Single Image Dehazing Using Deep Convolution Neural Networks

Shengdong Zhang[1], Jian Yao[1](✉), and Edel B. Garcia[2]

[1] School of Remote Sensing and Information Engineering, Wuhan University
[2] Advanced Technology Applications Center, Cuba

Abstract. Outdoor images taken in bad weather conditions often suffer from poor visibility. However, single image haze removal is an ill-posed problem, because the number of the equations is smaller than the number of unknowns. In this paper, a deep learning-based method called dehazeCNN, is proposed to estimate an clear image patch for a hazy image patch, which can be used to reconstruct a haze-free image. Our method recovers a clear image by a learning model containing no hazy information. Our method also adopts Deep Convolution Neural Networks which takes the patch atom that can be used to generate hazy image patch and haze-free patch as the input and outputs the corresponding haze-free patch. Then we reconstruct a haze-free image from those patches. Finally, we remove the color distortion in the haze-free image via contextual regularization effectively. Experimental results show that the proposed method outperforms the state-of-the-art haze removal methods.

Keywords: Haze removal, image restoration, Deep Convolution Neural Networks

1 Introduction

Outdoor scene images are often degraded because of the bad weather condition, such as air particles, fog, haze and smoke, which reduces the visibility and quality of the image. The light received by camera from an object in the distance is weakened along the line of sight. In addition, the receiving light is blended with the atmospheric light-the environment light reflected into the line of sight by air particles. The degraded images show low contrast and quality.

Haze removing or defogging is urgently needed in computer vision applications and commercial/computational photography due to its wide applications. However removing fog is a challenging problem due to the fog is decided by the unknown depth information. The problem is ill-posed, because single input image only provides three equation for a pixel, but there exists four unknown quantity. Therefore, a lot of methods have been proposed by using additional data or multiple images [1,2,3]. [1] remove the fog effect by taking multiple images of the same scene under the condition the depth of the scene is given. [2] remove the haze by taking two or more images with different degrees of polarization. [3] describe a depth based method which requires user to input depth data or a 3D model of the scene. Further more, removing haze from single image is a more difficult case. but significant progress was made for single image haze removal in recent. The series of methods rely on using stronger assumptions or priors. All this methods can be divided into two kind category. The first is contrast-based, the second is statistical approaches. [4] remove haze from single image by explaining the image through a model that accounts for surface shading and the scene transmission. By assuming that the surface shading and medium transmission functions to be locally statistically uncorrelated, they solve the problem of a constant albedo and the airlight-albedo ambiguity, and get a haze free image. This method is physically sound and can generate a high quality results. However, it cannot deal with heavily hazy images very well and may lose efficacy in the cases of the assumption is false. [5] proposed a simple but effective method to remove the haze, which is based on the statistical observation of the dark channel, which is called dark channel prior, using this observation can get a rough transmission map. In order to refine the transmission map, a time consuming matting was used to solve the unknown transmission region. He et al.'s results is high quality, but the time is very long, and maybe fail for some particular images. The first case is the scene objects are similar to the air light and no shadow in the image. The second case is the image is physical invalid. [6] found that scene albedo and depth have a natural ambiguity, they used novel probabilistic method(Factorial Markov Fandom Field) to solve this ambiguity,and treated the the scene albedo and depth as independent latent layers. By using natural image and depth statistics as priors they could get a haze free image. [7] introduced a novel Bayesian probabilistic method that jointly estimated the scene albedo and depth from a single foggy image by fully leveraging their latent statistical structures. [8] proposed a new dark channel prior for removing haze from the image. Unlike the dark-channel prior that assumes zero minimal value, the new prior searches for the darkest pixel average inside of each ellipsoid. [9]removes haze by using color-lines in natural images where pixels of small image patches typically show a one-dimensional distribution in RGB color space. He derives a local formation model that illustrates the color-lines in the context of hazy scenes and use it for solving the scene transmission. In contrast, By observing the haze free image and haze image, [10] find that the haze free images have higher contrast, so he remove haze from image by maximizing the local contrast of the result image and keeping the image smooth. The results are impressive but may not be physically sound. [11] also propose a contrast-based method in 2009, their method is computationally effective, but their method also have an assumption the transmission must be smooth except alone the edges regions with gradient jumps.

