**Dehazing using Generative Adversarial Network - A Review**

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**Abstract**

Dehazing is a difficult process in computer vision that seeks to improve the clarity and excellence of pictures taken under cloudy, foggy, and rainy circumstances. The Generative Adversarial Network (GAN) has been a viable method for removing haze from photos in recent years. This is because GAN can understand intricate data patterns and provide high-quality outcomes. This paper provides a thorough examination of the most advanced strategies in dehazing utilizing GAN. The study examines the various elements utilized in GAN-based dehazing, including generator and discriminator architectures, loss functions, and training strategies. It also explores the evaluation metrics employed to assess the effectiveness of GAN-based dehazing methods. It also examines the datasets often used to train and evaluate these models. This research concludes by examining prospective avenues for future study in the domain of dehazing, employing GAN to tackle the obstacles of real-time dehazing, managing intricate scenarios with various atmospheric conditions, and enhancing the resilience of GAN-based dehazing models.

**Keywords**

Atmospheric haze; Dehazing; Generative Adversarial Network (GAN); Performance evaluation metrics.

1. **Introduction**

In recent years, the degradation caused by atmospheric haze in outdoor images has become a significant concern in various computer vision applications, including autonomous driving, surveillance, and image enhancement. The presence of haze obscures important visual details, reduces image contrast, and diminishes overall visual quality, posing challenges for both human perception and machine vision systems. To address this issue, numerous dehazing methods [1-11] have been developed, aiming to restore clear and visually pleasing images from hazy inputs. Recently, the Generative Adversarial Network (GAN) [12] has emerged as a promising approach for effectively mitigating the effects of haze. GAN, a class of deep learning models, has demonstrated remarkable success in generating realistic and high-quality images by training a generator network to capture the underlying distribution of a target domain through adversarial learning [13, 14]. This ability to capture complex and non-linear relationships within the image data makes GAN particularly well-suited for dehazing tasks.

Haze is a prevalent natural weather occurrence where diverse particles of aerosols in the atmosphere result in significant light scattering and refraction. Consequently, the image quality captured by diverse imaging systems experiences substantial degradation, adversely affecting the visual impact [15-20]. The primary consequences include severe attenuation of image color, reduced color saturation and contrast, and inadequate prominence of details. This adversely affects image feature extraction and identification, exerting a profound impact on diverse fields including aerial photography, autonomous driving, urban surveillance, satellite-based remote sensing, video surveillance, target identification, and field exploration [21-27]. Therefore, addressing the dehazing of outdoor degraded images acquired in hazy conditions is crucial for enhancing image visualization quality, offering important practical implications and promising application prospects [28-30].

