Single Image Dehazing via Conditional Generative Adversarial Network

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Overview

In this supplemental material, we first show the effectiveness of the proposed method in Seciton 1 and then present more image dehazing results on both synthetic and real world images in Section 2.

1. The effect of the proposed method

As mentioned in the manuscript, several methods improve GANs to deal with low-level vision problem, e.g., image deraining [8]. We have also clarified the differences from these methods and show that they are not able to handle image dehazing problem well. In this supplemental material, we further show the effect of the proposed method and compare it with the most related methods. To demonstrate the effectiveness of the proposed algorithm, we retrain the baseline algorithm (cGAN) and GAN with perceptual loss [8] under the same experimental settings for fair comparisons.

Figure 1 shows that the baseline algorithm and GAN with perceptual loss [8] are not able to generate clear images and the generated images contain color distortion. In contrast, our algorithm generates much clearer images with few artifacts.

2. More experiment results

As stated in Section 4.4 in the manuscript, although our network is trained on synthesized dataset, it can be applied to real world hazy images. In this supplemental material, we conduct more experiments to demonstrate the effectiveness of the proposed network on both synthetic images and real world images. We evaluate the proposed algorithm against several state-of-the-art methods including Berman [1], Cai [2], Chen [3], He [4], Li [5], Meng [6], and Ren [7].

To evaluate the effectiveness of the proposed method on real images, we let twenty persons give a score (1-9) to each real world dehazing image in supplemental material and then compute their average value, where the higher score indicates the better quality of the estimated image. The results in Table 1 show that our method performs well.

Table 1: User studies on real world dehazing images.

Figure	He	Berman	Cai	Chen	Ren	Meng	Li	Ours
5	5.7	6.1	3.7	-	4.2	5.9	3.1	**7.1**
6	5.1	4.9	-	5.9	5.1	6.0	5.0	**6.2**
7	3.1	4.8	2.6	-	2.5	3.3	2.5	**5.3**
8	6.1	-	5.9	6.4	3.0	5.5	3.1	**6.8**
9	6.2	4.2	3.8	-	5.1	4.1	3.1	**6.6**
10	4.3	**6.2**	2.5	-	5.6	5.9	2.1	**6.2**

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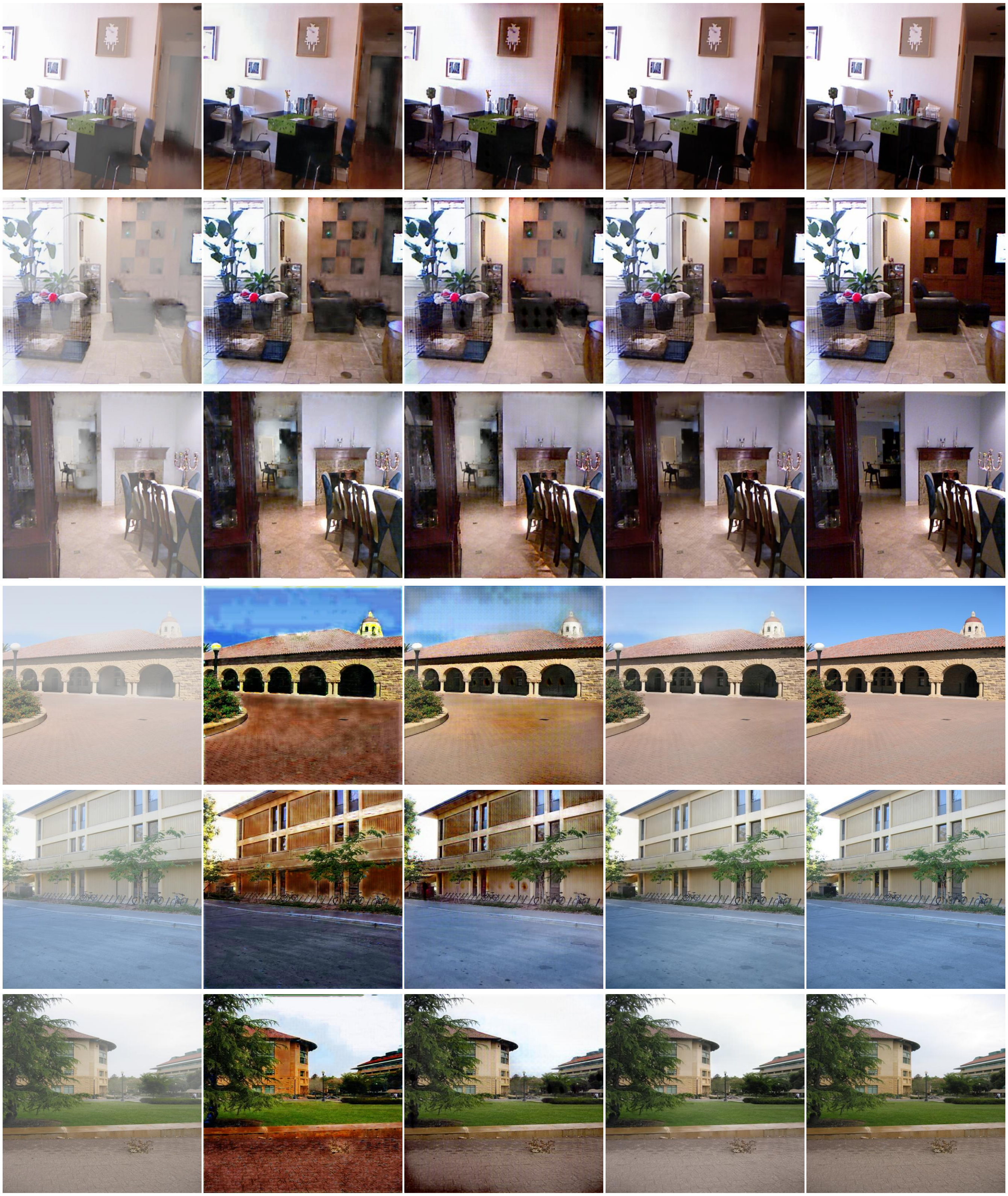


