Supplementary Material for
All-In-One Image Restoration for Unknown Corruption

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1. Introduction

In this material, we present more results of our AirNet including the evaluation on contrastive loss, generalization ability and additional results on qualitative comparisons.

2. Ablation Study on Contrastive Loss

In this section, we conduct experiments to demonstrate the effectiveness of the contrastive loss. Table 1 reports the experiments on the BSD68 dataset, where "AirNet w/o CL" denotes the variant by removing contrastive loss from our method. "AirNet w PCM" denotes the variant by using the restored images and ground truth as positive, and the restored image and the input degraded image as negative.

Table 1. Ablation study on contrastive loss and pair construction methods.

Noise Level	$\sigma = 15$	$\sigma = 25$	$\sigma = 50$
AirNet w/o CL	33.99/0.9340	31.34/0.8909	28.07/0.7982
AirNet w PCM	34.04/0.9353	31.39/0.8919	28.15/0.8030
AirNet	**34.14/0.9355**	**31.49/0.8928**	**28.23/0.8058**

3. Evaluation on Generalization Ability

In this section, we conduct experiments to demonstrate the generalization ability of AirNet by evaluating the pretrained AirNet on unseen degradation types or levels. More specifically, we synthesize the noisy images on BSD68 with noise level $\sigma \in \{10, 55\}$. Table 2 shows that AirNet could perform well on unseen degradation levels.

4. Qualitative Results on Single Degradation

In this section, we show the qualitative results on three separated image restoration tasks, *i.e.*, denoising, deraining, and dehazing.

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Denoise: Figure 1 reports the qualitative results on BSD68 [5] comparing with five denoising methods under the one-by-one setting. From the results, one could find that AirNet removes most of the noise from the pictures and preserves more details comparing with the baselines.

Derain: From Figure 2, it could be seen that AirNet outperforms all baselines in qualitative comparisons. For examples, although LPNet [4] could successfully removes most of rain streaks from the pictures, it fails to remove the rain streaks around the people. In contrast, our AirNet could be immune of these issues.

Dehaze: As reported in Figure 3, AirNet also shows superiority in image dehazing. In short, it could successfully recover the clean image from the degraded one, whereas the baselines suffer from color distortions around buildings.

5. Qualitative Results on Multiple Degradations

In this section, we conduct experiments to verify the effectiveness of the proposed method on multiple degradations, *i.e.*, the all-in-one setting. From Figure 4, one could find out that AirNet shows superiority in qualitative comparisons.

6. Qualitative Results on Spatially Variant Degradation

In this section, we show the qualitative results on spatially variant degradations. As shown in Figure 5, AirNet demonstrates better visualization results. To be specific, although CBM3D [1], IRCNN [9], FFDNet [10], and BRDNet could remove most of noise from the pictures, but they suffer from the over-smoothing and details lossing. In addition, DnCNN [8] and DL [3] could keep details in the picture, but they cannot remove all noise. In contrast, AirNet could remove the noise while keeping the image details.

Table 2. Quantitative results of image deraining on the BSD68 dataset. The best results are shown in boldface.

Sigma	Metrics	BRDNet [6]	LPNet [4]	FDGAN [2]	MPRNet [7]	DL [3]	AirNet
10	PSNR	34.05	28.52	31.03	33.55	33.14	**35.60**
	SSIM	0.9273	0.8294	0.9314	**0.9517**	0.8850	0.9476
55	PSNR	25.56	20.44	25.85	27.13	26.08	**27.17**
	SSIM	0.6056	0.5024	0.7606	0.7613	0.6887	**0.7689**