More recently, some learning based methods [12,13,14,15] was proposed to remove haze from single image effectively. In [13], Tang et al. investigate the different haze-relevant feature of hazy image, and use best suitable feature combination to estimate a transmission map for a hazy image. In [12], Zhu et al. propose a learning based method which consider the transmission as a linear combination of the saturation and brightness of pixels in a hazy image. They use a learning strategy to get the parameters of the model. The most related to our work is Cai et al.[14] and [15], which are also a deep learning-based method for estimating of transmission map. In [15], Ren et al. propose a multi-scale deep convolutional neural networks to remove haze from single image. In contrast, our method estimate a haze-free image from hazy image directly. Compared with other learning-based methods, our network is much simpler and generates high quality results. Regarding the training data, Cai et al. 's method uniformly samples 10 random transmissions $t \in (0, 1)$ to generate 10 hazy patches for a clear image patch [14]. In contrast, our method simple the training data collection. By finding the common image atoms shared by hazy image patch and clear image patch, we can generate one pair of image patch atom and clear image patch for a clear image patch.

The contribution of this paper is three-fold. First, we propose a deep convolutional neural networks to learn effective features from image patch atom shared by hazy image patch and haze-free image patch for the estimation of an approximate clear image patch. Our goal is to estimate an clear image patch for image patch atom, which can provide a way to estimate a clear image directly from hazy image. Second, our work is the first to explore the relation between the hazy image patch and clear image patch. As shown in Section 2, we can see that a clear image patch will share a same image patch atom with hazy image patch, which can help us to train a network without hazy information to remove haze from the single image. Third, we can use the image patch atom by hazy image patch and haze-free image patch to simple the preparation of the train data, we only need to consider the clear image and A, which also reduce the number of training data .

2 A image patch atom by shared hazy image patch and haze-free image patch

In this section, our goal is finding a image patch atom which can be used to generate hazy image patch and haze-free image patch.

2.1 Modeling of Haze Images

Our model used in this paper is very similar to [16], which is widely used in computer graphics and computer vision, which also explains the formulation of the haze :

$$\mathbf{I}(i, j) = J(i, j) * t(i, j) + (1 - t(i, j)) * A, \tag{1}$$

where $\mathbf{I}$ represents the haze image, J represents the haze free image, A represents the global atmospheric light, t represents the transmission describing the Probability of the light that is not scattered and absorption by air particle or mist and arrives at the camera. To remove haze from the haze image is equal to solve the A, t from $\mathbf{I}$. The first term we call it as direct attenuation and The second term we call it as air light A contributions.

2.2 Proofing

Based on the equation 1, we can derive the following equation:

$$\mathbf{I}(i,j) - A = (J(i,j) - A) * t(i,j), \tag{2}$$

Generally, we can assume that pixels in a small image patch will share a same transmission, which is use widely in single image dehazing [5,17,9,18]. Based on this assumption, we assume that the transmission in a local patch is constant. We use $\tilde{t}(x)$ represents this transmission. Then we use $(IA_1, \cdots, IA_n)$ represents $\mathbf{I}(x) - A$ and $(JA_1, \cdots, JA_n)$ represents $J(x) - A$. In the following equations, we use x represents (i, j).

We can normalize the hazy model equation 1:

$$N(\mathbf{I}(x) - A) = N((J(x) - A) \times \tilde{t}(x)) = \frac{(J(x) - A) * t(x)}{sqrt(\sum_{k=1}^{n}(JA_k \times \tilde{t}(x))^2)}$$
$$= \frac{(J(x) - A) * t(x)}{sqrt(\sum_{k=1}^{n} JA_k^2) \times \tilde{t}(x)} = (\frac{JA_1}{\sum_{k=1}^{n} JA_k^2}, \cdots, \frac{JA_n}{\sum_{k=1}^{n} JA_k^2}) = N((J(x) - A) \tag{3}$$

According to the equation 3, we can see that through a simple operation a hazy image patch can transfer to a image patch which can be used to generate the haze-free image patch. To the best of our knowledge, our work is the first study designed to explore the relation between the hazy image patch and haze-free image patch. Because the hazy image patch and haze-free image patch share same image patch atom, we can use the image patch atom to identify the haze-free image patch, the relation between image patch atom and the clear image patch can be learned from deep learning.

