DD-CycleGAN: Unpaired image dehazing via Double-Discriminator Cycle-Consistent Generative Adversarial Network

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Abstract

Despite the recent progress in image dehazing, the task remains tremendous challenging. To improve the performance of haze removal, we propose a scheme for haze removal based on Double-Discriminator Cycle-Consistent Generative Adversarial Network (DD-CycleGAN), which leverages CycleGAN to translate a hazy image to the corresponding haze-free image. Unlike other methods, it does not need pairs of hazy and their corresponding haze-free images for training. Extensive experiments demonstrate that the proposed method achieves significant improvements over the existing methods, both quantitatively as well as qualitatively. And our method can also achieve good effects qualitatively when applied to the real scenes too.

1. Introduction

High-quality images are critically desired in the fields of traffic and security monitoring. However, images captured by the camera from outdoor environments often suffer from floating particles in the atmosphere (e.g., smoke, dust, haze, and liquid droplets). Two main effects on images caused by haze are: contamination with an additive component to the image and attenuation of the light (Berman and Avidan, 2016). Specifically, hazy images captured in outdoor environments result in poor picture quality, and cause difficulty in distinguishing object features in the image. Therefore, image haze removal has become an important research field of computer vision.

In order to remove the effect of haze on the images, previous dehazing methods usually follow the similar pipeline of (1) modeling the medium transmission, (2) refining the coarse transmission model, (3) estimating the global atmospheric light, and (4) reconstructing the latent image according to the predicted model parameters (Li et al., 2017). Generally, these traditional dehaze methods are mainly divided into two types: image enhancement and model based dehazing algorithms.

In recent years, deep learning based methods have attracted much attention in various fields, such as image classification (Zhang et al., 2018; Fridadat et al., 2018), image inpainting (Yu et al., 2018), particular in single haze removal. However, methods based on traditional deep learning require paired datasets, i.e., hazy image and its corresponding haze-free image are needed. But currently we do not have enough datasets about paired hazy images, which impede the study of deep learning in the field of dehazing. Our method requires neither paired samples of hazy and ground truth images nor any parameters of atmospheric scattering model during the training and testing phases.

In 2014, Goodfellow proposed a new framework, called generative adversarial networks (GANs) for the generation of models through the process of confrontation estimation (Goodfellow et al., 2014), which effectively solves the problem of small amount datasets. There has been some state-of-the-art GAN based solutions (Zhang et al., 2017) for single image dehazing, which require hazy input image and its ground truth in a paired manner. In 2014, Goodfellow et al. (Goodfellow et al., 2014; Li et al., 2017c) propose a novel generative adversarial net (GAN), which has achieved great results in representation learning (Salimans et al., 2016; Mathieu et al., 2016) and image generation (Mathieu et al., 2015; Li et al., 2017c). Recent methods adopt the similar idea for image generation applications, such as future prediction (Pathak et al., 2016), and image inpainting (Wu et al., 2016), as well as to other domains like 3D data (Vondrick et al., 2016) and videos (Chen et al., 2017).

The algorithm uses the data without labels to train the generated model, which learns the real data characteristics and distribution, through the help of the simultaneously trained discriminator model.
with a small amount of data with labels. The network uses random noise as input to generate a sample (fake) image, and then sends it to a discriminative model, which identifies the true and false samples as accurately as possible so that both models are constantly optimized to achieve equilibrium, that is, the discriminative model cannot judge the current sample being from the generated sample or the real sample. In this way, a one-to-one paired mapping between training data is needed. The idea of adversarial loss is the key point to GANs’ success, which can force the generated images to be more real and indistinguishable from real samples.

In 2017, Zhu et al. (2017) proposed a Cycle-Consistent Adversarial Network (CycleGAN), which does not require paired images any more, and provides solutions to the problem of scarce datasets. By effective aggregation of cycle-consistency and perceptual losses, Cycle-Dehaze network (Engin et al., 2018) architecture has also been proposed for an end-to-end image dehaze scheme.

Inspired by the Cycle-Consistent Adversarial Networks, this paper proposes a new type of networks, called Double-Discriminator Cycle-Consistent Adversarial Networks (DD-CycleGANs), for dehazing road scenes. In this method, only a small amount of unpaired data is needed, greatly reducing the difficulty of data collection.

In summary, following are the major contributions of this work:

1. In traditional GANs, it is hard to balance the generator and the discriminator, and it gets mode collapse easily. So, we use weight clipping instead of cross entropy, it can solve the problem of training instability and mode collapse and the converge speed of training is faster than that in GANs.