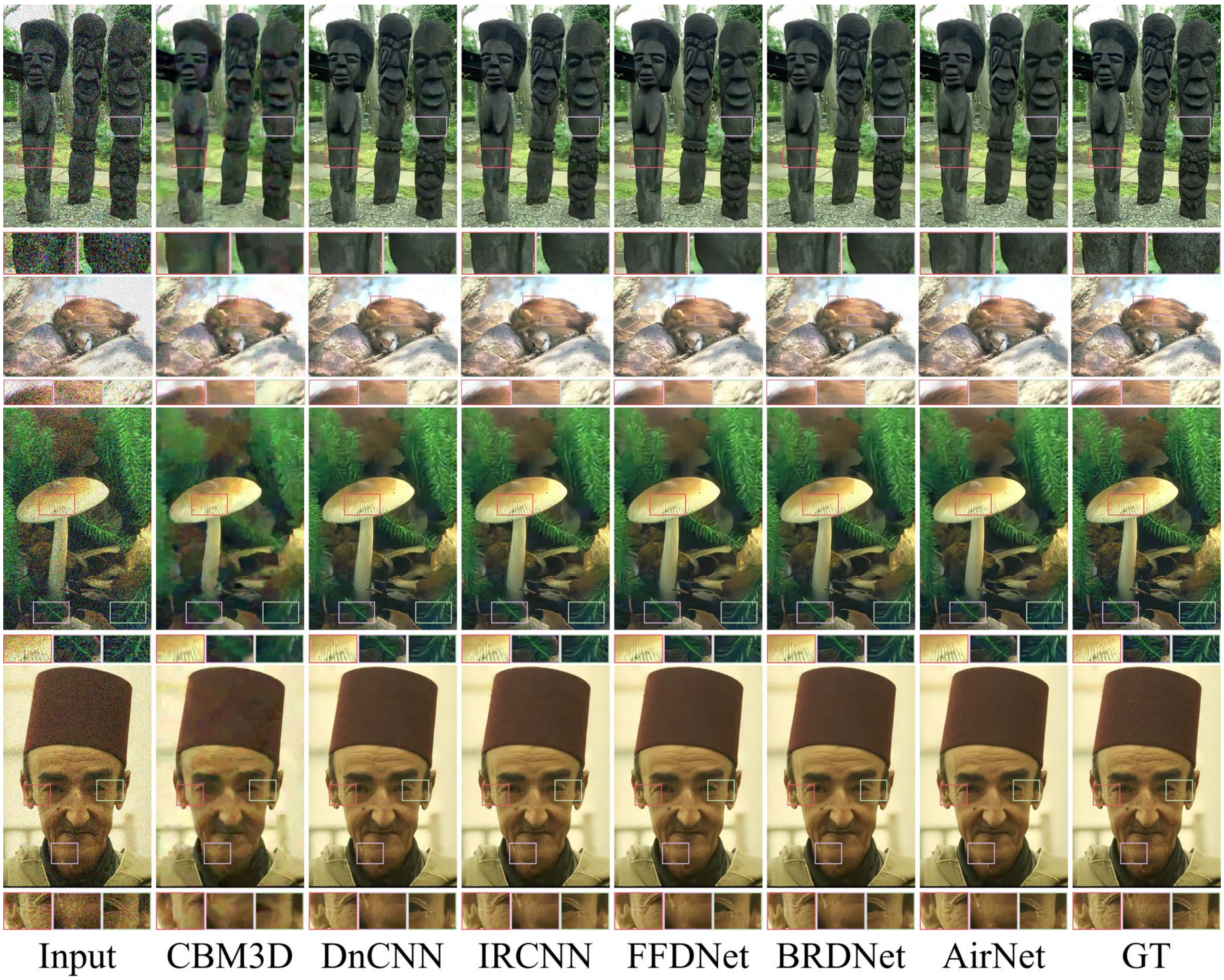

Figure 1. Comparisons of the SOTA denoise methods on the BSD68 database. Some areas are highlighted in colored rectangles and zooming-in is recommended for a better comparison.

