Single Image Haze Removal using Inception-Dense Model

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Abstract-The quality of images captured in bad weather is often affected by chromatic casts and low visibility due to the presence of atmospheric particles. In most of the existing image de-hazing methods restoration of the color balance is often ignored. In this paper, we propose a image de-hazing network which enhances the visibility of images captured in hazy environment. The proposed network consists of multi-scale convolution filters comprised by inception module to extract the multi-scale features. Along with the multi-scale feature extraction, we propose a use of dense connections to propagate learned features within the inception modules. Combinely, the proposed network is designed by incorporating the principles of both inception and dense module, thus named as inception-dense network. To train the proposed network for image de-hazing, we make use of structural similarity index metric along with the L_1 loss. Existing benchmark databases are utilized to evaluate the pro-posed network for image de-hazing. Experimental analysis shows that the proposed network outperforms the existing approaches for image de-hazing.

Keywords –De-hazing, Inception, Dense , Database

I. INTRODUCTION

Dust and smoke particles accumulate in relatively dry air results in Haze. Industrial pollution can result in a dense haze, which is called smog. The visibility of pictures taken in a hazy environment degrades the ability of humans or computer vision algorithms. This results in difficulty to perceive the scene information. Thus, the presence of the haze or fog particles in the atmosphere degrades the performance of computer vision algorithms such as object detection [7], moving object segmentation [27] etc. Therefore, image de-hazing is required to improve the precision of vision algorithms for images taken in the hazy environment. Research in the field of image de-hazing is roughly divided into prior based methods [2, 12, 13, 17, 20, 38, 39, 48] and learning based methods [3, 6, 28]. Among these, prior based methods rely on the haze relevant prior and extract haze relevant features. These haze relevant features are further used to estimate the scene transmission map and atmospheric light [17] to recover the haze-free scene. Learning-based approaches foresee these parameters using the trained deep network. Along with remarkable **succession** of these approaches, it also Cascades error which is upstretched due to the employed priors.

Figure1. Haze-free image recovered by the proposed method. Left column: Input hazy image Right column: Haze-free image recovered using the proposed method.

To resolve this issue, we propose an end-to-end conditional generative adversarial network (cGAN) for image de-hazing. Figure 1 shows the outdoor recovered haze-free image from hazy image which is recovered by the proposed net-work. The

proposed network uses basic principles of two modules-inception and dense. So, named as inception-dense network (ID-Net). Directly we can recover the haze free image by estimation of intermediate feature maps using proposed ID-net.
The proposed work of this network are listed below:

1. ID-Net is proposed for image de-hazing which is nothing but an End-to-end conditional generative adversarial network.
2. By combining both inception and dense module, A novel generator network is designed
3. Extensive experimental analysis has been carried out on two existing benchmark datasets.

The paper is organized as Section I and II illustrate the introduction and literature survey on image de-hazing respectively. Section III presents the proposed method for image de-hazing. Section IV depicts the training of the proposed ID-Net. Further, the experimental results are discussed in Section V. Finally, Section VI concludes the proposed method for image de-hazing.

II. Literature Survey

Effect of the haze is directly proportional to the depth of an object from the camera device. To understand this non-linearity, various approaches have been proposed such as polarized filters [31, 33], use of multiple images of same scenery [5, 25], prior based hazy models [2, 12, 13, 17, 20, 38, 39, 48] etc. Initially, in the area of image de-hazing, Schechner et al. [31, 33] proposed the polarized filters. Their approach works with multiple images of the same scene but differs in polarization angle. This approach fails because of its multi-image dependancy. Nayer et al. [25] overcame the hardware complexity by correlating dissimilarity between multiple images of the same scene but captured in different weather. With this approach, it is unable to restore the haze-free scene immediately, if multiple images of the same scene are not available for different weather conditions. Cozman et al. [5] resolved multi-image dependency by utilizing 3D geometrical model which is based upon the depth information of the hazy scene. In the last decade, image de-hazing has made remarkable progress due to the convincing assumptions re-garding the haze spread or haze density. Tan et al.[38] proposed contrast enhancement of the hazy scene. They removed haze by maximizing the local contrast of the hazy image. However, this method fails and create blocking artifacts when there is a depth discontinuity in the hazy image. He et al. [17] proposed dark channel prior (DChP) to restore the visibility in the hazy scene. It comprises of dark pixels i.e. pixels which are having very low intensity among one of the color channels for a given hazy-free scene. This simple but effective assumption is used to estimate the haze density and atmospheric light to recover the haze-free scene. DChP fails in complicated edgy structures and undergoes the halo effect [3]. The efficiency of [17] depends upon the accurate estimation of the scene transmission map. To estimate the robust trans-mission map of the hazy scene, researchers follow post-processing techniques such as guided filtering [16], median filtering [20, 45] etc. Lai et al. [22] proposed two priors to estimate the optimal transmission map. They estimated locally consistent scene radiance and context-aware scene transmission and utilized atmospheric scattering model to recover the haze-free scene. Wang et al. [41] utilized multi-scale retinex algorithm to estimate the brightness components. Further, with the help of a physical model, they are covered the haze-free image. Zhu et al. [48] proposed a color attenuation prior (CAP) which considers a HSV color space to extract the haze-relevant features.

