LAP-Net: Level-Aware Progressive Network for Image Dehazing
Supplementary Material

1. More details about the t-net

In this section, we unfold the structure of our t-net, which is described in Section 3.3 of the manuscript. The basic model for t-net consists of four successive "down-up" groups. In each "down-up" group, we use the convolutional layer with $stride = 2$ for encoding the feature maps. The convolutional layer is followed with the BN [5] and ReLU layers. After that, the inverse operation is implemented by bilinear interpolation [3] to decode them. The numbers of output features for layers of the four "down-up" groups are fixed as "$8, 16, 16, 8$".

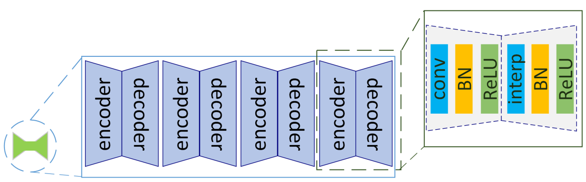

Figure 1. Illustration of the basic units of t-net. We employ four cascaded hourglass-shaped units to decompose the input image. Each hourglass module contains a group of "conv-BN-ReLU" block for downsampling and "Interp-BN-ReLU" for upsampling.

2. More comparisons on two benchmarks

In this section, we give more results on two synthetic outdoor dehazing benchmarks, namely outdoor images of SOTS [7] and O-HAZE [1]. We compare our results with the state-of-the-art methods mentioned in the manuscript, including dark channel prior (DCP) [4], multi-scale CNN (MSCNN) [9], DehazeNet [2], all-in-one net (AOD) [6], gated fusion network (GFN) [10], densely connected pyramid dehazing network (DCPDN) [12], conditional generative adversarial network (cGAN) [8] and proximal dehazenet (PDN) [11].

Fig.2 is an example of SOTS [7]. For the images with mild haze, the most significant advantage is our method can preserve the color fidelity better than the previous approaches. The sky region of our restoration in Fig.2 has the closest color to the ground truth. The trees at the bottom of the image are also vivid in our result.

Fig.3 further shows how our method achieves better performance than the previous algorithms when facing denser haze of O-HAZE dataset [1]. Our method removes the influence of uneven haze on the ground. Thus the ground has a similar appearance with the ground truth. By contrast, the remaining haze whitens the ground more or less as marked in the red boxes in others' results. The better performance of our method benefits from our level-aware dehazing strategy, which removes different levels of haze in different regions.

3. More comparisons on the real-world images

In this section, we give more comparisons on real-world images with eight state-of-the-art methods. The images are also with different haze conditions. The detailed analysis of each image is demonstrated below.

Fig.4 is an example of mild haze. In this case, most of the methods can reveal the texture of the hall clearly. However, the main concern for this case is the color fidelity. Ours can preserve the color fidelity in the restoration better when compared with the other methods like [4, 9, 11]. There is no over-saturation, darkness or halo effect along with the depth discontinuous regions in our result.

For the image in Fig.5, we can see the texture of distant building can also be restored by most methods since the haze is mild. However, our method can restore color better. The color of the building in our method seems more natural.

In Fig.6, the texture of trees in the farthest regions is hard to be seen clearly. Compared with other methods, the outline of the distant trees is clearer in our restoration as marked in the red box. Meanwhile, unlike [9, 2, 10], the texture of foreground trunks in our result is also visible. It verifies our method is not at the expense of close details.

In Fig.7, the color of distant buildings is faded. Our method restores a clearer view of these buildings as marked in the red box. Meanwhile, ours also avoids the over-saturation or the halo effect problem of previous methods as marked in the blue box.

In Fig.8, the haze affects the distant object more apparently. In this case, our method can restore the texture and color of the train and bushes. Meanwhile, it does not darken the corresponding regions like [4, 2, 10] or brighten the scene too much like [12].

Fig.9 is a good example that shows a significant diversity between close and distant regions. The objects in close regions are clear, while those in distant regions suffer from the haze seriously. As mentioned in the manuscript, one possible reason is that the haze in real-world can distributes unevenly, and the distant ones can be affected by more factors and become more blurry. Therefore, the textures of bushes and buildings in the distant region remain unclear in the results of most other methods. Ours solve this problem and restore a clear detail of these objects.

Fig.10 verify that our method can restore the distant objects while preserving the details of close regions. The gate in Fig.10 is covered by dense haze. In our result, we restore the texture of it clearly. Meanwhile, the car and the road in close region are still vivid and not darkened like previous methods.