2. In order to make the discriminator better approximating the optimality and solve the difficulty to balance the generator and the discriminator, we increase the number of discriminators to providing reliable feedback for the generator more stable. Therefore, we proposed Double-Discriminator CycleGAN (DD-CycleGAN) for haze removal.

3. To our best knowledge, this is the first attempt of using Double-Discriminator CycleGAN (DD-CycleGAN) for dehazing, which can be readily and effectively adapted to traffic scenes to enhance the diversity of haze removal algorithm application scenarios.

The remainder of this paper is organized as follows: Section 2 reviews the related works on dehazing and several existing deep learning models. Section 3 presents our proposed DD-CycleGAN and the corresponding modifications on the CycleGAN. Section 4 shows our simulation results and comparisons with those of other competing solutions, followed by the Conclusion in Section 5.

2. Related works

The existing haze removal methods can be broadly classified into following three categories: Image enhancement algorithms (Ying Xu et al., 2006; Rahman et al., 2004; Tan, 2008; Kim et al., 1998; Stark, 2000), Model based haze removal algorithms (Swami and Das, 2018; Jean-Philippe and Hautiere, 2009; Fattal, 2008; He et al., 2011; Nayar and Narasimhan, 1999; Narasimhan and Nayar, 2002, 2003, 2000). Nayer et al. (Nayar and Narasimhan, 1999; Narasimhan and Nayar, 2002, 2003, 2000) divide the influence of atmospheric reflections on the light into the atmospheric attenuation of the scene light and the superposition of ambient light, and mitigate their adverse impacts separately, resulting in haze-free images with less information being lost. Fattal (2008) estimates albedo and transmission of a scene by using Independent Component Analysis (ICA), however, unsatisfactory performance in dense haze and extensive computation time limits the application of this method (Swami and Das, 2018). He et al. (2011) propose a novel dark channel prior algorithm, by taking advantage of the observation that the image captured in the outdoor environments contains many dark pixels. This method fails to work in scenes where a major portion of an image is covered by light or other similar object, such as sky, and the computation is extensive.

2.2. Deep learning

Recent years, with the rapid developments of deep learning, problems of haze removal are also addressed using deep learning approaches (Li et al., 2017c; Ren et al., 2016; Ling et al., 2016; Cai et al., 2016; Cai et al., 2016; Ren et al., 2018). Cai et al. (2016) present an End-to-End system for image haze removal called DehazeNet, which uses the deep learning to intelligently learn the characteristics of haze and solve the difficulties of manual feature design. This DehazeNet learns a mapping from a hazy image to the scene transmission map. Ren et al. (2016) present a network based on multi-scale convolutional neural network (MSCNN). This approach requires manual tuning parameters of hazy input image for gamma correction, which is complicated. AOD-Net (Li et al., 2017c) estimates a new variable based on the transformation of the atmospheric scattering model.

2.3. Image-to-image translation via CycleGANs

The idea of image-to-image translation goes back to Hertzmann et al.’s Image Analogies (Hertzmann et al., 2001), where a nonparametric texture model is employed on a single input–output image pair (Efros and Leung, 1999). Recently, many approaches use a dataset.
of input–output examples to learn translation function using CNNs (Long et al., 2015). Many problems in image processing, computer graphics, and computer vision can be formulated as an image-to-image translation task. For example, label to scene, aerial to map, day to night, edges to photo and generating photographs from sketches or from attribute and semantic layouts (Sangkloy et al., 2017; Karacan et al., 2016). In this paper, we also formulate haze removal as an image-to-image translation task, but unlike prior works, we learn the mapping with unpaired training examples.

In certain cases, the labeled ground truth is hard to obtain. Recently, some methods based on unpaired images have been developed to overcome this problem (Zhu et al., 2017; Dong et al., 2017; Yi et al., 2017a). Owing to a lack of labeled data, Dong et al. (2017) design an unsupervised framework, which succeeds in gender transformation and face swapping. Zhang et al. (2017) proposed a general supervised framework, called Cycle-Consistent GAN (CycleGAN) as inspired by pix2pix (Isola et al., 2016), which aims to minimize the reconstruction error between two sets of training data (Zhu et al., 2017). Although CycleGAN works well for the same task of pix2pix in the unsupervised way, it does not perform as good as pix2pix. Compared to the traditional GANs, the input of the network is no longer a noise but a picture and no longer dependent on the paired datasets, and a cycle consistency (Chen et al., 2017; Godard et al., 2017) is introduced in the loss function of CNN training.

