Single Image Dehazing: An Analysis on Generative Adversarial Network

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Summary
Haze is a very common phenomenon that degrades or reduces the visibility. It causes various problems where high quality images are required such as traffic and security monitoring. So haze removal from images receives great attention for clear vision. Due to its huge impact, significant advances have been achieved but the task yet remains a challenging one. Recently, different types of deep generative adversarial networks (GAN) are applied to suppress the noise and improve the dehazing performance. But it is unclear how these algorithms would perform on hazy images acquired "in the wild" and how we could gauge the progress in the field. This paper aims to bridge this gap. We present a comprehensive study and experimental evaluation on diverse GAN models in single image dehazing through benchmark datasets.

Keywords:
Image dehazing; deep learning; convolutional neural networks (CNN); generative adversarial networks (GAN).

1. Introduction

Atmospheric aerosols i.e. fog, dust, fumes and other particles which are generally known as haze. These result poor visibility. Hazy images are responsible for several visibility problems by making images blur. Several computer vision applications, like object detection, video surveillance, object tracking, remote sensing, vehicle autonomous driving, are collapsed because of hazy environment. Sometimes, this leads to serious accidents in bad weather conditions. In order to overcome such complications, it is necessary to dehaze the degraded images. Image dehazing is a pre-processing technique that generates dehazed images from the corresponding hazy images captured in bad weather condition. Image dehazing extracts some major contexts from hazy images using computer vision algorithms.

Image dehazing techniques can be broadly divided into three categories; multiple images dehazing, polarizing filter-based dehazing and single image dehazing. Among them, the first two are not applicable in real-world applications because several filters are required to simulate the changes in different weather conditions. Also, they are not efficient in obtaining spare information about hazy scene through one single image. For these reasons, researchers attempted different approaches using single image dehazing with additional geometrical or depth information.

Single image dehazing is a quite challenging task as single image contains insufficient information. Most of the previous solutions were handcrafted priors dependent due to this limitation. Recently, convolutional neural networks (CNNs) [1], [2] along with advanced image filters are used to learn haze-related priors. Also, generative adversarial networks (GANs), introduced by Goodfellow [3], have showed better performance for image dehazing via image generation and manipulation. It is also capable of generating a desired output distribution for a given noise distribution as an input.

The main objective of this paper is to analyze the success of different types of GAN methods in dehazing. It also compares the accuracy by using benchmark datasets consisting of both synthetic and real-world hazy images. Finally, we put some recommendations for future research.

The remainder of this paper is structured as follows: a brief overview of the related work and the proposed method is described in Section 2 and 3, respectively. Experimental results are presented and discussed in Section 4. Finally, the conclusions are drawn in Section 5.

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2. Related Work

In order to remove the effect of haze in scene images, researchers attempted different methods earlier which mainly based on either image enhancement algorithms or model-based haze removal algorithms. Recently, they concentrate their attentions to deep learning especially GAN in order to explore how well it performs in the task of haze removal, inspired by the outstanding

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results of CNNs [4]. Therefore, a variety of deep-learning approaches have been proposed to overcome the degradation caused by haze concerning either single image or multiple-frame or video-based dehazing.

Cheng et al. [5] presented a CNN based dehazing method. Their model implemented on both synthetic and real-world hazy images and obtained better performance by recovering clean images from challenging scenarios with strong ambiguity. However, this model should be trained with a wider range of images of natural outdoor scenes.

Li et al. [1] introduced a flexible cascaded CNN that jointly estimated the transmission map and the atmospheric light. Their model outperformed other state-of-the-art techniques for synthetic and real-world hazy images. But they did not investigate end-to-end networks for image dehazing capable of generating haze-free images directly.

Rashid et al. [2] presented a CNN based encoder and decoder architecture, eliminating multiple dehazing obstacles using high-intensity pixel value for single image dehazing. Their model provided more efficient results than the previous results, but it should be elongated to dehaze images without having scattered shades.

Ren et al. [6] worked on a multi-scale deep neural network by estimating hazy images along with their medium transmission maps. Their algorithm applied on the NYU Depth dataset [7] and showed better efficiency compared to the state-of-the-art results for both synthetic and real-world hazy images based on quality and speed.

Yeh et al. [8] proposed a deep CNN architecture for dehazing images through image restoration without mapping each pair of hazy images and its corresponding ground truth. The method outperformed other state-of-the-art dehazing algorithms, however it is time consuming process to decompose an input hazy image in extracting detail components.

Song et al. [9] presented a new ranking-CNN model which is capable of learning haze-relevant features automatically. The proposed method obtained more effective results for both synthetic and real-world data against the classical CNN, but its efficiency should be improved further by reducing redundant computations.

Goncalves et al. [10] illustrated an end-to-end CNN model, resulting in a more generic method without requiring any additional parameters. It introduced novel guided layers which adjusted the network weights using the guided filter and restored dehazed images by reducing structural information loss. This method showed outstanding performance by reducing spatial information loss compared to other machine learning models.