For images with very dense haze in Fig.11, our method is more likely to give a clear restoration. The distant trees, the henge, and pedestrians can be clearer in ours. Meanwhile, ours also avoid over-exposure like [12] or darkening like [8].

References

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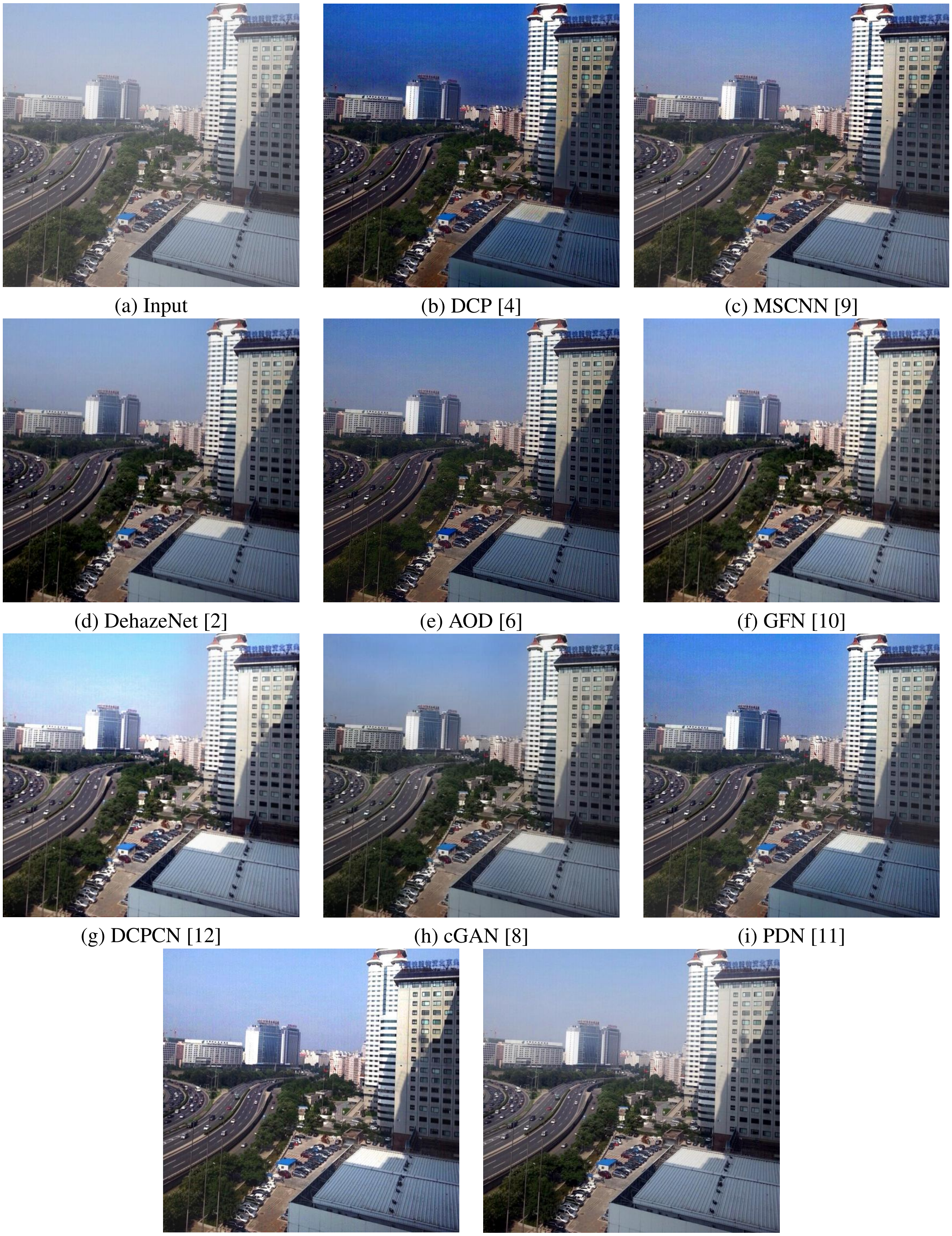
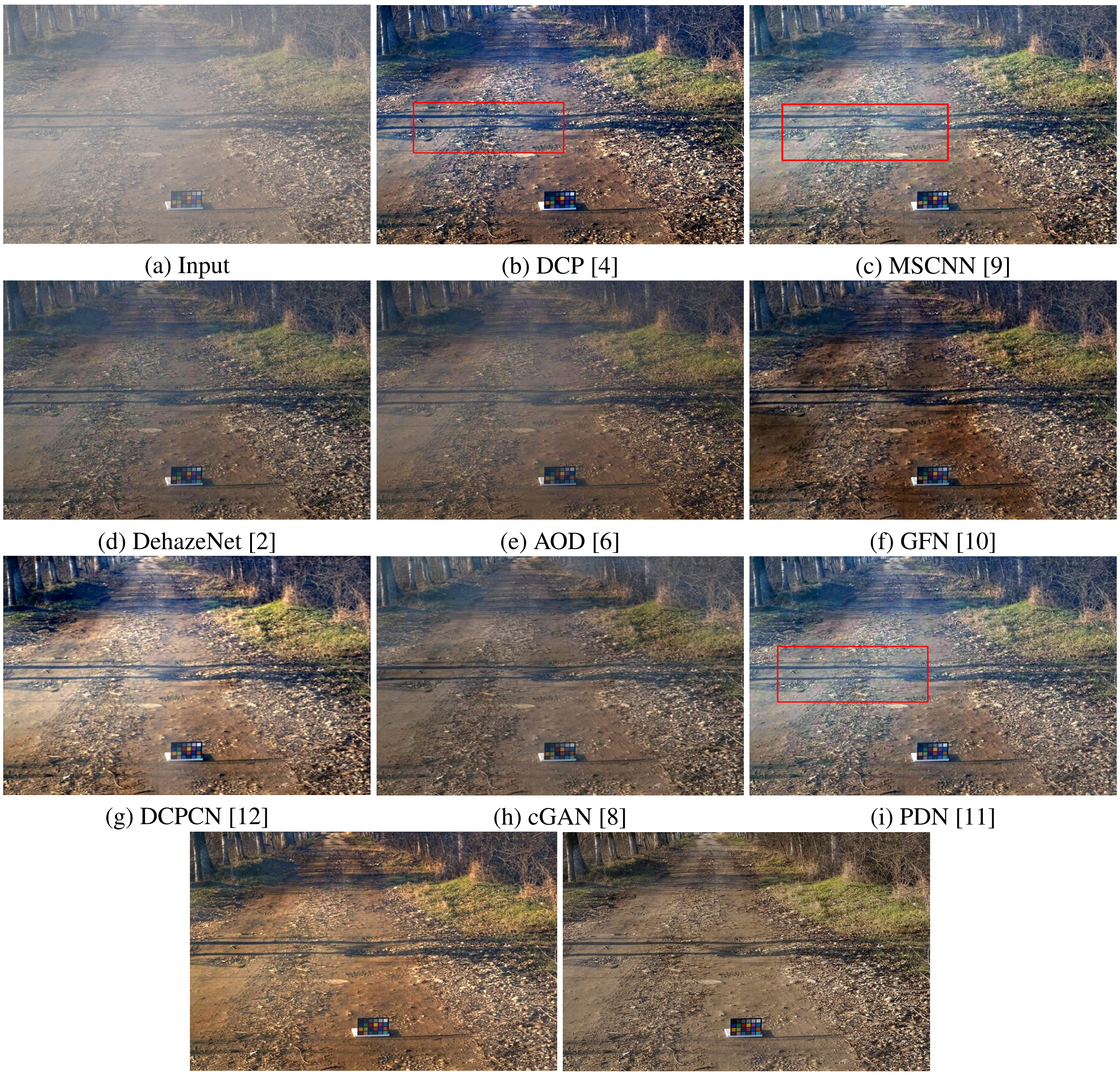