Traditional haze removal from individual images can be broadly categorized into two groups: image enhancement methods relying on a non-physical model [31-35] and image restoration techniques using a physical model [36-38]. In the non-physical model category, the emphasis lies on enhancing the overall or local characteristics of the degraded image, including the saturation and contrast of the scene, thereby improving image quality to some extent for dehazing purposes. Commonly utilized techniques include histogram equalization [32], Retinex [33, 39], homomorphic filtering, and wavelet transformations [34]. Although these strategies improve image clarity, they do not explore in-depth hazy images deteriorate, leading to the distortion of specific image information. In contrast, the picture restoration approach based on physical models utilizes the atmospheric scattering physical model. High-quality pictures are acquired by resolving the physical model while adhering to restrictions derived from previous information. This method entails analyzing the deterioration process of hazy photos and developing a comprehensive degradation model. In 2009, He et al. [37] proposed the dark channel prior (DCP) approach to estimate the overall ambient light and the first transmission picture. Later on, soft matting or guided filtering [38] was used to enhance the image to recover a clear image without haze. Zhuang et. *al.* [39] develops a Bayesian retinex algorithm for enhancing single underwater image with multi-order gradient priors of reflectance and illumination. Their experiment demonstrates the effectiveness of the proposed method in color correction, naturalness preservation, structures and details promotion, artifacts or noise suppression. But, this approach tended to overestimate the level of haze present, leading to a general reduction in the brightness of the picture after the haze removal process. Although, retinex variational models show remarkable capacity of enhancing images by estimating reflectance and illumination in a retinex decomposition course, ambiguous details and unnatural color still challenge the performance of retinex variational models on underwater image enhancement. To overcome these limitations, Zhuang et. *al.* [40] proposes a hyper-Laplacian reflectance priors inspired retinex variational model to enhance underwater images. Additionally, distortions were frequently noticed in the sky region. In recent times, a growing number of researchers have started utilizing deep learning techniques in the domain of picture dehazing [41-45]. For example, Cai et al. [41] created DehazeNet, which uses the haze imaging model and a large dataset of clear photos to produce haze images. Subsequently, a convolutional neural network [42, 43] was used to acquire knowledge about hazy picture properties and estimate the transmissivity map, resulting in impressive dehazing outcomes. Nevertheless, the utilization of patch-based training data selection resulted in certain drawbacks, such as the occurrence of color distortion and insufficient dehazing in certain hazy image processing cases. Ren et al. [44] introduced a single-image dehazing technique called multi-scale convolutional neural networks (MSCNNs), which consists of a rough network and a refined network, similar to DehazeNet. The first method approximated the overall transmissivity map, whereas the second method improved it in specific areas to achieve the final transmissivity map. During the transmission learning process, both deep learning algorithms failed to differentiate between the structural and textural characteristics of the hazy picture, resulting in gaps in their learning. Furthermore, the pooling technique employed in the model resulted in the loss of information and other associated problems. In 2017, Li et al. [45] introduced the All-in-one dehazing network (AOD-Net), an image dehazing model that relies on the rebuilt atmospheric scattering model. AOD-Net successfully employed end-to-end training, enabling the immediate generation of high-quality pictures from hazy images without the need for single or intermediate parameter estimate procedures.

Although this technique enhanced the dehazing impact in comparison to prior algorithms, it still displayed problems such as color distortion. Generative adversarial networks (GANs) have gained significant attention in the field of deep learning since 2014. Researchers started employing GANs to restore and reconstruct pictures. In 2017, Isola et al. [46] introduced Pix2Pix, a method for translating images to other images using conditional adversarial networks. Pix2Pix showed its capability to convert hazy photographs into haze-free images by being trained on pairs of these two types of images. However, it was difficult to acquire a genuine haze-free counterpart that corresponds to a natural haze image in real-life scenarios.

This survey centers on deep learning algorithms that utilize GAN and provides a comprehensive analysis of their application in image dehazing. In recent years, significant advancements in hardware have contributed to the notable progress of GAN [47-51]. These advancements have enabled the training of deeper and more sophisticated neural network architectures for both the Generator and Discriminator components of GAN, resulting in increased model capacity. The network comprises a generator that utilizes an encoder-decoder architecture to restore images free from haze. Additionally, a multi-scale discriminator is employed to assess the credibility of the generated image. Ultimately, with the oversight of a multi-scale discriminator, the generator can enhance the level of detail present in the image devoid of haze. By incorporating supplementary prior knowledge, GANs are capable of acquiring a proficient mapping function that is suitably tailored to both indoor and outdoor environments [52-69]. Conversely, the convolutional neural network (CNN) can eliminate the artifacts associated with the traditional prior-based approach. The significant contributions of this survey are delineated as follows.

* This paper endeavors to present a comprehensive overview of the diverse variations of GAN utilized within the realm of image dehazing. To our knowledge, this review represents the inaugural effort to thoroughly scrutinize the utilization of GANs within this specific domain. Our objective is to furnish researchers with a detailed understanding of GAN functionality and to elucidate their wide-ranging applications.
* We provide the details of existing datasets used for the performance evaluation of dehazing techniques along with the quantitative metrics.
* We provide a list of state-of-the-art dehazing techniques along with their merits and demerits. Besides, we present the various technical challenges present in the current system long with future research direction.