To avail the advantages of multiple haze priors, Tang et al. [39] proposed regression framework for image de-hazing. They have proposed the extraction of different haze relevant features using existing haze relevant priors and learned the integrated features to estimate the robust scene transmission map. This approach improved the accuracy in single image haze removal. However, it propagates the errors upstretched due to the employed priors. Thus, to minimize the cascading error, researchers make use of convolutional neural networks (CNN). Existing learning-based approaches [3,6,7,28] estimate the scene transmission map using CNN. Further, a global airlight estimation followed by atmospheric scattering model restores the haze-free scene.

Methods discussed above share the same belief that in order to recover a haze-free image, estimation of an accurate scene transmission map is essential. The atmospheric light is calculated separately and the clean image is recovered using the atmospheric scattering model. Although being intuitive and physically grounded, such a procedure does not directly measure or minimize the reconstruction distortions. As a result, it will undoubtedly give rise to the sub-optimal image restoration quality. The errors in each separate estimation step will accumulate and magnify the overall error. In this context, Li et al. [23] de-signed an end-to-end architecture known as AOD-Net for image de-hazing. They analyzed the internal relationship between the end-to-end de-hazing network and traditional atmospheric model. Further, Swami et al. [36] proposed an end-to-end network based on conditional GAN for image dehazing. Recently, researchers [8, 11, 26] make use of unpaired training approach for various computer vision applications. [8, 11] utilized unpaired training approach for image de-hazing whereas [26] found its use for moving object segmentation. In the next Section, we have discussed the proposed method for single image haze removal.

III. Proposed Method for Image Dehazing

As discussed in the previous Section, cascaded error up-stretched due to the employed priors. Thus, in this paper, we propose an end-to-end generative adversarial network i.e. ID-Net for image de-hazing. The proposed network integrates advantages of both inception and dense network modules.

3.1. Proposed Generator Network

The number of computations in CNN are directly proportional to the spatial size of the feature maps those which are processed through the network Also it is use to reduce the computations. The number of computations in CNN are directly proportional to the spatial size of the feature maps those which are processed through the network. To reduce the number of computations and to increase the receptive field, down-sampling operation is purposefully designed. We design filters having a spatial size of 3 3 as shown in the Figure 2. Parameter details are discussed in Section 3.1.1. The inception block consists of three convolution layers of 1 1, 3 3 and 5 5 spatial size as shown in the Figure 2. The proposed feature map integration approach differs from original inception module [37] as it integrates the feature maps in two stages i.e. dense concatenation followed by element-wise summation. Here, we make use of identity mapping [15] .