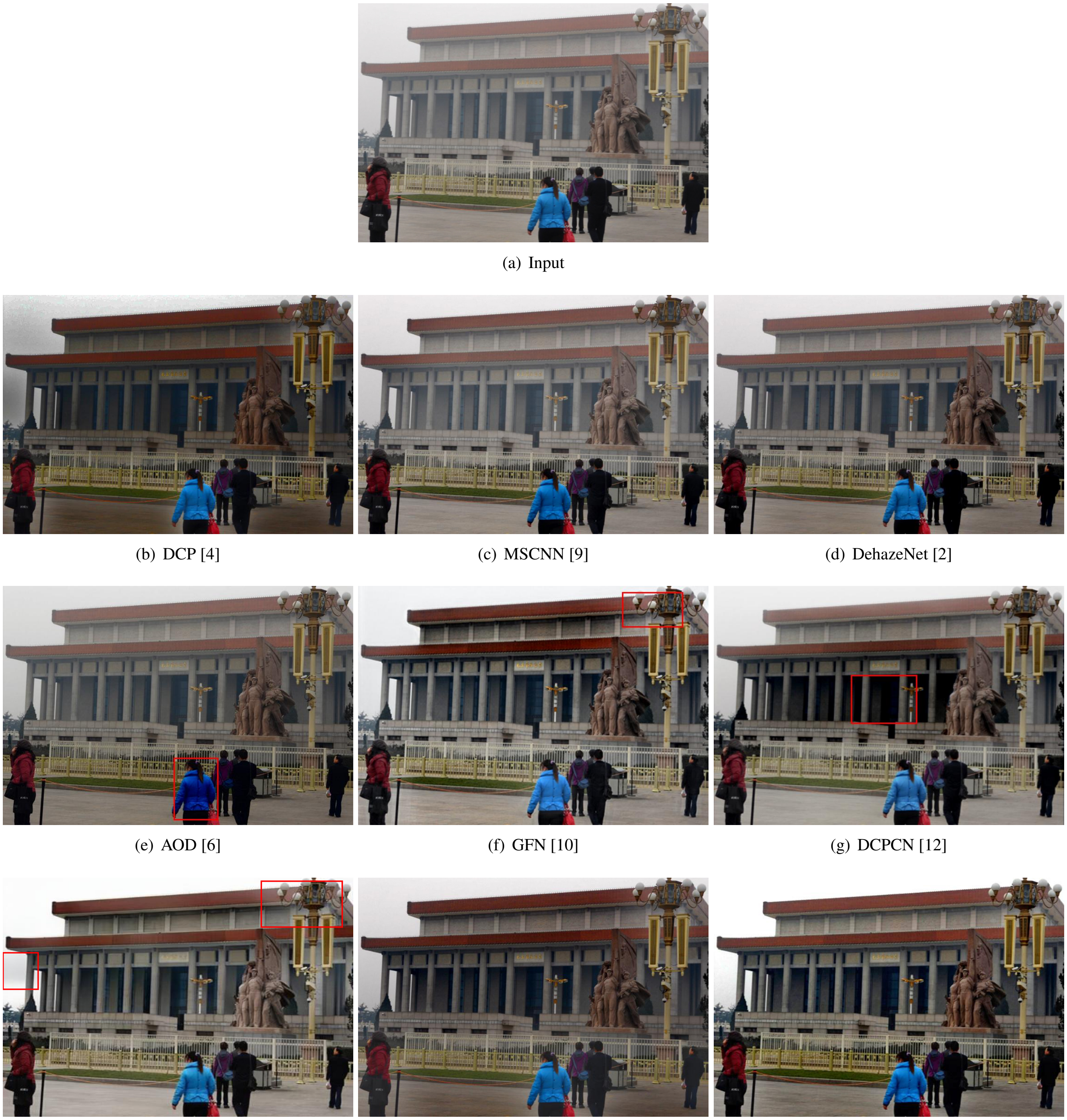
(a) Input (b) DCP [4] (c) MSCNN [9]
(d) DehazeNet [2] (e) AOD [6] (f) GFN [10]
(g) DCPCN [12] (h) cGAN [8] (i) PDN [11]
(j) Our (k) Ground truth