The subsequent sections of this article are structured as follows to clarify the overall flow of this paper: Section 2 provides the basic concepts of hazing and dehazing mechanisms. Section 3 describes various dehazing techniques classifying into three categories putting emphasis on the GAN-based strategies. Section 4 provides the details of available dehazing datasets. Section 5 presents the evaluation metrics along with the performance analyses of the important dehazing techniques. Section 6 highlights the advantages and disadvantages of the state-of-the-art GAN-based dehazing techniques. Section 7 shows the prevailing research obstacles and prospective avenues for further exploration. Finally, Section 8 draws the conclusion of this study.

1. **Basic Concepts of Hazing and Dehazing**

**2.1 Atmospheric Scattering Model**

Dehazing is a process used in computer vision and image processing to enhance the visibility of distant objects in hazy or foggy images. While atmospheric scattering is a factor in dehazing, it's important to note that dehazing models are typically designed to address a broader set of challenges beyond just the scattering phenomenon [70-72].

A prevalent method for dehazing is the estimation and elimination of haze or fog from photographs. The atmospheric scattering model is frequently employed in this procedure to estimate the transmission and subsequently the radiance of the scene. Figure 1 illustrates the imaging concept of the Atmospheric Scattering Model (ASM). The light captured by the camera is influenced by the airborne particles. The ASM is employed in certain studies to depict the process of haze production. The atmospheric scattering model has parameters that are either explicitly or implicitly solved. The ASM significantly influences dehazing research, including supervised [73-75], semi-supervised [6, 10] and unsupervised methods [9, 76].

The dark channel prior (DCP) approach [1] is a commonly used dehazing model. It relies on the fact that in outdoor photographs, the intensity of the dark channel (the lowest intensity in a small area) is often low in regions without haze. The fundamental dehazing equation employing DCP is as follows:

(1)

Where:

is the dehazed image,

is the observed hazy image,

is the atmospheric light,

is the transmission map,

is a small positive constant to prevent division by zero.

The transmission map can be estimated using the atmospheric scattering model. It is often formulated as:

(2)

Where:

represents the color channels (e.g., red, green, blue),

is the intensity of the channel at the pixel ,

is the atmospheric light component for channel c,

is a weight to control the strength of the transmission.

This transmission map is then used in the dehazing equation mentioned earlier to estimate the dehazed image. The imaging principle of ASM is shown in Fig. 1. It's important to note that various dehazing methods and models exist, and the choice of model can depend on the specific characteristics of the images being processed. Additionally, some dehazing methods incorporate more sophisticated atmospheric scattering models to handle complex scenes and lighting conditions.

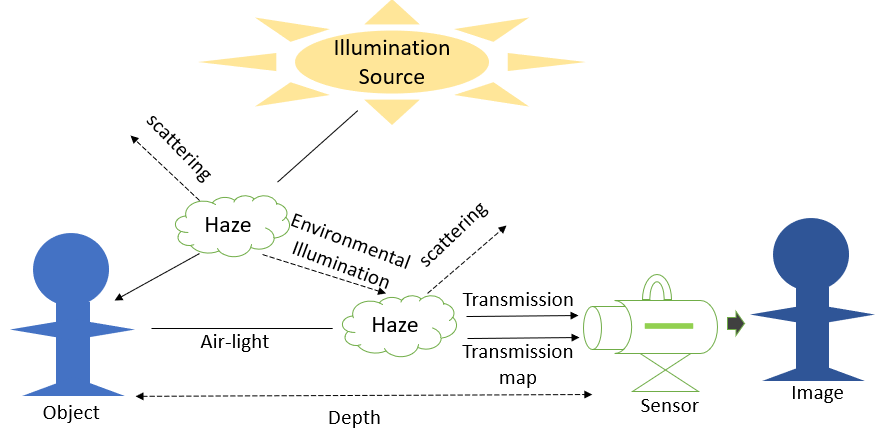


Figure 1: Atmospheric scattering model.