(a) Input image (b) Zhang [8] (c) cGAN (d) Ours (e) Ground truth

Figure 1: The effectiveness of the proposed method. Compared with the baseline method (cGAN) and GAN with perceptual loss [8]. Our algorithm generates much clearer images as shown in (d).

(a) Synthesized hazy image (psnr/ssim)

(b) Ground truth ($+\infty/1$)

(c) He [4] (24.59/0.6419)

(d) Chen [3] (24.91/0.6501)

(e) Berman [1] (24.31/0.5435)

(f) Cai [2] (25.15/0.6133)

(g) Ren [7] (24.80/0.6417)

(h) Ours (**28.67/0.8596**)

Figure 2: Visual comparison on synthetic image. Our method generates a much clearer image.

(a) Synthesized hazy image (psnr/ssim) (b) Ground truth ($+\infty/1$)

(c) He [4] (36.24/0.8977) (d) Chen [3] (37.01/0.8660)

(e) Berman [1] (35.77/0.7862) (f) Cai [2] (37.09/0.9340)

(g) Ren [7] (35.98/0.8775) (h) Ours (**37.25/0.9674**)

Figure 3: Visual comparison on synthetic image. The dehazing results of He [4], Chen [3], Berman [1], Ren [7] and Cai [2] contain color distortion on the ceiling and ground. Our method generates a much clearer image as shown in (h).