2.3 Validation

In this subsection, we conduct some experiments to validate our theory. In order to show the result visually, we choose to apply absolution and scale operation to common feature. We choose to use 1000×1000 patch size for showing the result, which is not correct for dehazing. In our dehazing program we use patch size 16×16, which is based on the assumption in a local image patch pixels share same transmission value. In the Figure 1 we can see that our feature is determined by the A and the haze-free image patch, one haze-free image patch will get same image patch atom for all hazy image patches with same A.

In this part, we also study the influence of A. In Fig 2 we show the influence of A, and we can see the different A have different image patch atom, and find that $A = (160, 160, 160)$ and $A = (200, 200, 200)$ have some similarity in image patch atom.

2.4 Motivation

Our patch image atom is inspired by the sparse coding, which uses dictionary to represent an image. In this paper, we use patch image atom to reconstruct a

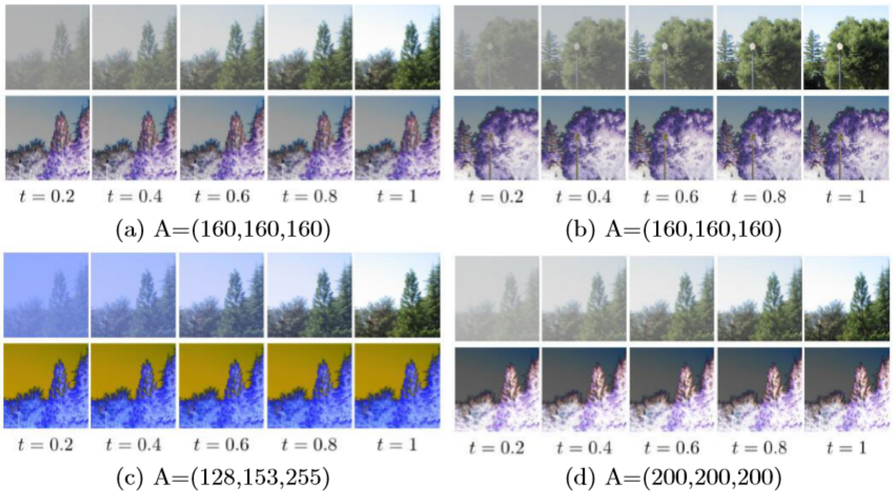

Fig. 1: The hazy image patch and corresponding image patch atom.

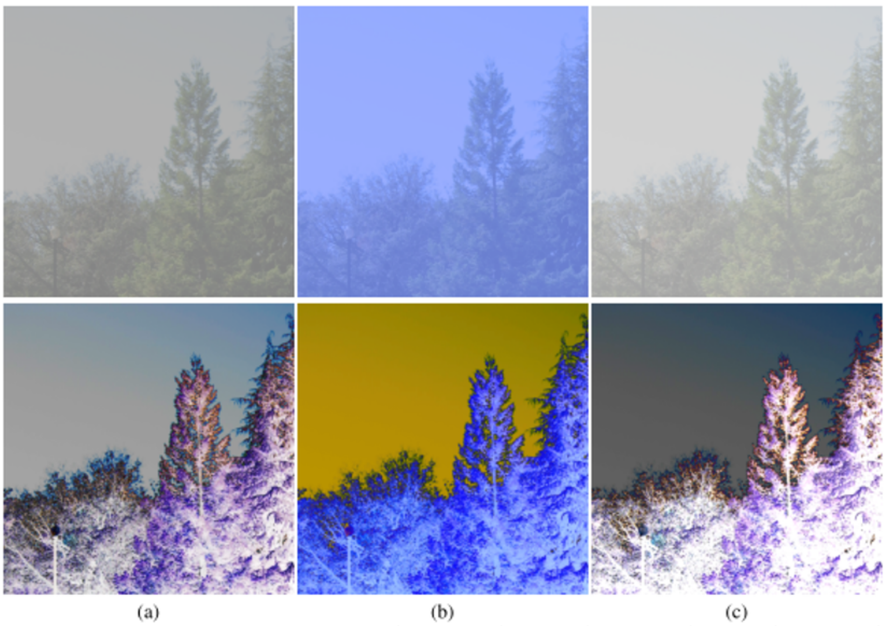

Fig. 2: Comparison on the influence of A: (a) $A = (160, 160, 160)$. (b) $A = (128, 153, 255)$. (c) $A = (200, 200, 200)$.