* 1. **Modeling of Haze**

Haze is a naturally occurring phenomenon that may be roughly described by the Atmospheric Scattering Model (ASM). McCartney [70] initially introduced the fundamental ASM to elucidate the processes behind the creation of haze. Subsequently, Nayar [71] and Narasimhan [72] expanded and refined the ASM, which is now extensively utilized. The ASM offers a dependable theoretical foundation for studying picture dehazing. The formula for it is

(3)

𝑥 represents the pixel position, whereas 𝐴 is the global ambient light. In several academic articles, 𝐴 may be denoted as either "alright" or "ambient light." In this survey, 𝐴 is denoted as ambient light for clarity. In dehazing approaches that rely on ASM, the value of 𝐴 is often unspecified. The symbol 𝐼 (𝑥) represents the blurred picture, while 𝐽 (𝑥) represents the sharp and distinct scene image. In the context of most dehazing models, 𝐼 (𝑥) represents the input image, whereas 𝐽 (𝑥) represents the intended output image. The symbol 𝑡(𝑥) represents the medium transmission map, which is formally defined as;

(4)

𝛽 represents the atmospheric scattering parameter, whereas 𝑑(𝑥) represents the depth of 𝐼 (𝑥). Therefore, the value of 𝑡(𝑥) is defined by 𝑑(𝑥), which may be utilized in the creation of a blurred image. The haze-free picture 𝐽 (𝑥) may be produced by applying the following formula, provided that the values of 𝑡(𝑥) and 𝐴 are known and can be calculated:

(5)

The following Fig. 2 shows the haze modeling stages using the ASM method.

|  |  |
| --- | --- |
| 1. Original Image | 1. Depth map calculation |
| 1. Transmission estimation | 1. Haze image |

Figure 2: Haze Modeling Steps.

* 1. **Dehaze Principle**

Dehazing is a technique employed in the fields of image processing and computer vision to improve the clarity and visibility of objects in photographs that have been distorted by atmospheric haze or fog. The main objective of dehazing is to mitigate the influence of scattering and absorption of light caused by haze particles, hence enhancing the visibility of objects in the picture and increasing the overall quality of the image.

Dehazing often starts with comprehending the picture creation model. The standard components of this model encompass scene radiance, transmission, and ambient light. The hazy image (I) may be expressed as the multiplication of the scene radiance (J), transmission (T), and ambient light (A).

The dark channel prior, defined by the range [1], is a fundamental notion in the process of dehazing. It capitalizes on the finding that in the majority of outdoor photos without haze, there are often pixels that exhibit extremely low-intensity values in at least one of the color channels. The dark channel is determined by selecting the lowest intensity value from a local patch across all color channels. The dark channel prior aids in the estimation of the transmission map, which quantifies the fraction of light that passes through the atmosphere.

The transmission map plays a vital role in dehazing algorithms [77-79]. Haze transmittance is the proportion of light that reaches the camera from the scene, and it is inversely correlated with the density of the haze. Estimating the transmission map can be achieved through a variety of methods, such as the dark channel prior, color attenuation, and polarization-based techniques.

Atmospheric light refers to the specific color of light that is dispersed by particles in the atmosphere, such as haze particles. The assumption is typically made that it remains constant within a small area of the picture. Accurately determining the ambient light is crucial for precisely restoring the brilliance of the image. The estimation of atmospheric light may be derived by analyzing statistical data from the most intense pixels in the picture, under the assumption that these pixels represent areas impacted by haze.

After estimating the transmission map and ambient light, the dehazing method entails using these factors to restore the brilliance of the scene without haze. To produce the dehazed picture, one can use a dehazing model that includes dividing the observed image by the estimated transmission map and subsequently removing the estimated atmospheric light. Initially, we compute the depth map of a picture. The linear model described in Equation (6) is utilized for scene depth restoration. The density of haze grows as the scene depth decreases. Haze density refers to the difference in intensity and saturation of light. Subsequently, it can generate a linear model.

We can express this linear model as:

(6)

The variables in the equation are defined as follows: x represents the location inside the picture, *d* represents the scene depth, *v* represents the brightness component of the hazy image, s represents the saturation component, θ0, θ1, θ2 are unknown linear coefficients, and *ε*(*x*) represents a random variable that reflects the random error of the model, which is considered as a random image. An uncomplicated and effective supervised learning technique is employed to ascertain the coefficients θ0, θ1, θ2. The training data is required to determine the coefficients θ0, θ1, θ2. Here, a training sample comprises a picture and its accompanying ground truth depth map. Figure 3 displays the picture at various stages of dehazing. The raw depth map is computed under the assumption that the depth of the picture remains constant within local regions. The variables in question are as follows: *x* represents the position inside the image, *d* represents the scene depth, *v* represents the brightness component of the hazy image, and *s* represents the saturation component. To smooth the white object *M*(x), grayscale optimization *D*(x) is performed using the filtering as *Mavg*(x).