Figure 2. Visual comparison on SOTS [7]. Our result can preserve the color fidelity better so that the color of sky region is natural and similar to the ground truth.



(a) Input (b) DCP [4] (c) MSCNN [9]
(d) DehazeNet [2] (e) AOD [6] (f) GFN [10]
(g) DCPCN [12] (h) cGAN [8] (i) PDN [11]
(j) Our (k) Ground truth

Figure 3. Visual comparison on O-HAZE [1]. For the image with unevenly distributed haze, our method can adaptively remove haze of different levels so that there is no remaining haze and the restoration is more natural than the result of previous methods.



(a) Input

(b) DCP [4]

(c) MSCNN [9]

(d) DehazeNet [2]

(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

(h) cGAN [8]

(i) PDN [11]

(j) Ours

Figure 4. Visual comparison on the real image. For the image with mild haze, the main merit of our method is it can keep the color fidelity better than the previous methods like [4, 2, 6, 8, 11]. The ground, the clothes and the roof of the hall are natural in our result since there is no over-processing or halo effect along with the depth discontinuous regions.

(a) Input

(b) DCP [4]

(c) MSCNN [9]

(d) DehazeNet [2]

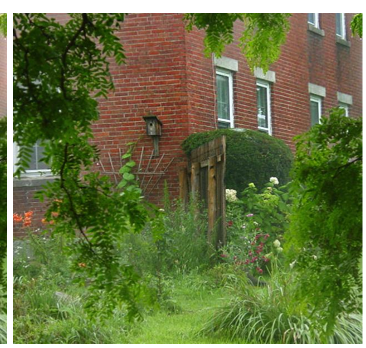
(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

(h) cGAN [8]

(i) PDN [11]



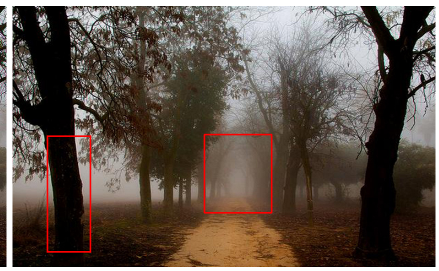
(j) Ours

Figure 5. Visual comparison on the real image. Most methods can restore the texture of the building. However, the color can be more natural in our result. Meanwhile, our method avoids halo effect like [8].

(a) Input

(b) DCP [4]

(c) MSCNN [9]



(d) DehazeNet [2]

(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

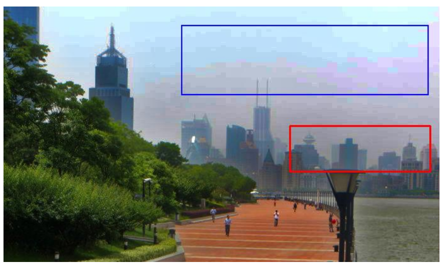
(h) cGAN [8]

(i) PDN [11]

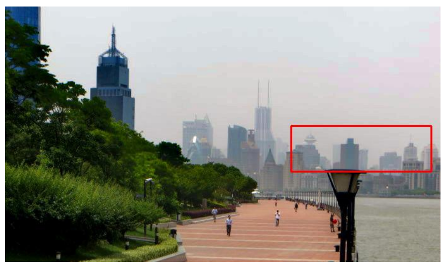
(j) Ours

Figure 6. Visual comparison on the real image. The image is with medium level of haze. As marked in the red box, the distant trees in the result of ours can be slightly clearer than the other methods. The texture of trunks marked in the red box in close view is not darkened like the previous methods.

(a) Input



(b) DCP [4]



(c) MSCNN [9]

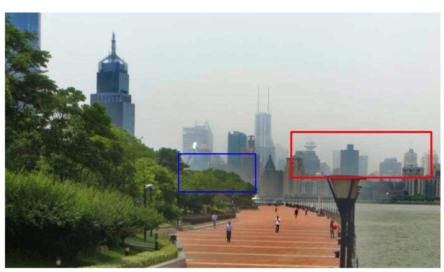
(d) DehazeNet [2]

(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

(h) cGAN [8]



(i) PDN [11]

(j) Ours

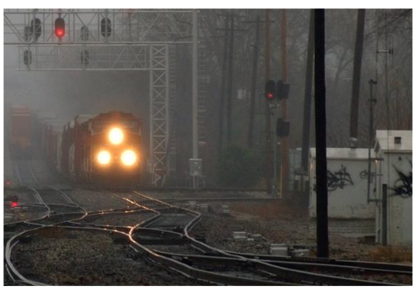
Figure 7. Visual comparison on the real image. Our method can restore the distant buildings more clearly as marked in the red box, and avoid the over-processing of regions like the sky in [4] or halo effect in [11] as marked in blue.

(a) Input

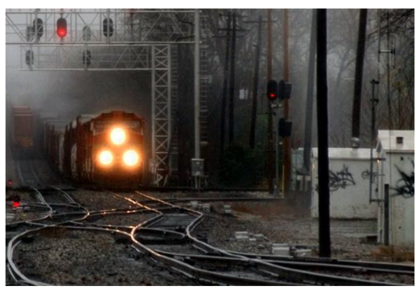
(b) DCP [4]

(c) MSCNN [9]

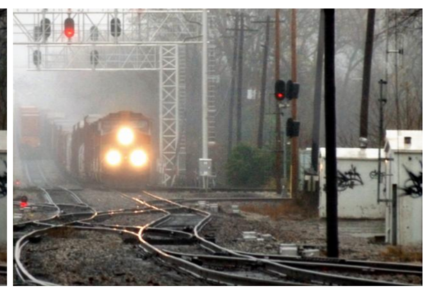
(d) DehazeNet [2]