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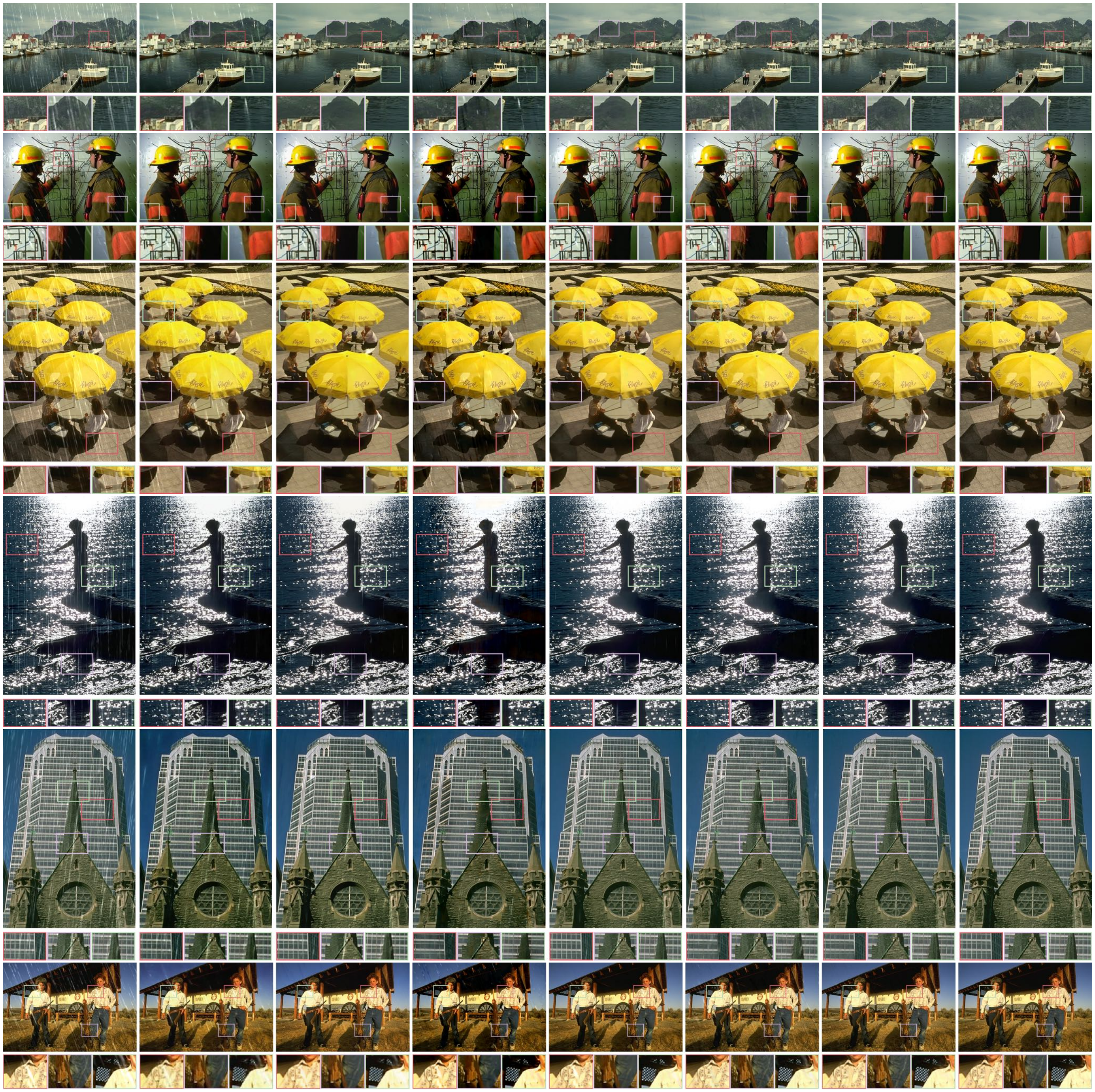

Figure 2. Comparisons of the SOTA derain methods on the Rain100L database. Some areas are highlighted in colored rectangles and zooming-in is recommended for a better comparison.