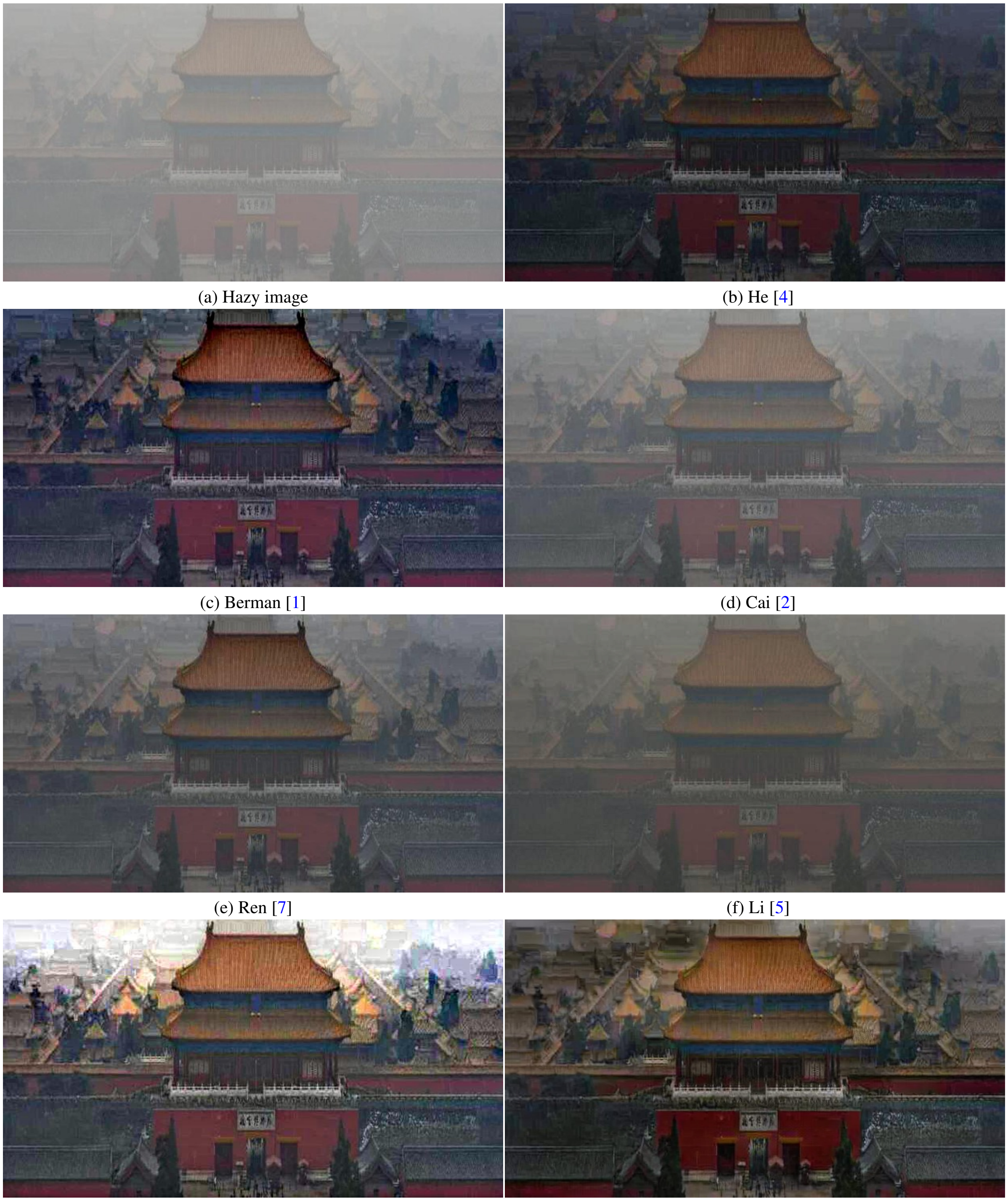
(a) Synthesized hazy image (psnr/ssim) (b) Ground truth (+∞/1)

(c) He [4] (34.48/0.8573) (d) Chen [3] (32.28/0.8371)

(e) Berman [1] (27.89/0.7824) (f) Cai [2] (31.05/0.8740)

(g) Ren [7] (28.79/0.7906) (h) Ours (**32.87/0.9505**)

Figure 4: Visual comparison on synthetic image. The dehazing results of He [4], Chen [3] and Berman [1] contain significant color distortion on the ground. The dehazing results of Ren [7] and Cai [2] contain some haze residue in red rectangles. Our method generates a much clearer image as shown in (h).



(a) Hazy image (b) He [4]

(c) Berman [1] (d) Cai [2]

(e) Ren [7] (f) Li [5]

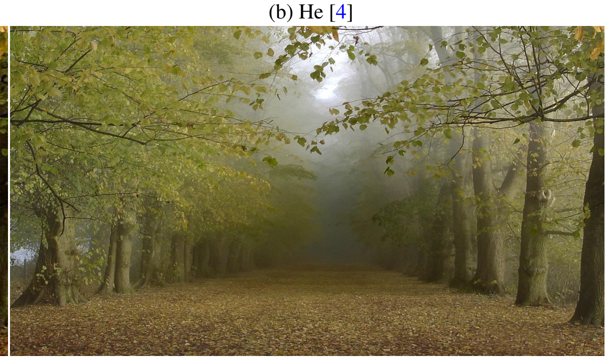
(g) Meng [6] (h) Ours

Figure 5: Visual comparison on real image. The dehazing results of Cai [2], Ren [7] and Li [5] contain significant haze residue. The method of He [4] tends to produce darker images. The result generated by Berman [1] has low contrast. The dehazing result of Meng [6] appears to be overexposed in the distance. Our method generates a much clearer image as shown in (f).