Learning inter-domain mappings from unpaired data can improve performance in structured prediction tasks, such as haze removal in this paper, by reducing the need for paired data. It is particularly powerful because it requires only unpaired examples from two image domains X and Y. The Cycle-Dehaze network (Engin et al., 2018) architecture is one of the early attempts of using CycleGAN proposed for an end-to-end image dehazing scheme. The Cycle-Dehaze network effectively aggregate cycle-consistency and perceptual losses, so it can achieve the dehazing tasks better. To be able to obtain high-resolution dehazed images, the Cycle-Dehaze employed a simple upsampling method based on Laplacian pyramid, and successfully applied on the NTIRE 2018 challenge on single image dehazing datasets, i.e., I-HAZE (Ancuti et al., 2018a) & O-HAZE (Ancuti et al., 2018b).

Inspired by this idea, we further introduce a more effective loss in our work to push two generators to be consistent with each other, along the same line of research by Yi et al. (2017b), who use a similar objective as ours for dual learning in machine translation (He et al., 2016). To overcome the commonly observed model collapse problems in adversarial training and to achieve more stable results, the Wasserstein GAN (WGAN) (Arjovsky et al., 2017) with the weight clipping technique is introduced to solve the problem of training instability and mode collapse in the GAN. More specifically, limiting the absolute changes of weight updating in the discriminators with a predefined threshold to ensure the discriminator will not give very different values for two slightly different input samples.

Since CycleGANs have been successfully used to translate images from one style to another, thanks to its lower requirement on the scale and label of the data, we believe it is also suitable for the situation of less available hazy image datasets. By treating image restoration as an image-to-image translation, we are certain that CycleGANs can restore the haze scenes if trained with the original hazy images and some unpaired haze-free image. More specifically, a hazy image serves as the input, the haze-free image will be restored successfully by the trained generator (Chen et al., 2017).

2.4. GANs with multiple discriminators

Durugkar et al. (2016) extend GANs with multiple discriminators, which are supposed to be more stable on providing feedback for the generator. And for one generator, multiple discriminators of the same structure with random initialization are utilized as teachers for the generator.

To be specific, multiple discriminators can approximate the optimal discriminator. Take for an example, when one of the discriminators reaches a far superior converged state to the generator, the other discriminator can still be used to provide constructive gradients for updating the generators, instead of stopping the learning of the generators.

3. Proposed method

As shown in Fig. 1, our proposed Double-Discriminator CycleGAN (DD-CycleGAN) translates a hazy image to the corresponding haze-free image. In this section, an overview of the general architecture is first given, then the formulation is presented, and finally, the learning procedure is provided in details.

3.1. Double-Discriminator CycleGAN (DD-CycleGAN)

The method (DD-CycleGAN) proposed in this paper has two discriminators with the same structure against one generator, which solves the problem of mode collapse in the traditional GANs. By extending to multiple discriminators of the same structure, DD-CycleGAN can approximate the optimal discriminator better (Durugkar et al., 2016), and is more stable on providing reliable feedback for the generator (Xu et al., 2017). A bijective mapping is created between these two generators, so that the images in the X domain can correspond in the Y domain (Zhu et al., 2017).

Fig. 1 shows the flow chart of the proposed Double-Discriminator Cycle-Consistent Adversarial Network (DD-CycleGAN). As illustrated in Fig. 1(a), our model includes two mappings: G maps X to Y with two discriminators, D_Y1 and D_Y2, on domain Y, and F maps Y to X with two discriminators, D_X1 and D_X2, on domain X. In addition, an image x in X domain is mapped to the Y domain by generator G to generate image y, that is, G(x) = y. Similarly, take y as the input of the Generator F maps back to the X domain and generates x, that is, F: Y → X, with F(y) = x. Note that D_X1 and D_X2, encourage F to translate Y into outputs indistinguishable from domain X, and we hope when we translate one image into another image and back again, we should return to the original image where we began. Fig. 1(b) shows forward training process for the DD-CycleGAN. An image x is taken as the input and sent to generator G to generate image y. The discriminators D_Y1 and D_Y2, judge whether the image y is either generated or real image. The image x is then generated by generator F, which encourages the final output be indistinguishable from the input image, i.e., x = (G(x)) ∼ x. Fig. 1(c) shows reverse training process for the proposed DD-CycleGAN. An image y is taken as the input of the generator F to generate image x. The two discriminators D_X1 and D_X2, judge whether the image x is either generated or real image. The image y is then generated by generator G, which also encourages the final output be indistinguishable from the input image, i.e., y = (F(y)) ∼ y.