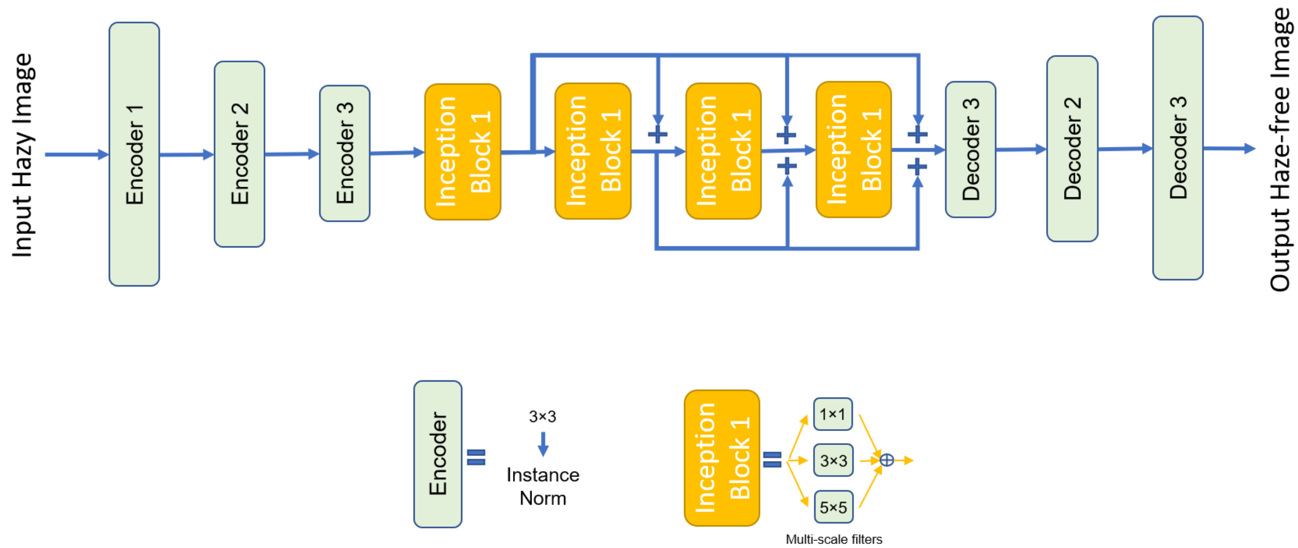

Figure 2. Generator network of the proposed Inception-Dense Network

To extract the multi-scale features, five inception blocks are connected in a cascaded manner as shown in the Figure 2. Which are densely connected via dense connections. In Figure 2, dense connections are shown by dotted black lines. Therefore, the proposed network is named as an inception-dense network. The architecture of proposed generator network is divided into three parts namely: (1) Encoder block (2) Inception block, and (3) Decoder block. Encoder/Decoder does simple convolution/de-convolution followed by non-linear activation function (ReLU).We use instance normalization [40] to normalize the network feature maps. Figure 2 show the encoder blocks. We have designed encoder blocks among which down-samples the input feature maps. Its purpose is to increase the receptive field in the network. 3.1.1Parameter Details of the Proposed Generator Network Let a 3 3 Convolution-Instance Normalization-ReLu layer with n filters and stride '1' denoted asconv3sd1-n.Similarly, a 3 3 De-Convolution-Instance Normalization- ReLu layer with n filters and up-sampling Factor '2' denoted as deonv3up2-n. Each inception block consists of parallel convolution layers of filter-size 1 1, 3 3 and 5 5 having stride 1 and 64 filters is denoted by Ins-64. Hence, the proposed Inception-Dense network is represented as: conv3sd1-32, conv3sd2-64, conv3sd2-64, Ins_1, Ins_2, Ins_3, Ins_4, Ins_5, deonv3up2-64, deonv3up2-32, and conv3sd1-3. 3.2. Network Loss Function. To recover the structural details by image restoration technique. The scene visibility is improved in obtained haze-free image by retaing structural details in image de-hazing. Thus, it is required familiarize the network learning about structural loss along with the L1 loss and adversarial loss [21]. Along with traditional L1 loss, we utilize

the structural similarity index metric (SSIM) as a loss function. While training the proposed Inception-Dense Network, we have generated the true edge information with consideration of the edge loss
Therefore, overall loss function is,

$$L\ (G; D) = l_{cGAN}\ (G; D) + l_{SSIM}\ (G) + l_{Edge}\ (G) + \ l_{L1}\ (G) \qquad (1)$$

Where, l_{cGAN} (G; D) is a conditional GAN loss [21], l_{L1}, l_{SSIM} , l_{Edge} represents the traditional L1 loss, SSIM loss and Edge loss respectively, and is loss weightage[1]. Thus, overall objective of the proposed GAN is given as,

$$G = \arg\ \min\ \max\ L\ (G\ ; D) \qquad (2)$$

G is used during testing phase, in order to generate haze- Inception network outperforms the other existing methods by a large margin for image de-hazing. Specifically, proposed network increases SSIM by almost 9% as compared to the prior-based deep learning approaches [3, 6, 28] and increases by 5% as compared to end-to-end deep learning methods [11, 23, 44, 47] which shows the robustness of RI-GAN to recover the haze-free scene. Also, there is a significant improvement in the PSNR and CIEDE2000 of the proposed RI-GAN as compared with the existing state-of-the-art methods.