(a) Hazy image

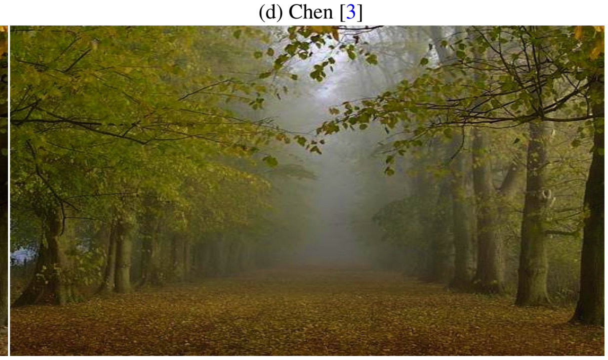
(b) He [4]

(c) Berman [1]



(d) Chen [3]

(e) Ren [7]



(f) Li [5]

(g) Meng [6]

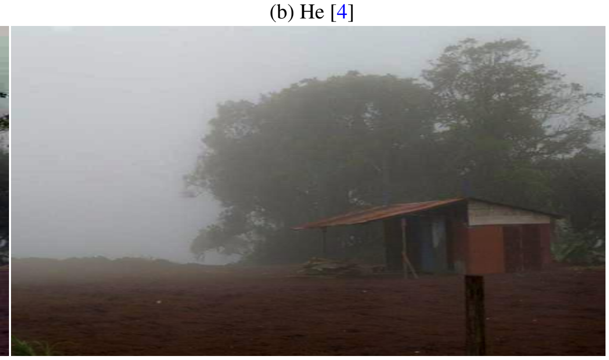
(h) Ours

Figure 6: Visual comparison on real image. Methods by Berman [1] and Ren [7] fail to estimate the transmission maps thus leading to the images with darker regions, e.g., leaves. Our method generates a much clearer image as shown in (f).

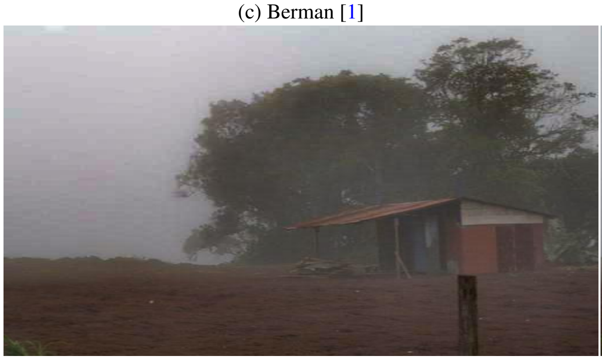
(a) Hazy image

(b) He [4]

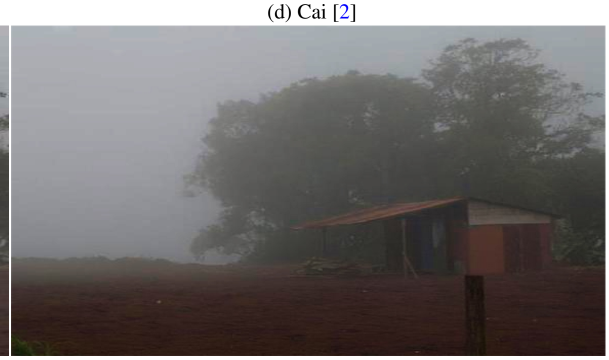
(c) Berman [1]



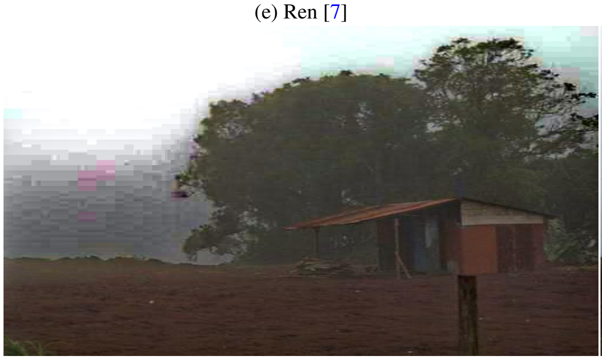
(d) Cai [2]