Dehazenet [11] and AOD-Net (All-in-One Dehazing Network) [12] show promising performance in single image dehazing using higher priors and assumptions. However, the atmospheric scattering model should be learned with a deep neural network to directly optimize the haze and corresponding dehaze images via an end-to-end mapping without estimating the medium transmission map.

Valeriano et al. [13] presented a comparison among Dehazenet, DCP [16], FAST [17] and CLAHE [4] methods using CHIC database [14], [15]. DCP estimated the transmission map using the dark channel to invert the Koschmieder model, FAST estimated an atmospheric veil responsible for the variation in the intensity of images, and CLAHE introduced a contrast-limited adaptive histogram equalization.

A robust end-to-end convolution model, known as de-haze and smoke GAN (DHSGAN) [18] is used for dehazing and desmoking, trained under a GAN architecture to effectively recapture indoor as well as outdoor haze-free scenes from different degradation scenarios, such as fog, smoke, mist, fumes, haze and so on.

Suarez et al. [19] presented a stacked conditional GAN model to remove haze degradations in RGB images including fast training convergence and a homogeneous model for generalization and obtained high quality dehazed images.

Dudhane and Murala [20] introduced a cycle-consistent GAN architecture known as CDNet that examined on four datasets, such as D-HAZY [21], ImageNet [22], SOTS [23] and real-world images and obtained superior results.

Li et al. [24] proposed a conditional GAN (cGAN) algorithm to recover clear images from hazy images directly by an end-to-end architecture including a trainable encoder and a decoder. For better results, they modified the basic cGAN by including the VGG features with an L_1-regularized gradient prior. It outperformed other state-of-the-art models for synthetic and real hazy images.

Raj and Venkateswaran [25] proposed a conditional GAN for dehazing without explicitly estimating transmission map or haze relevant features and replaced the classic U-Net [26] with the Tiramisu model [27]. It obtained better efficiency and performance for both synthetic and real-world hazy images.

Dudhane et al. [28] proposed an end-to-end GAN that outperformed other existing algorithms through conducting experiments on NTIRE 2019 dehazing challenge dataset [29], D-Hazy [21] and indoor SOTS [23] datasets for single image dehazing.

3. GAN-Based Dehazing

Several methods exist for image dehazing, but conventional approaches mostly work by estimating the transmission map and the corresponding air light component of the hazy scene using an atmospheric scattering model to reduce the effect of haze in order to recover the haze-free scene. These methods are based on one or more key assumptions, which exploit haze relevant features. Some of these assumptions do not hold true in all possible cases. A way to circumvent this issue is to use deep learning techniques, and let the algorithm decide the relevant features. Recently, different types of generative adversarial networks (GANs), introduced by Ian Goodfellow et al. [3] proved to be immensely effective in image dehazing. This paper aims to systematically evaluate four state-of-the-art single image dehazing methods: AOD-Net, cGAN and DHSGAN.

i. AOD-Net

All-in-One Dehazing Network (AOD-Net) [12] is a light-weight CNN architecture, based on a re-formulated atmospheric scattering model. AOD-Net is capable to generate clean images directly via the joint estimation of transmission matrix $t(x)$ and the atmospheric light, A. Thus equation (1) can be reformulated as,

$$J(x) = K(x)I(x) - K(x) + b \tag{1}$$

$K(x)$ can be defined as,

$$K(x) = \frac{\frac{1}{t(x)}(I(x) - A) + (A - b)}{I(x) - 1} \tag{2}$$

where, $\frac{1}{t(x)}$ and A are compacted into one variable $K(x)$ and b is a constant bias.

However, Dehazenet and AOD-Net contain few limitations such as (i) the Koschmieder model provides narrow validity for massive amount of haze; (ii) networks may confine generalization capabilities by reducing performance levels on real data according to the training on simulated data.

ii. cGAN

Conditional Generative Adversarial Network (cGAN) [24] presents a conditional model in which both the generator module and the discriminator module are conditioned on some additional information i.e. class labels or data from several modalities. Image generation can be conditional by feeding this information into both discriminator and generator. A cGAN algorithm is capable of generating clear images through optimization of loss function including adversarial loss, perceptual loss and L_1-regularized gradient prior [23]. It can be expressed as,

$$\min_{G}\max_{D} E_{I,z}[\log(1 - D(I, G(I, z)))] + E_{I,J}[\log D(I, J)] \tag{3}$$

Here, I is the input hazy image, J is the clean image and z is a random noise. The generator G generates a clear images from an input hazy image, thus it does not preserve the structural details of the inputs. An encoder-decoder architecture is used as the generator that performs convolutional and batch normalization operations with ReLU activation. The discriminator D distinguishes whether an image is real or fake. A sigmoid function is applied to the feature maps at the final layer of the discriminator to normalize the probability score into 0 to 1. A loss function is used to recover the structural details in the haze-free scene that improves the scene visibility. cGAN is optimized by three components of the loss function i.e. adversarial loss, perceptual loss and smooth L_1-regularized loss [25].