haze-free image. Sparse coding use a linear combination of atoms to reconstruct an image. Different from traditional sparse coding, we use only one atom to

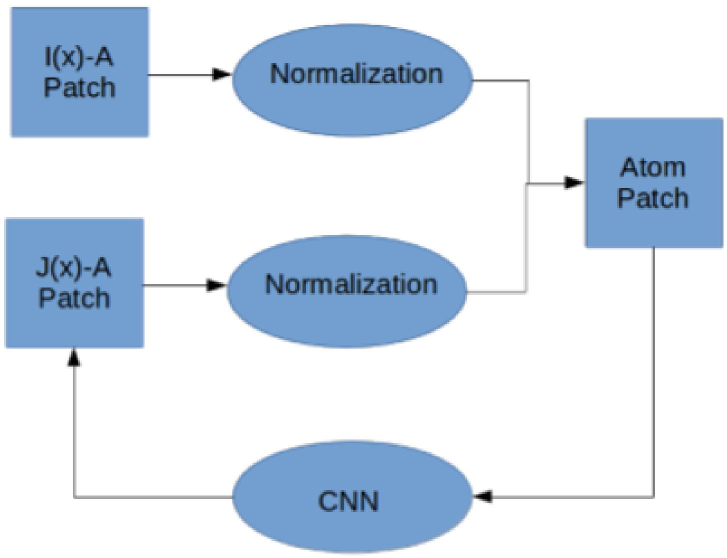

Fig. 3: The relation between the hazy image patch, the haze-free image patch and the corresponding image patch atom.

reconstruct $J(x) - A$. Our method learned a relation between the atom and haze-free image patch, we use this relation to reconstruct a haze-free image. In Fig 3, we show the relation between the image hazy patch, image haze-free patch and image patch atom, and we can use image patch atom to reconstruct the haze-free image patch.

3 Haze removal

In this section, we describe our method how to use image patch atom to remove haze from single image. Our method consists of four essential steps: normalizing the hazy image, extracting patches from hazy image, estimating approximate clear image patches using Deep Convolution Neural Networks, removing color distortion and block artifacts (see Alg. 1).

Patch Extraction and Normalization: We estimate A using one of the previous methods [5,17]. We define $\mathbf{I}_A$ as:

$$\mathbf{I}_A(x) = \mathbf{I}(x) - \mathbf{A} \tag{4}$$

$$\mathbf{I}_A(x) = ||\mathbf{I}_A(x)|| \tag{5}$$

In order to use image patch atom described in Section 2, we need to extract patches from the $\mathbf{I}_A$, and then normalize these patches. In our program, we set the patch size as $16 * 16$ and the patches are non-overlapped. Then we normalize

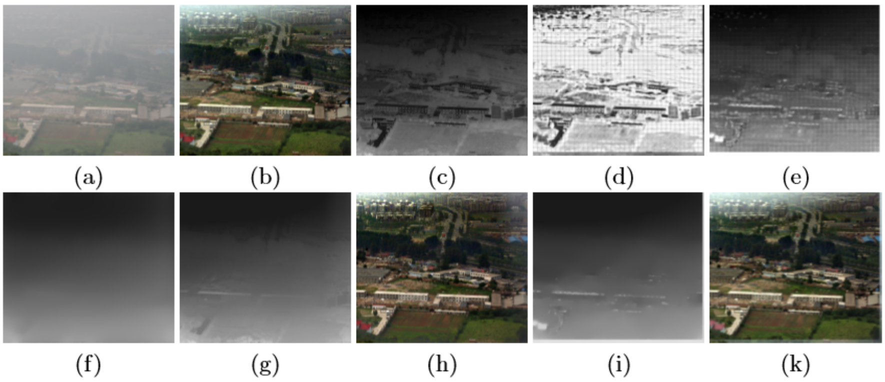

Fig. 4: Intermediate and final results of our method: (a) An input hazy image; (b) The output image; (c) The distance $r(x)$ of every pixel of the hazy image to the airlight; (d) The estimate distance $\tilde{r}(x)$; (e) The init $\tilde{t}(x)$; (f) The final $t(x)$; (g) The guided filter output; (h) The dehazed result using transmission (g); (i) The contextual regularization output without guided filter; (k) The dehazed result using transmission (i)

the patches, which will convert an hazy image patch into an image patch atom shared by haze-free image patch and hazy image patch.