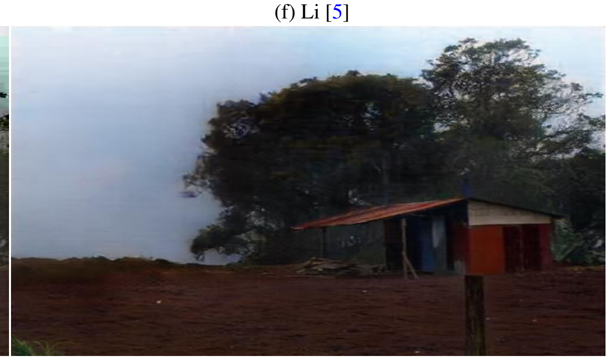
(e) Ren [7]



(f) Li [5]



(g) Meng [6]



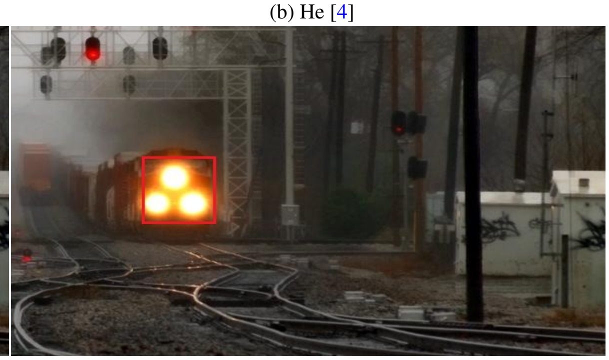
(h) Ours

Figure 7: Visual comparison on real image. The dehazing results of He [4], Berman [1] and Meng [6] contain color distortion and artifacts in the sky. There exist significant haze residual in the images generated by Cai [2], Ren [7] and Li [5]. Our method generates a much clearer image as shown in (f).

(a) Hazy image

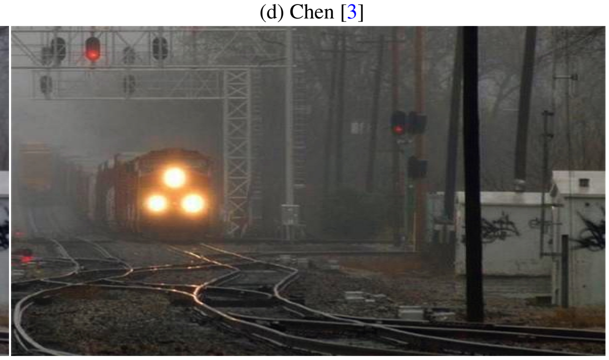
(b) He [4]

(c) Cai [2]

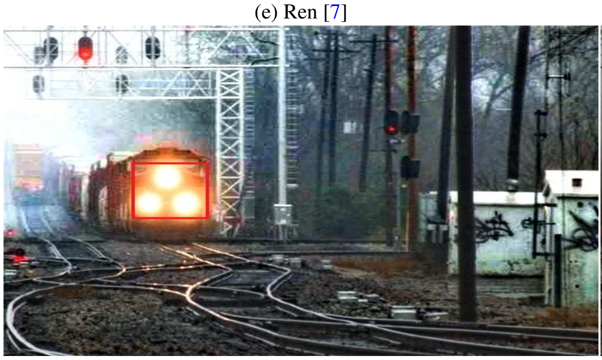


(d) Chen [3]

(e) Ren [7]



(f) Li [5]



(g) Meng [6]

(h) Ours

Figure 8: Visual comparison on real image. The dehazing methods of He [4], Chen [3] and Meng [6] do not perform well on the bright regions, such as the train lights. The dehazing result of Meng [6] appears to be overexposed in the distance. The dehazing result of Ren [7] and Li [5] contain significant haze residual. Our method generates a much clearer image as shown in (f).

(a) Hazy image
(b) He [4]
(c) Berman [1]
(d) Cai [2]
(e) Ren [7]
(f) Li [5]
(g) Meng [6]
(h) Ours

Figure 9: Visual comparison on real image. The dehazing method of He [4] and Meng [6] generates the image with color distortion. The dehazing methods of Berman [1] and Ren [7] generates the results with some artifacts, e.g., the leaves enclosed in the red boxes. Our method generates a much clearer image as shown in (f).

(a) Hazy image (b) He [4]

(c) Berman [1] (d) Cai [2]

(e) Ren [7] (f) Li [5]

(g) Meng [6] (h) Ours

Figure 10: Visual comparison on real image. Our method generates a brighter image with fine details and structures.

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