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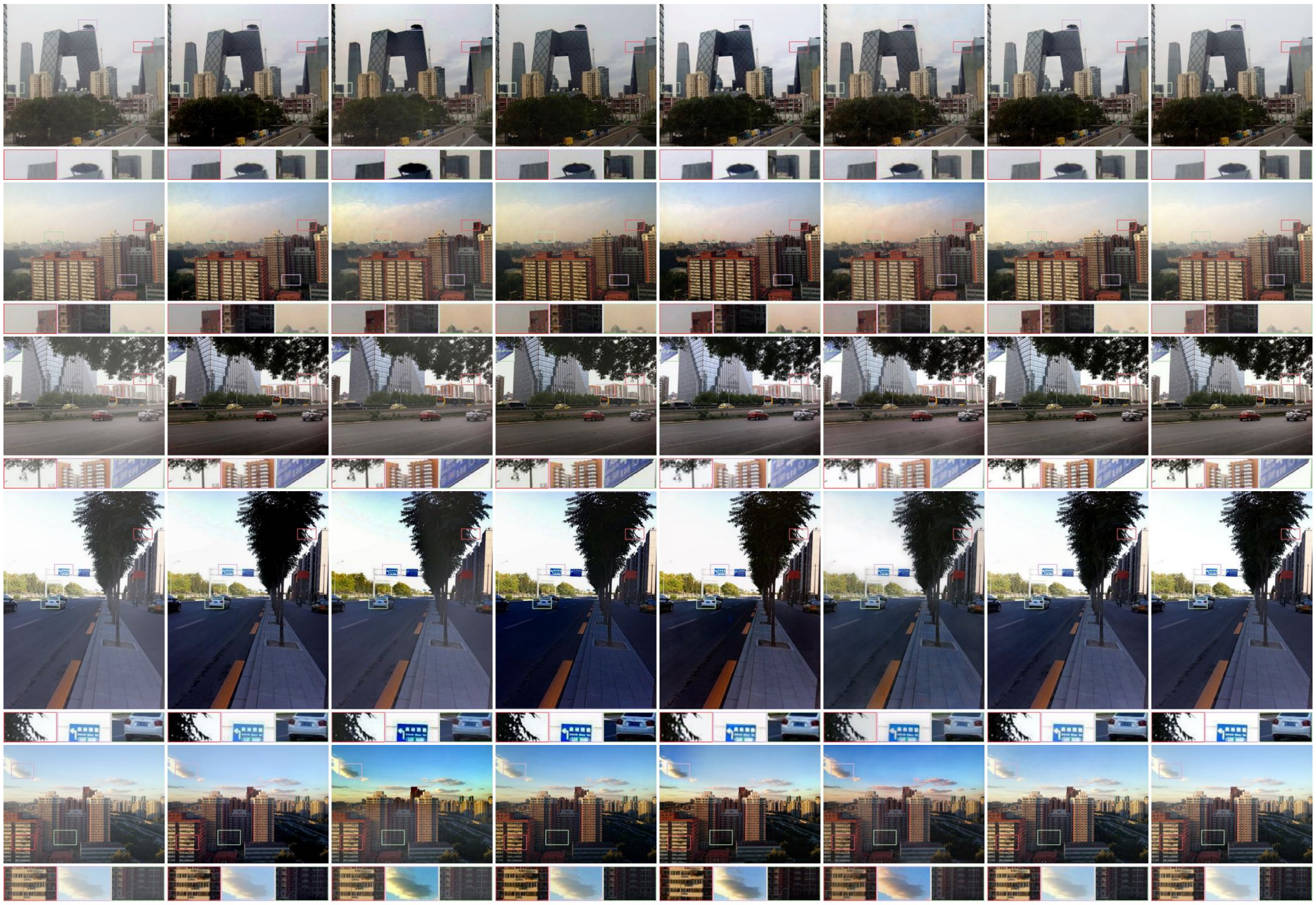
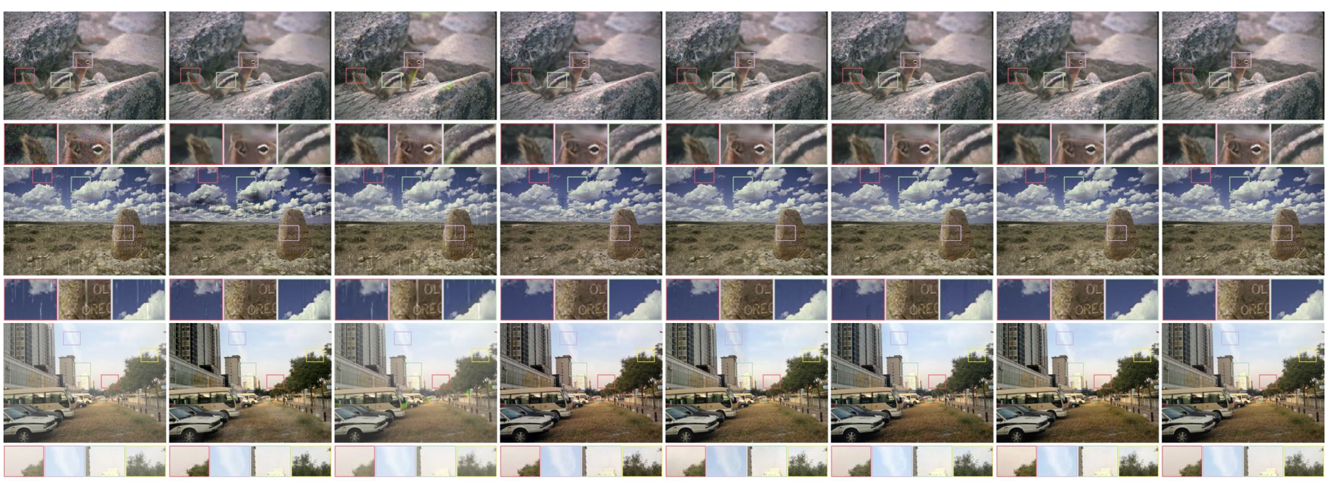