Estimating Initial Clear Patches: Based on the fact that that weights sharing allows for relatively larger interactive range than other fully connected structures, we choose convolutional neural network (CNN) architecture. Our CNN architecture is very simple, which can be implemented easily. Our convolutional network architecture can be expressed as:

$$F^0(Y) = Y, \tag{6}$$

$$F^n(Y) = \max(W^n * F^{(n-1)}(Y) + B^n, 0), n = 1, 2 \tag{7}$$

$$F_W(Y) = W^n * F^{(n-1)}(Y) + B^n, n = 3 \tag{8}$$

n represents the layers, which ranges from 1 to 3. Our convolutional network architecture consists of five layers and contains four hidden layers for convolution generation. For the bottom layer with index 0, which is the input layer and expressed by equation 6. In each intermediate layer, which is expressed by equation 7, represents a convolution process for the nodes in the convolution network regarding its neighbors. By convention, $*$ represents the convolution operation, W^n represents the convolution kernel and B^n is the bias. The top layer with $F_W(I)$ in equation 8 generates the initial clear patches from the network. Then we can get the initial clear image.

Remove Color Distortion and Block Artifacts: Our estimating result may shift from the line formed by $\mathbf{I}(x)$ and $\mathbf{A}$. In order to recover a high quality result, we need apply an regularization operation. Because we recover $\mathbf{J}(x) - \mathbf{A}$ from the image patch atom, we can use this information and $\mathbf{I}_A(x)$ to recover the initial transmission of each pixel. Geometrically the hazy model 1 implies that In RGB color space, the vector $\mathbf{I}(x)$, $\mathbf{J}(x)$, $\mathbf{A}$ is coplanar and the end points form a line. The transmission is the ratio of the two line segments [5]:

$$\tilde{t} = r(x)/\tilde{r}(x), \tag{9}$$

Where $r(x)$ represents the distance in RGB space of every pixel in the hazy image to the airlight, $\tilde{r}(x)$ represents the distance in RGB space of our estimated clear pixel to the airlight. We define $r_J(x)$ as following:

$$r_J(x) = ||\tilde{\mathbf{J}}(x) - A(x)||, \tag{10}$$

We can replace the $\tilde{r}(x)$ with $r_J(x)$ and get the initial transmission map $\tilde{t} = r(x)/r_J(x)$. Then we use guided filter to get a smooth transmission map. We find that the result of guided filter is not smooth enough, because our method may have some areas not are predicted, so we use the context regularization on the result of guided filter. After that we get the final transmission map.

Dehazing: Once the transmission map is estimated, we can recover the haze-free image using Equation 1 :

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{t(x)} + \mathbf{A} \tag{11}$$

In Figure 4, we show an example of our method, which is summarized in Algorithm 1. We find that for some images whose size can't be divided by 16, a contextual regularization need be applied to get a smooth transmission map.

Algorithm 1 Our proposed single image dehazing framework.

Input: The hazy image.
Output: The haze free image.
1: Compute the atmospheric light $\mathbf{A}$ using Meng et al.'s method;
2: $\mathbf{I}_A(x) = \mathbf{I}(x) - \mathbf{A}$;
3: Compute $r(x)$ using Equation 10;
4: Extract patches with size 16×16 from $\mathbf{I}_A(x)$, normalizing each patch;
5: Compute $\tilde{r}(x)$ using deep convolutional network;
6: Compute transmission:$\tilde{t} = r(x)/r_J(x)$.
7: Smooth transmission $\tilde{t}$ using guided filter.
8: Get the finial dehazing result using Equation 11.

3.1 Training of dehazeCNN

In general, deep models [19] need a vast amount of labelled data to solve the parameters of the network. In this paper, we seek to find a way to reduce the number of training data. By intensive study of haze image patch and haze-free