3.2. Formulation

In a traditional GAN, it may happen that two different images in the source domain X are both mapped to the same image in the target domain Y. Pathak et al. (2016) show that adding a traditional loss function to the network can increase the effectiveness of the network. In this paper, we follow Zhu et al. to adopt L1 norm (Badrinarayanan et al., 2017) to measure the cycle consistency loss, and the images mapped to the Y domain can still be mapped back to the X domain through the other generator, so that the final output looks more like a real picture and is more like the input image. Furthermore, our method uses a different loss function that can better represent the state of the network training, as can be seen in Fig. 2 that in the continuous iteration process of the generator, the L1 norm decreases continuously. Therefore, the dehazing effect of the image is also better.
trainig. Each generation model corresponds to two discrimination models of the same structure to enhance the stability of the training and make the effect of the image haze removal more ideal. For the generator G and its corresponding discrimination networks $D_Y$ and $D_Z$, the loss function is defined as follows:

$$L_{GAN} (G, D_Y, X, Y) = E_{y \sim P_{data}}[D_Y(y)] - E_{x \sim P_{data}}[D_Y(G(x))]$$  \hspace{1cm} (2)$$

Where mapping function $G$ tries to make image $G(x)$ look like as images from domain $Y$, at the same time, discriminator $D_Y$ aims to distinguish the image to be a real sample $y$ or from a generated image $G(x)$. $G$ is expected to minimize this function via $D_Y$. We introduced a similar loss function for the discriminator $D_Z$:

$$L_{GAN} (G, D_Z, X, Y) = E_{x \sim P_{data}}[D_Z(x)] - E_{y \sim P_{data}}[D_Z(G(y))]$$  \hspace{1cm} (3)$$

For generator $G$, we express the objective loss as:

$$L_{GAN} (G, D_Y, D_Z, X, Y) = \lambda_1 L_{GAN} (G, D_{Y_1}, X, Y) + (1 - \lambda_1) L_{GAN} (G, D_{Y_2}, Y, X)$$ \hspace{1cm} (4)$$

Similarly, the loss function is defined as follows for mapping function $F$ and its corresponding discriminating networks $D_X$ and $D_Z$:

$$L_{GAN} (F, D_X, X, Y) = E_{x \sim P_{data}}[D_X(x)] - E_{y \sim P_{data}}[D_X(F(y))]$$ \hspace{1cm} (5)$$

$$L_{GAN} (F, D_{X_1}, D_{X_2}, Y, X) = \lambda_2 L_{GAN} (F, D_{X_1}, Y, X)$$

$$+ (1 - \lambda_2) L_{GAN} (F, D_{X_2}, Y, X)$$ \hspace{1cm} (7)$$

The final objective loss function is as follows:

$$L (G, F, D_{X_1}, D_{X_2}, D_{Y_1}, D_{Y_2}) = L_{GAN} (G, D_{Y_1}, D_{Y_2}, X, Y)$$

$$+ L_{GAN} (F, D_{X_1}, D_{X_2}, Y, X) + \lambda_3 L (G, F)$$ \hspace{1cm} (8)$$

Where $\lambda_1$, $\lambda_2$ and $\lambda_3$ are respectively the weights of $L_{GAN} (G, D_{Y_1}, X, Y)$, $L_{GAN} (F, D_{X_1}, Y, X)$ and $L (G, F)$. We will show the effect of the weight in Section 4.2.

In the original CycleGAN, it fixes the weight of the adversarial loss to 1.0 and the cycle consistency of two generators share the same weight parameter. In addition, we find that the susceptibility to mode collapse is different when using different datasets, so we introduce $\lambda_3$ as a hyperparameter.

Our final objective is

$$G^*, F^* = \arg \min_{G, F} \max_{D_{X_1}, D_{X_2}, D_{Y_1}, D_{Y_2}} L (G, F, D_{X_1}, D_{X_2}, D_{Y_1}, D_{Y_2})$$ \hspace{1cm} (9)$$

Among them, generator $G$ wants to minimize the objective loss function, in contrast, discriminator $D$ wants to maximize the objective function.
3.3. Network architecture

The CNN network structures of the generator model and the discriminator model used in this paper are as follow:

(1) Generator Architecture

Generator networks contains three parts: encoder, converter and decoder, which are composed of stride 2 convolutional layers, 6 residual blocks, and 3 fractionally-stride convolutional layers. The network is illustrated in Fig. 4.