iii. DHSGAN

De-Haze and Smoke GAN (DHSGAN) [18] is a dehazing network without requiring the inversion of an atmospheric model or any kind of post processing. It directly generates haze-free image using the final layer of a fully convolutional network. This network works robustly on different scene degradation conditions caused by fog, smoke, mist, haze and so on. DHSGAN can be categorized into two sub-modules: (i) Transmission Module (T) and (ii) GAN Module followed by a loss function. DHSGAN can be defined as,

$$J(x) = G[t(x), I(x)] = G[T\{I(x)\}, I(x)] \tag{4}$$

T is a fully convolutional recurrent architecture, initialized with convolution layers of VGG19 [30] and pre-trained on the ImageNet [31] dataset for the estimation of the transmission map of hazy input images. The initial VGG19 convolution layers work as multi-scale feature extractors where the initial 8 layers are excluded from training, followed by three inception [32] modules. Two ConvLSTM [33] layers are used to utilize the temporal correlation of the input frames during video stream.

GAN module consisting of a generator (G) and a discriminator (D). G contains 16 identical residual blocks [34] with 3×3 kernels with batch-normalization followed by parametric ReLU activation function. G uses zero padding to obtain spatial dimension for dehazed image as same as the input image. D is trained to distinguish between the real and the generated dehazed image consisting of 8 conv layers along with batch-normalization and ReLU activation (leaky) followed by a sigmoid layer.

4. Experimental Results and Discussions

i. Dataset Description

In this work, **REalistic Single Image DEhazing (RESIDE) [23] dataset is used for investigation.** RESIDE dataset is a large-scale dehazing benchmark dataset consisting of single images along with an empirical and expletive extension, called **RESIDE-β**. It can be categorized into five subsets: a synthetic large-scale Indoor Training Set (ITS), a Synthetic Objective Testing Set (SOTS) and a Hybrid Subjective Testing Set (HSTS), Outdoor Training Set (OTS) and Real-world Task-driven Testing Set (RTTS). An overview of **RESIDE** dataset can be found in Table 1.

ii. Experimentation

For experimentation, we have worked only on SOTS subset (Synthetic Objective Testing Set), containing both hazy and corresponding ground truth images for indoor as well as outdoor scenes. It contains approximately 550 indoor images and 992 outdoor images. Some sample hazy and ground truth images from both indoor and outdoor sets are shown in Figure 1 to Figure 4.

Fig. 1: Sample indoor ground truth images.

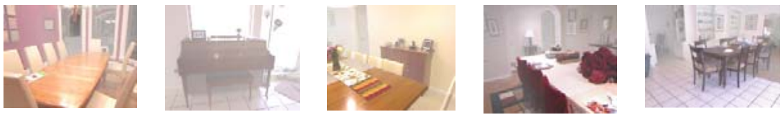

Fig. 2: Sample corresponding indoor hazy images of Figure 1.

Fig. 3: Sample outdoor ground truth images.

Fig. 4: Sample corresponding outdoor hazy images of Figure 3.

Table 1: Dataset Statistics (RESIDE and RESIDE-β).

Name of the Subset	***Types of Images***			***Number of Images***
Indoor Training Set (ITS)	Indoor	Synthetic		13990
Synthetic Objective Testing Set (SOTS)	Indoor	Ground Truth		50
		Hazy		500
	Outdoor	Ground Truth		492
		Hazy		500
Hybrid Subjective Testing Set (HSTS)	Outdoor	Real-World		10
		Synthetic	Original	10
			Synthetic	10
Outdoor Training Set (OTS)	Outdoor	Synthetic		72135
Real-world Task-driven Testing Set (RTTS)	Outdoor	Real		4322

Tables 2 and 3 list out the PSNR, and SSIM score values of the four methods for the quantitative analysis. It is seen from the tables that DHSGAN performs comparatively well than other methods. The visual results are shown in Figure 5 and Figure 6.

Table 2: Average PSNR and SSIM results on SOTS (indoor) dataset.

Metrics	DehazeNet	AODNet	cGAN	DHSGAN
PSNR	17.94	22.03	20.13	22.19
SSIM	0.883	0.903	0.89	0.91

Input AODNet cGAN DHSGAN Ground Truth

Fig. 5: Qualitative results on SOTS (indoor) Dataset.

Table 3: Average PSNR and SSIM results on SOTS (outdoor) dataset.

Metrics	***AODNet***	***cGAN***	***DHSGAN***
PSNR	21.93	20.13	21.84
SSIM	0.85	0.92	0.90

Input AODNet cGAN DHSGAN Ground Truth

Figure 6: Visual results using SOTS (outdoor) dataset.

5. Conclusion

Removing haze from images for clear vision is one of the most challenging tasks in computer vision. This research is reported on the comprehensive study of four GAN-based image dehazing methods, such as DehazeNet, AODNet, cGAN and DHSGAN. We objectively and subjectively compared the state-of-the-art methods by using RESIDE dataset, on both synthetic and natural haze images. It is observed that among the four methods, DHSGAN generates better haze free image from the corresponding hazy ones. However, the size of the input image is restricted to (256×256) pixels; so, further work can be done to make this flexible. In future, we expect to present haze model and also a detailed analysis of the model's effectiveness.

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