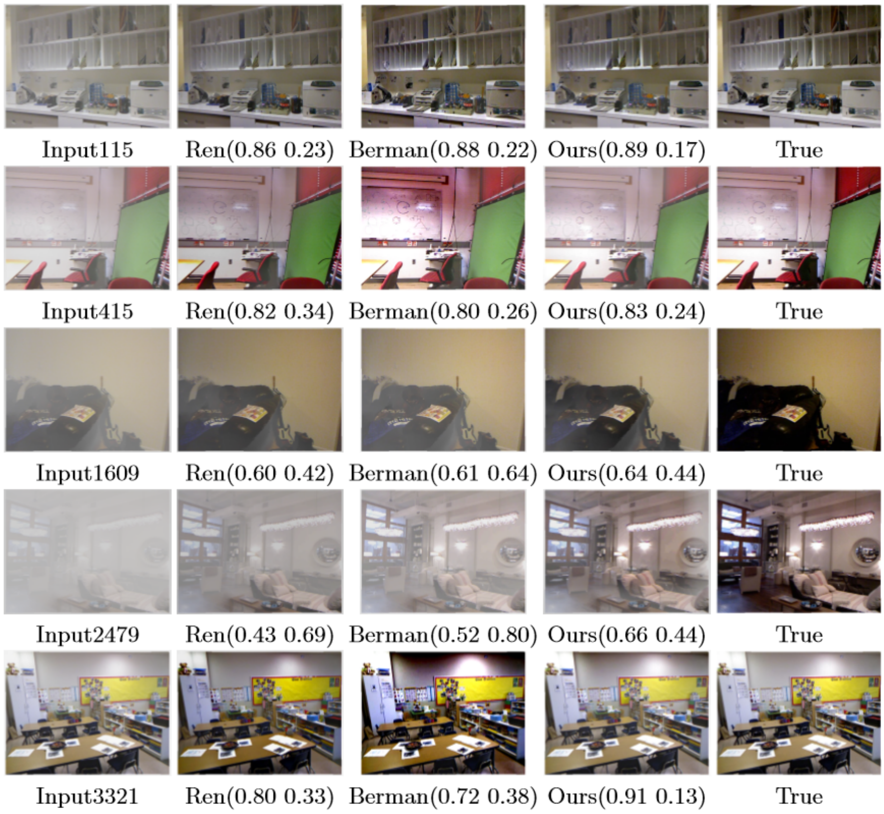

Fig. 5: Comparison on Indoor hazy images. The number in left is SSIM value and the right is L1ERR

image patch, we find that we can use a image patch atom to generate haze-free image patch and hazy image patch. We use this observation to reduce the number of training data. For training of a network to remove haze from single input image, it is even more hard as the pairs of haze-free image and hazy image. We use the same assumptions [13]: first, image content and medium transmission have no relation with each other; second, the pixels in a local patch have same transmission. According to this two assumptions, Cai et al. assume an arbitrary transmission for an individual haze-free image patch. For a haze-free image $\mathbf{J}^p$, Cai et al. [14] assume $t \in (0, 1]$, and generate a haze image patch $\mathbf{I}^p$ according to the haze model $\mathbf{I}^p = t * \mathbf{J}^p + (1-t) * \mathbf{A}$. In contrast, according to the relation of haze-free image patch, hazy image patch and image patch atom, we generate a pair image patch atom and haze-free image patch, because we eliminate the influence by normalization, we only need one pair of image patch atom and haze-free image patch for a haze-free image patch which is different from Cai et al. 's method. According to [14], they collect 10000 haze-free image patch from Internet. For a haze-free image patch, they uniformly sample 10 random transmissions $t \in (0, 1]$ to generate 10 hazy patches. So a training dataset contain 100000 image patches was generated. In contrast, our training data only need one image patch atom for a haze-free image patch, so for a training dataset contain same number of image patches, our dataset includes more diversity. Therefore, our method can get a better result than Cai ta al. 's method.

4 Experiment results

In this section, we evaluate our method on a large dataset containing both synthetic and natural images and compare our performance with state-of-art methods [5,9,18,14,15]. First, we show a comprehensive compare with other state-of-the-art method on indoor synthetic hazy images. Second, we show a comprehensive compare with other state-of-the-art method on outdoor synthetic hazy images. Third, we show a comprehensive compare with other state-of-the-art method on natural images. In this section, we use the $L1err = \frac{1}{N}\sum_{c \in R,G,B} |\mathbf{J}^c - \mathbf{G}^c|$ as metric, where $\mathbf{J}$ resents the dehazing result image and $\mathbf{G}$ resents the ground truth image. In order to evaluate the dehazing methods, we generate an indoor hazy image dataset. This dataset is based on the indoor RGBD dataset [20], we use $\mathbf{A} = [0.78, 0.78, 0.78]$ and choose three value for β as $0.06, 0.3, 0.5$. The outdoor image dataset is from [9].

