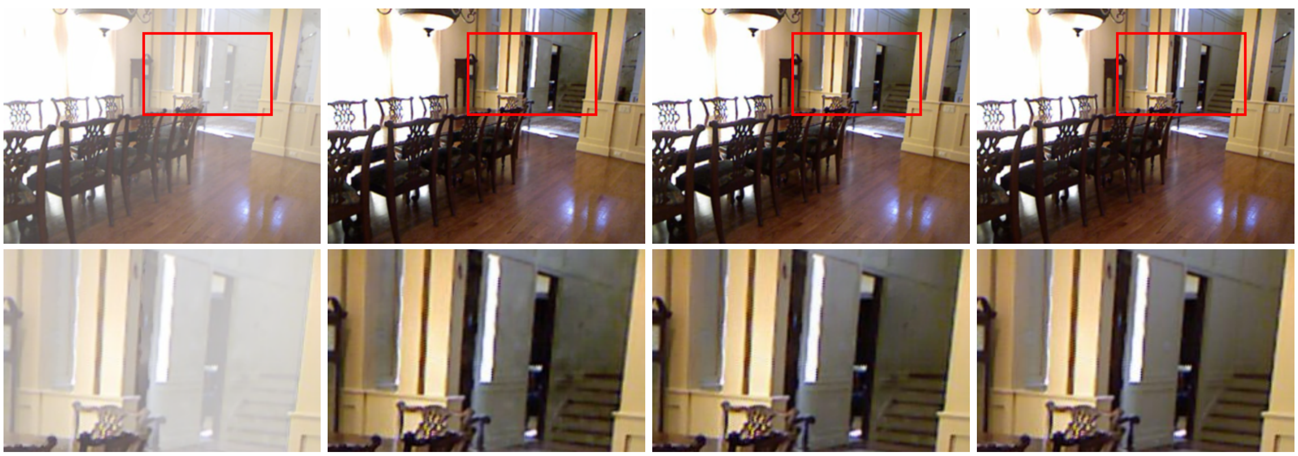
Figure 2. Visual comparison on SOTS [3] dataset.



(a) Hazy input (b) DCP [17] (c) DehazeNet [5] (d) AOD-Net [25] (e) GridDehazeNet [30]

(f) FFA-Net [34] (g) MSBDN [10] (h) KDDN [23] (i) Ours (j) Ground-truth

Figure 3. Visual comparison on NH-HAZE datasets. Zoom in for best view.

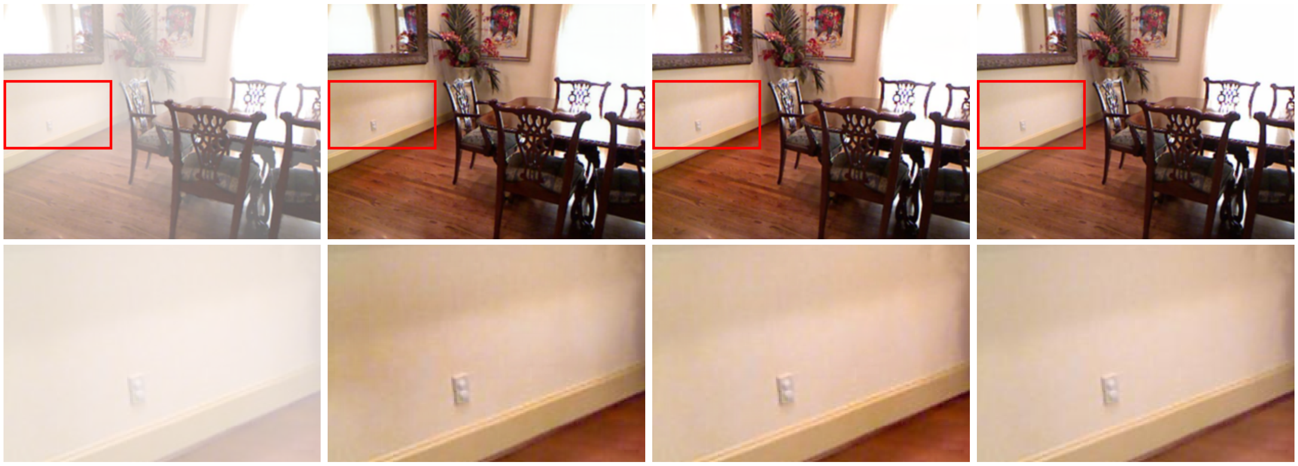


(a) Hazy input (b) Ours (L1) (c) Ours+CR (d) Ground-truth

Figure 4. Visual comparison on the effect of CR on our AECR-Net.