The encoder performs a series of downsampling on the input image, then the converter transforms the feature vectors of the pictures in the source domain to the feature vectors in the target domain, followed by a series of upsampling performed in the decoder, which achieves low-level features from feature vectors.

(2) Discriminator Architecture

For the discriminator networks we use PatchGAN (Isola et al., 2016), rather than the whole image, which aims to identify whether each patch is generated by the generator or not. As shown in Isola et al. (2016), it is found that visually similar results can be created with 256 × 256 receptive fields using ImageGAN and 70 × 70 receptive fields using PatchGAN. Therefore, in this paper, we mainly experiment on 70 × 70 PatchGAN. Then the average response values of all patches are obtained on the entire image as the final judgment of the image result. The network is illustrated in Fig. 5.

4. Experimental results and discussions

4.1. Training details

The experimental platform for this paper is implemented with Python3.5 and Tensor-Flow1.3. Note that the hardware configuration used is a server with 1.80 GHz, 64-core CPU, GPU GeForce GTX 1080Ti and 128 G of memory.

In our experiments, we use the method presented by Shrivastava et al. (2017), updating the discriminators using history images rather
than the image generated by the latest generative networks. We store 50 images generated previously in the image buffer. We have tested based on CycleGAN, so parameters are identical to those in the original CycleGAN, and we have verified some parameters to ensure the best results. So in all experiment presented, we set $\lambda_1 = 0.5$, $\lambda_2 = 0.5$ (Durugkar et al., 2016), $\lambda_3 = 10$ (Zhu et al., 2017) and the Adam solver (Kingma and Ba, 2014) is used in this paper with a batch size of 1. We conducted experiments and intercepted the 1000 steps of the experiment to observe the effect of the choice of learning rate on the experimental process. The results are shown in Fig. 6. At the beginning, the learning rate is 0.0002. At the first 100 epochs we keep the same learning rate and at the next 100 epochs the rate decays to 0 linearly.

4.2. Dataset

We provide results of our experiments based on Realistic Single Image Dehazing (RESIDE) dataset (Li et al., 2017b). RESIDE dataset contains 50 high-resolution monocular videos (21260 frames) generated from five different virtual worlds in urban settings under different image and weather conditions. At the same time, we also focused on O-HAZE dataset, it contains 45 pairs of real hazy and corresponding haze-free outdoor images. Haze has been generated with a professional haze machine that imitates with high fidelity real hazy conditions.

4.3. The effect of discriminator in DD-CycleGAN

To illustrate the influences of different factors in the proposed DD-CycleGAN, two widely used metrics, PSNR and SSIM (Wang, 2004). They are adopted to evaluate the haze removal quality regarding signal and structure similarities. Specifically, we evaluate the difference between the haze-free output and the corresponding ground truth via these two metrics.

As can be seen in Fig. 7, we try different experiments based on different networks. In Fig. 7(c), we use the weight clipping rather than cross entropy used in vanilla CycleGAN, the effect is good. In Fig. 7(d), we add the double discriminators to the vanilla CycleGAN, the effect of haze removal is further improved. In Fig. 7(e), we combine the above methods, and it can be seen in Table 1, our proposed DD-CycleGAN method can achieve the highest performance, which verifies the feasibility of our method. In addition, an ablation studies are performed to demonstrate the improvements obtained by different modules in the proposed method.

4.4. Different architecture of generator

In our method, we add 6 ResBlocks in the network. For purpose of proving the effectiveness of residual block, we experiment on DD-CycleGAN with 6 ResBlock and without ResBlock respectively, and compare the experimental results.

As can be seen from Fig. 8, Fig. 8(c) is DD-CycleGAN without ResBlock. Some of the haze is still not removed in the processing results. Fig. 8(d) is DD-CycleGAN with ResBlock, and the results show good dehaze effect and achieve higher PSNR and SSIM. It can be seen in Table 2, and DD-CycleGAN with ResBlock can achieve the highest performance.

4.5. Effect of the weight in loss function

Taking into account the advantages of Multi-Discriminator, we set the weight in loss function from Durugkar et al. (2016). The $\lambda_1$ and $\lambda_2$ is set to be 0.5 and 0.5 respectively which can balance the performance of double discriminators when necessary.