4.1 The effectiveness of guided filter

In this subsection, we show that our output of network have high quality. First, we do an operation of projection, which projects the pixel into the line form by $\mathbf{I}$ and $\mathbf{A}$, we denote this result as **NR**. Then we apply a guided filter on $\tilde{t}$, and get a smooth transmission map, then use this transmission map to recover a haze-free image, we denote this result as **GR**.

As shown in Table 1, we can see that the guided filter will result in image degradation, but will improve the visual quality. The output of the network is more similar to the original image both for indoor image and outdoor image. So our network result has contained enough information to recover a complete hazy free image. Due to the guided filter reduce the performance of our method, we need to find a new method to reduce the halo and artifacts.

type	**NR**	**GR**
outdoor	1.82e+01	2.18 e+01
indoor	1.57 e+03	1.60 e+03

Table 1: Quantitative comparison on indoor hazy images and outdoor hazy images. Red color indicates best result, blue color indicates better.

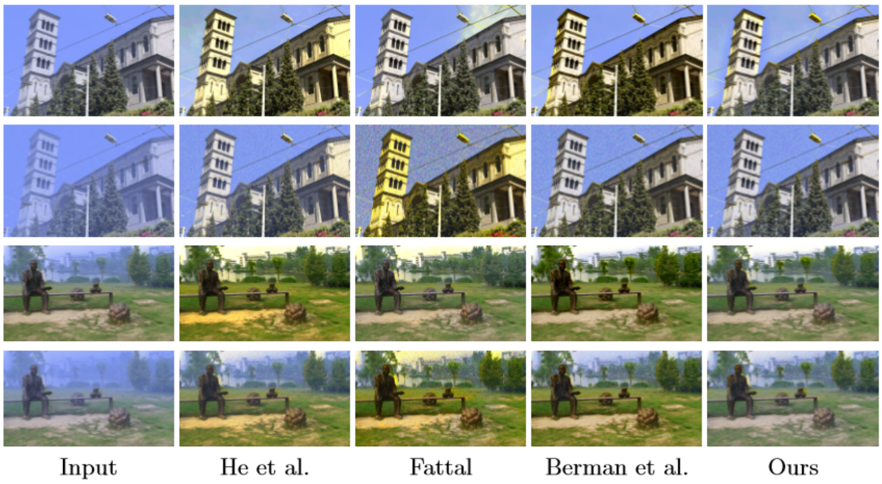

Fig. 6: Comparison on Outdoor hazy images.

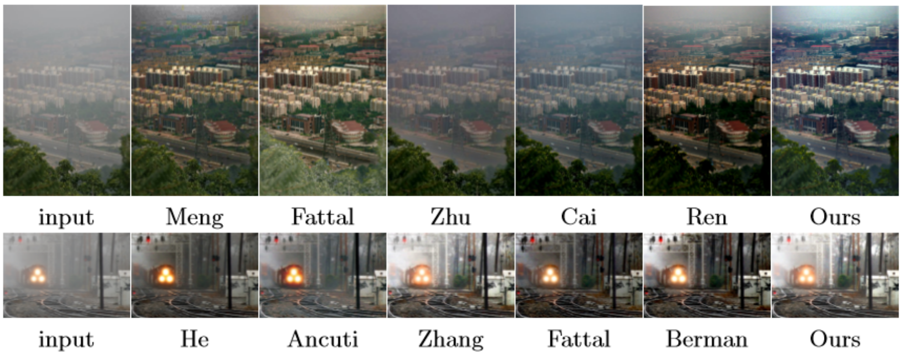

Fig. 7: Comparison on natural images:[Left] Input images. [Right] Our result. Middle columns display results by several methods, since each paper reports results on a different set of images.

4.2 Synthetic hazy images

In this subsection, we compare our method with state-of-the-art methods on both indoor and outdoor synthetic hazy images. First, we compare our method with other state-of-the-art methods, and list the overall results. Second, we show some results on some images in Fattal's dataset and some images in our dataset.