3.2. Real World Hazy Images

For image de-hazing the performance of the pro-posed network is compared with the existing state-of-the-art methods on D-Hazy [1] database as shown in Table 1From Figure 4, we can clearly observe that the proposed RI-GAN generates the appropriate scene in recovered haze-free scene. We compare the results of existing prior-based hand-crafted and learning approaches [3, 6, 17] and end-to-end dehazing approach [23]. Qualitative analysis shows that proposed Inception-Dense Network outperforms the other existing approaches and generates a visually pleasant haze-free scene. It is difficult to carry quantitative analysis of image de-hazing algorithms for real-world hazy scenes due to the unavailability of pair of the real-world hazy and haze-free scenes,. Therefore, we carry only qualitative analysis for the real-world hazy scenes. Five frequently used real-world hazy scenes are utilized here for analysis. Result comparison of proposed and existing approaches on these images is shown in Figure free scene. [42], peak signal to noise ratio (PSNR) and color difference measure (CIEDE 2000) [32] for quantitative evaluation. The experiments are categorized into two parts: performance of the proposed Inception-Dense Network on synthetic and real-world hazy image.

3.3. Performance on Synthetic Hazy Images

We used D-Hazy [1], database to validate the proposed network for image de-hazing. Quantitative Analysis D-Hazy [1] is a standard dataset used to evaluate the performance of various algorithms for image de-hazing. It comprises of pair of 1,449 indoor hazy and respective haze-free scenes. We utilized the entire database i.e. 1,449 images for quantitative analysis of the proposed network. We compare the results of existing prior-based hand-crafted and learning approaches [3, 6, 17] and end-to-end dehazing approach [23]. Qualitative analysis shows that proposed Inception-Dense Network outperforms the other existing approaches and generates a visually pleasant haze-free scene. From Figure 4, we can clearly observe that the proposed RI-GAN generates the appropriate scene in recovered haze-free scene. We compare the results of existing prior-based hand-crafted and learning approaches [3, 6, 17] and end-to-end dehazing approach [23]. Qualitative analysis shows that proposed Inception-Dense Network outperforms the other existing approaches and generates a visually pleasant haze-free scene.