Table 3 shows the validation of our experiments further demonstrates the rationality of the parameter settings.

The experimental result can be seen in Table 3, when $\lambda_1 = 0.5$, $\lambda_2 = 0.5$, the PSNR and SSIM are the highest.

4.6. Effect of optimizers in DD-CycleGAN

We experimented on three optimizers: SGD, RMSProp and Adam, and the results can be seen as following.

As can be seen in Fig. 9 and Table 4, when we use DD-CycleGAN with Adam, the SSIM and PSNR are the highest, and it can remove haze better.

4.7. Quantitative evaluation

In this paper, we experiment on two different datasets. As can be seen in Tables 5 and 6 whatever which dataset we choose, the performance of our method is the best, as indicated by the achieved highest PSNR and SSIM.

4.8. Image analysis

Fig. 10 shows a comparison of the dehazing results of the five methods. It can be seen from the experimental results that the result under MSCNN is not good as others, and the results under DCP, DehazeNet and AOD-Net are not bright enough. But our proposed method still has a good dehazing capability, which greatly enhances the contrast of the image.

4.9. Test for realistic image

In this paper, DD-CycleGAN is also applied to the real scenes, and it can also achieve good effects qualitatively, which proves the feasibility of this method. (See Fig. 11.)
Fig. 7. Qualitative dehazing performance of images in ablation studies. From left to right: input hazy image, ground truth, CycleGAN + weight clipping, CycleGAN + Double discriminators, DD-CycleGAN (ours).

Fig. 8. Qualitative dehazing performance of images with and without resblock. From left to right are Input, Ground truth, DD-CycleGAN without ResBlock and DD-CycleGAN with ResBlock.

Fig. 9. The effect of the optimizers in our method. From left to right: Input, Ground truth, DD-CycleGAN with SGDM (Wang, 2004), DD-CycleGAN with RMSProp and DD-CycleGAN with Adam.
Table 4
The effect of optimizers.

<table>
<thead>
<tr>
<th>Optimizer</th>
<th>SSIM</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD-CycleGAN with SGDM</td>
<td>0.7846</td>
<td>24.163</td>
</tr>
<tr>
<td>DD-CycleGAN with RMSProp</td>
<td>0.7812</td>
<td>24.723</td>
</tr>
<tr>
<td>DD-CycleGAN with Adam</td>
<td>0.7957</td>
<td>25.859</td>
</tr>
</tbody>
</table>

Table 5
Dehazing results on RESIDE.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>DCP</th>
<th>MSCNN</th>
<th>DehazeNet</th>
<th>AOD-Net</th>
<th>Ours</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>SSIM</td>
<td>PSNR</td>
<td>SSIM</td>
<td>PSNR</td>
</tr>
<tr>
<td>HSTS</td>
<td>16.62</td>
<td>0.8179</td>
<td>17.57</td>
<td>0.8102</td>
<td>21.14</td>
</tr>
<tr>
<td>SOTS</td>
<td>14.84</td>
<td>0.7609</td>
<td>18.64</td>
<td>0.8168</td>
<td>0.9153</td>
</tr>
</tbody>
</table>

Fig. 10. Dehaze results on RESIDE. From left to right are experiments under different methods as DCP, MSCNN, DehazeNet, AOD-Net and Ours.

Fig. 11. Dehaze results on RESIDE. From left to right are experiments under different methods as DCP, MSCNN, DehazeNet, AOD-Net and Ours.

Table 6
Dehazing results on O-HAZE.

<table>
<thead>
<tr>
<th>Method</th>
<th>DCP</th>
<th>MSCNN</th>
<th>DehazeNet</th>
<th>Ours</th>
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<tbody>
<tr>
<td></td>
<td>SSIM</td>
<td></td>
<td>SSIM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PSNR</td>
<td>16.586</td>
<td>19.068</td>
<td>16.207</td>
</tr>
</tbody>
</table>

5. Conclusion

In this paper, we leverage CycleGAN and make improvements based on it for image dehazing, namely Double-Discriminator Cycle-Consistent Adversarial Network (DD-CycleGAN). CycleGAN learns a one-to-one mapping, which ensures all source hazy image to be mapped to a target corresponding haze-free image. This two-discriminator architecture are better approximate the optimal discriminator and achieve better result in image with different haze concentrations and scene depths, and the reasonable prediction of the area with higher concentration of haze is better than the current mainstream dehaze methods, which proves the feasibility of this method.

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