An outdoor synthetic hazy images dataset was introduced by [9], which is available online. In order to evaluate the dehazing methods for indoor hazy images, we generate an indoor hazy image dataset. This dataset is based on the indoor RGBD dataset [20], we use $\mathbf{A} = [0.78, 0.78, 0.78]$ and choose three value for β as $0.06, 0.3, 0.54$ to generate hazy image [15].

Indoor Hazy Images: In this part, we compare our method with Ren et al. [15] and Berman et al. [18]. The structural similarity (SSIM) image quality assessment index [21] is used to evaluate performance of the methods. The higher value of SSIM shows the dehazing result is better. First, we show some results use SSIM and L1Err. Second, we compare all image in our dataset using SSIM and L1Err. For quantitative performance evaluation, we select 5 images from our dataset, The results shows in Figure 5. We can find that Berman et al. [18] may overestimate the haze thickness in some slight regions in Input3321. Ren et al. [15] may underestimate the haze thickness in some heavy hazy regions. In contrast, our method can estimate the hazy thickness more reasonable than Ren et al.and Berman et al. We also compare the overall result for our dataset, the result is shown in talbe 2, we can find that our method can get the best performance of all. We also test that our method can highest score for 1698 images using SSIM and 2106 highest score for 1698 images using L1ERR in 4347 images.

type	Ren et al.	Berman et al.	Our
L1	1.58e+03	1.65e+03	1.4e+03
SSIM	3.12e+03	3.19e+03	3.24e+03

Table 2: Quantitative comparison on our dataset. Red color indicates best result, blue color indicates better.

Outdoor Hazy Images: In this part, we also compare our method with some state-of-art methods [5,9,18] on some images in dataset. We show the qualitative result in Table 3. As we can see from the results, our method can get a very similar results to the ground truths in general and also can get highest quality result for particular image. In Figure 6 we show some results on four hazy images, we can see our network output is very similar to haze-free image.

image	He et al.	Fattal	Berman et al.	Our
road1-D1	0.176	0.115	0.442	0.172
road1-D2	0.246	0.100	0.117	0.134
road1-D3	0.133	0.080	0.220	0.061
road1-S10	0.166	0.116	0.133	0.146
road1-S25	0.209	0.198	0.184	0.184
road1-S50	0.299	0.346	0.286	0.263
road1	0.146	0.098	0.117	0.134
road2	0.177	0.132	0.120	0.115

Table 3: Quantitative comparison on road1. Red color indicates the best results and blue indicates the second.

4.3 Quantitative Evaluation on Benchmark Natural Images Dataset

In this subsection, we compare our method with state-of-the-art methods. As previously pointed by [5], the image after dehazing might look dim, since the scene radiance is usually not as bright as the airlight. For display, we perform a global linear contrast stretch on the output, clipping 0.5% of the pixel values both in the shadows and in the highlights.

Figure 7 compares our method with state-of-the-art methods [5,17,22,12,14,15]. Some of the results are provided by Fattal [9] , Berman [18] and Cai [14], which are online. We also get some results via the program provided by Ren [15]. As shown in Figure 7, Ancuti et al.'s method can't remove haze completely. He et al.'s method can yields an excellent results in general but lack some micro-contrast details when compared to [9] and ours. This is obvious in the zoomed-in buildings shown in Cityscape results, where in our result and [9] the windows are clearer than in [5]. We also find that the result of Ren et al. loss some details of tree in Cityscape. In contrast, our method can deal this area well, our result shows much better details of tree. For "train" image, the result of Zhang et al. [22] can't deal with the boundary between segments well, which results in a lot of artifacts. The Ancuti's result can't remove haze completely from the hazy image. Fattal's and Berman's method can't deal with tree area well. In contrast, our method can deal tree area well.

5 Conclusions

In this paper, we have proposed a deep learning-based method for removing haze from single input image. First, we study the relation between the hazy image patch and haze-free image patch, and find that image patch atom can be used to generate haze image patch and haze-free image patch, we use this relation to simple the preparation of training data. Second, we propose a deep network to remove haze from single input image, and shows our method can get a high quality and quantitative results. Third, we show that the guided filter can reduce the halo and artifacts, but reduce the quality of dehazing result. Finally, we do an extensive evaluation of the method on different types of datasets that demonstrates its high accuracy. In order to improve our method we will extend our method by using haze-line as a regularization. Inspired by [18], we can use a few hundreds of distinct colors to represent an image, and we can reduce the halo and artifacts.

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