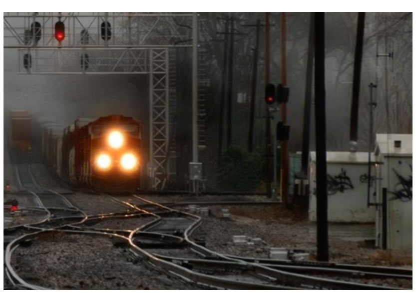
(e) AOD [6]



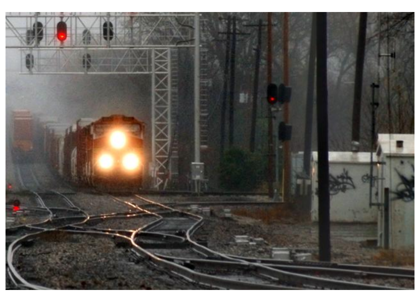
(f) GFN [10]



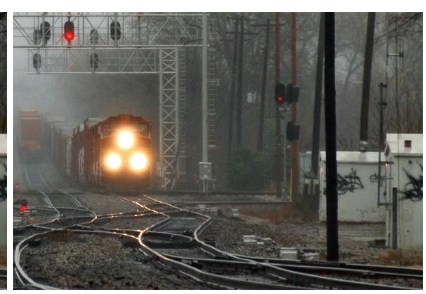
(g) DCPCN [12]



(h) cGAN [8]



(i) PDN [11]



(j) Ours

Figure 8. Visual comparison on the real image. The impact of haze is more significant. Our method can restore the texture of distant train and bushes more clearly, and there is no problem like darkening or over-exposure.

(a) Input

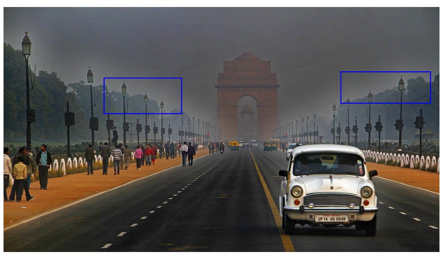
(b) DCP [4] (c) MSCNN [9] (d) DehazeNet [2]

(e) AOD [6] (f) GFN [10] (g) DCPCN [12]

(h) cGAN [8] (i) PDN [11] (j) Ours

Figure 9. Visual comparison on the real image. The dense haze diverges the appearance between close and distant regions. The methods of [9, 2, 6, 10, 12, 8, 11] are not able to restore the details of the building in distant regions, which is covered by dense haze. DCP [4] even leads to a severe color distortion. In comparison, texture and color can be better in our restoration.

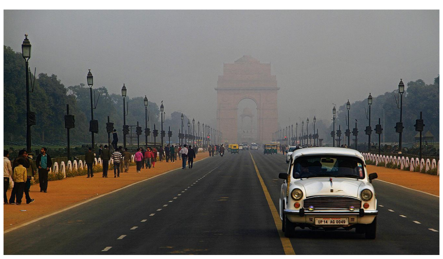
(a) Input



(b) DCP [4]

(c) MSCNN [9]

(d) DehazeNet [2]

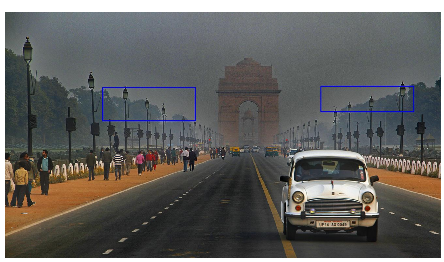


(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

(h) cGAN [8]



(i) PDN [11]

(j) Ours

Figure 10. Visual comparison on the real image. The dense haze makes the gate in distant regions almost invisible. Compared with the previous methods, ours not only restores a clear view of the gate and other distant objects, but also avoids darkening the ground or the sky in the restoration. We also avoid the halo effect around the regions where trees touch the sky.

(a) Input

(b) DCP [4]

(c) MSCNN [9]

(d) DehazeNet [2]

(e) AOD [6]

(f) GFN [10]

(g) DCPCN [12]

(h) cGAN [8]

(i) PDN [11]

(j) Ours

Figure 11. Visual comparison on the real image. The image is with dense haze that leads to the unclear distant textures. The results of [9, 2, 6, 10, 8, 11] still retain some haze, and DCPCN [12] even leads to the over-exposure. Ours can restore a more vivid and clearer result. The trunks and the distant people become more visually pleasing, and the red and blue clothes are also brighter in our restoration.