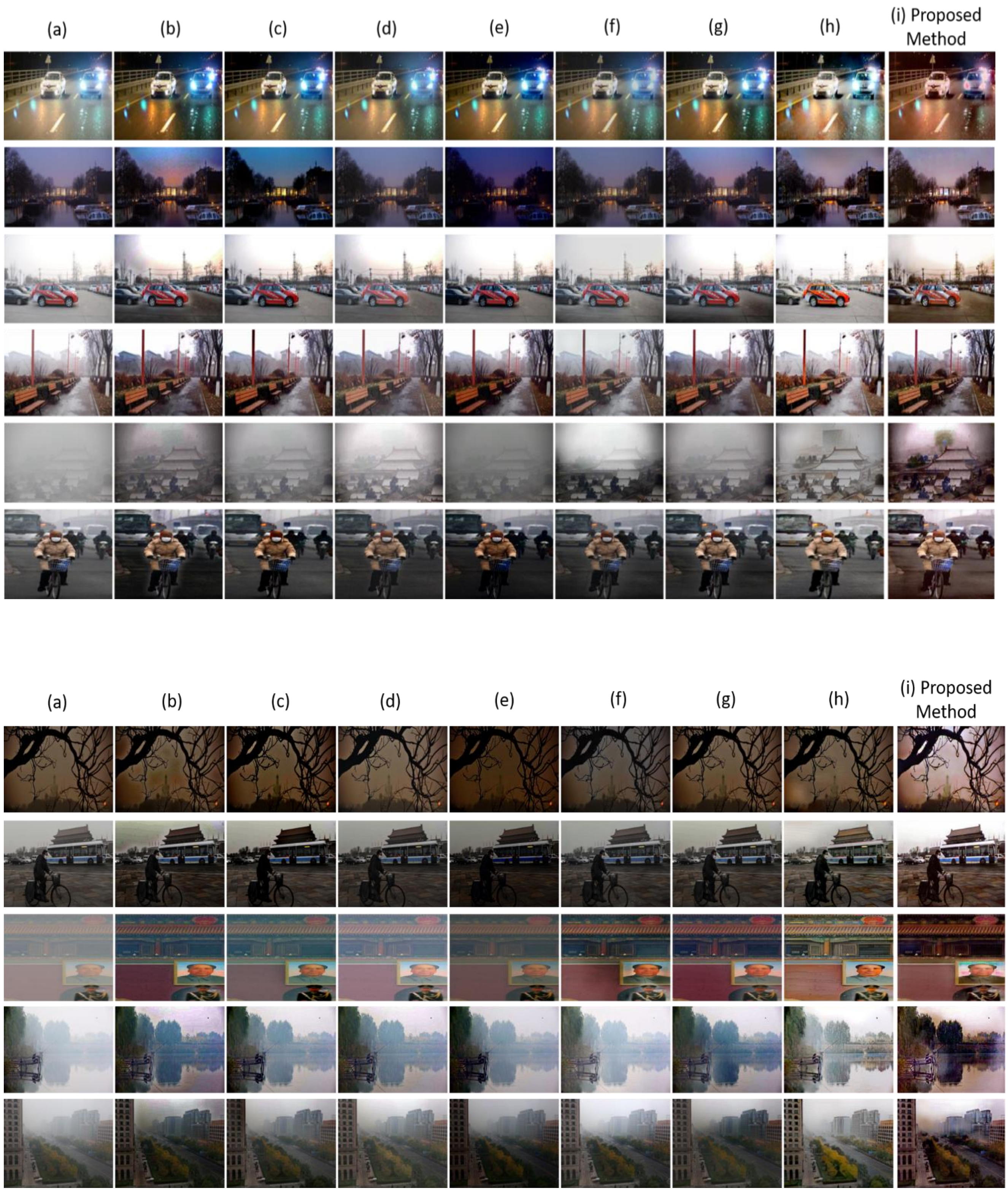

Figure 4. Visual result of proposed and existing methods on real-world hazy images. (a) Input hazy image. Results of (b) [17], (c) [28], (d) [6], (e) [23], (f) [29], (g) [43], (h) [14].

Table 1.Quantitative Analysis of Image De-hazing

D-Hazy	SSIM	PSNR	CIEDE2000
DChP (TPAMI-11)	0.7060	11.5876	15.2499
CAP (TIP-14)	0.7231	13.1945	16.6783
DehazeNet (TIP-16)	0.7270	13.4005	13.9048
MSCNN (ECCV-16)	0.7231	12.8203	15.8048
AODNet (ICCV-17)	0.7177	16.6565	12.4110
CycleGAN (ICCV-17)	0.5200	14.7930	13.3800
DDN (NIPS-18)	0.7726	10.9600	15.5456
C2MSNet (WACV-18)	0.7201	12.7148	12.4800
CycleDehaze (CVPRW-18)	0.6490	15.0263	15.4130
PQC (TIP-18)	0.7300	0.0000	13.0360
TANLTV (TIP-18)	0.7700	0.0000	12.2700
PDehazeNet (ECCV-18)	0.7620	13.8450	13.3995
RI-GAN (CVPRW-19)	0.8179	18.8167	9.0730
Proposed Method	0.7486	16.3305	11.9365

IV. CONCLUSION

In this work, for image de-hazing we propose an end-to-end generative adversarial de-hazing network. A novel generator which is designed using Inception block and dense connections is proposed for image de-hazing named as Inception-Dense Network. Performance of the proposed network has been evaluated on two benchmark datasets namely: D-Hazy [1], SOTS [24] to preserve the structural information in the recovered haze-free scene and real-world hazy images. The qualitative analysis has been carried out for image de-hazing by comparing and analysing the results of proposed network with existing state-of-the-art methods. Experimental analysis shows that the proposed method out-performs the other existing methods for image de-hazing. For future, this work can be extended to analyze the effect of haze on the performance of different algorithms for high-level computer vision task such as object detection, human action recognition, and person re-identification. Also, the architecture of the proposed Inception-Dense module can be extended for other computer vision applications such as Semantic Segmentation, Image depth estimation etc.

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