Input DehazeNet MSCNN AOD-Net EPDN FDGAN AirNet GT

Figure 3. Comparisons of the SOTA dehaze methods on the SOTS database. Some areas are highlighted in colored rectangles and zooming-in is recommended for a better comparison.



Input BRDNet LPNet FDGAN MPRNet DL AirNet GT

Figure 4. Comparisons of the SOTA methods on multiple degradations. Some areas are highlighted in colored rectangles and zooming-in is recommended for a better comparison.

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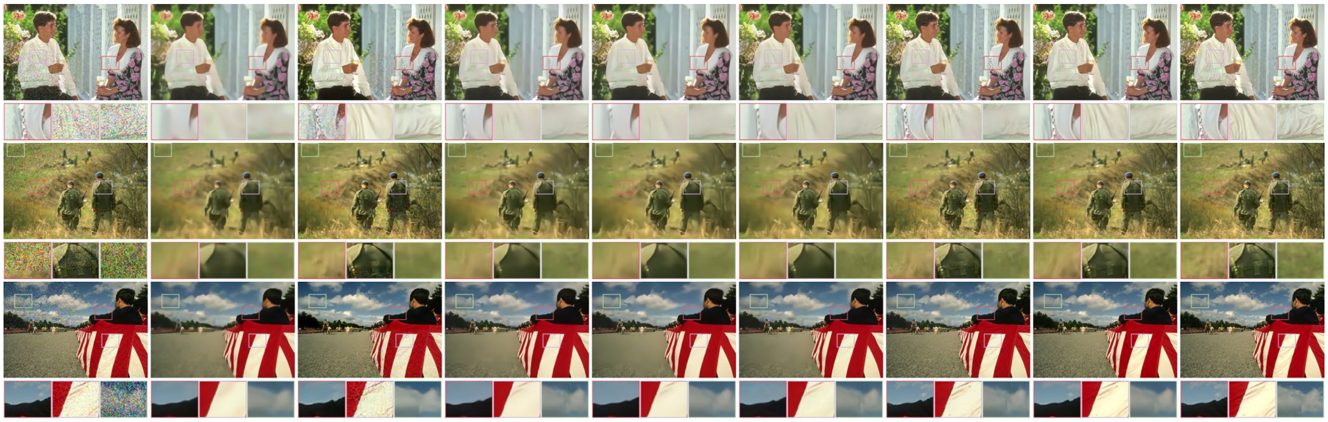

Figure 5. Comparisons of the baselines on BSD68 database with spatially variant degradations. Some areas are highlighted in colored rectangles and zooming-in is recommended for a better comparison.

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