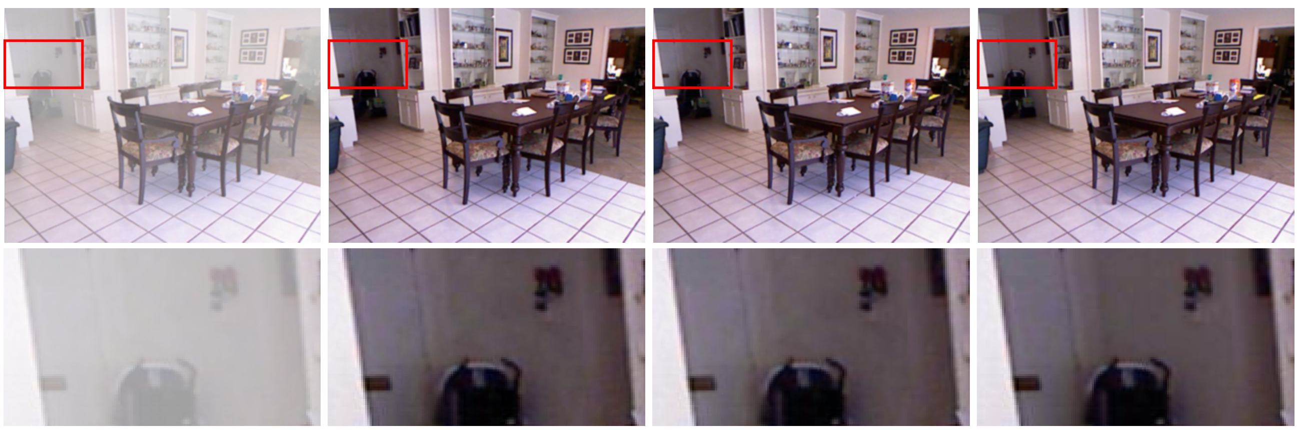
(a) Hazy input (b) FFA-Net [34] (c) FFA-Net+CR (d) Ground-truth

Figure 5. Visual comparison on the effect of CR on FFA-Net [34].



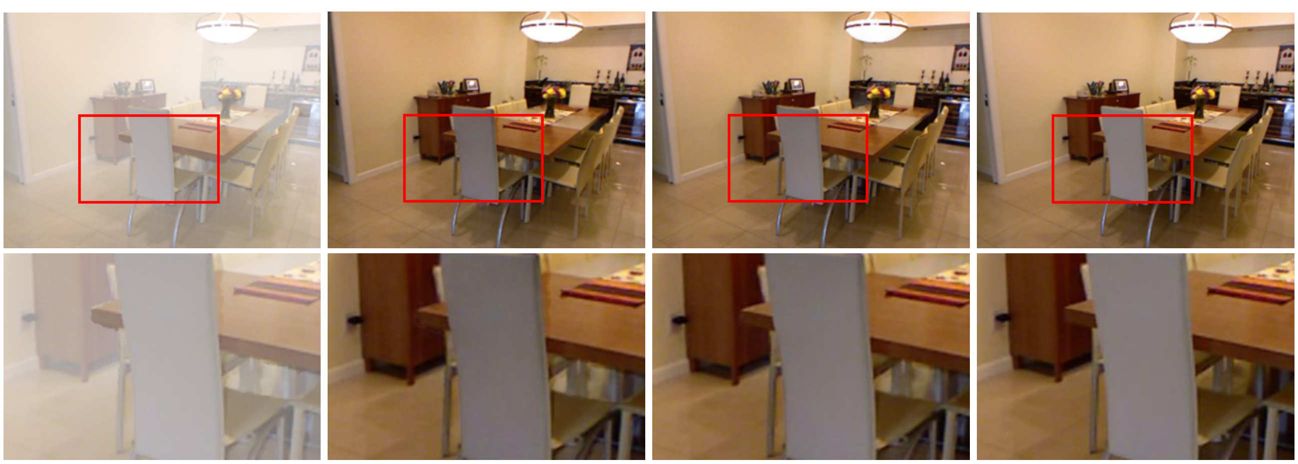
(a) Hazy input (b) GridDehazeNet [30] (c) GridDehazeNet+CR (d) Ground-truth

Figure 6. Visual comparison on the effect of CR on GridDehazeNet [30].



(a) Hazy input (b) KDDN [23] (c) KDDN+CR (d) Ground-truth

Figure 7. Visual comparison on the effect of CR on KDDN [23].



(a) Hazy input (b) MSBDN [10] (c) MSBDN+CR (d) Ground-truth

Figure 8. Visual comparison on the effect of CR on MSBDN [10].