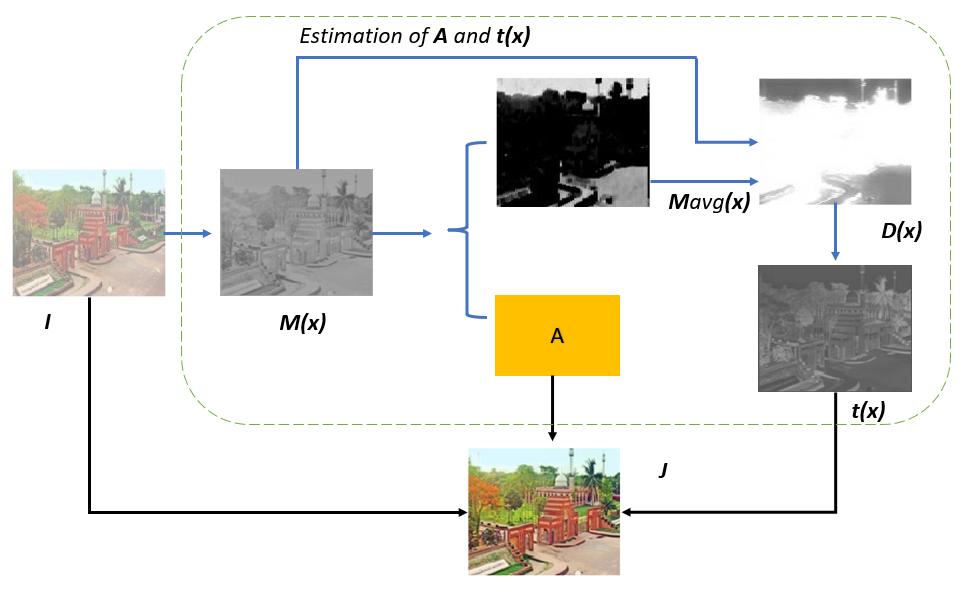


Figure 3: Image dehazing framework.

1. **Dehazing Methods**

This section primarily examines how to enhance single images by reducing haze. These methods may be broadly categorized into three groups: prior-based methods, learning-based methods, hybrid methods

1. **Prior-based dehazing**

The majority of current dehazing techniques rely on the ASM [70-72], which may be formally expressed by Equation (3). According to the ASM, prior methods for removing haze have been thoroughly investigated in various studies [78-85]. For instance, Kim et al. [78] improved the atmospheric scattering model by including saturation and then computed the contrast of the picture without haze by expanding the contrast of the hazy image, leading to the development of a transmission rate map. Berman and Avidan [81] introduced a non-local method prior to generating clear images. Ju et al. [82] examined the intrinsic shortcomings of the atmospheric scattering model and suggested an enhancement to rectify these shortcomings. In their study, He et al. [37] discovered that in most non-sky local locations, there exist pixels that regularly display at least one-color channel with a significantly low value. Their proposed strategy for picture dehazing involves using a dark channel a priori methodology [1]. Liu et al. [83] introduced a technique for enhancing the clarity of hazy photographs using a process called single-picture dehazing. This method employs a transmission-adaptive regularized image recovery approach. Typically, these initial assumptions are used to enhance the distinction between objects and the surrounding light to get the desired dehazing result. The utilization of prior-based approaches can produce dehazing outcomes that significantly improve visibility, owing to the influence of contrast. Nevertheless, the absence of previous information poses challenges in adjusting to different surroundings, resulting in a significant magnification of discrepancies and the production of undesired color distortions and artifacts.

1. **Learning-Based Dehazing**

Researchers like image dehazing methods that utilize deep learning due to its robust capacity to represent nonlinearity. Several advanced dehazing models, such as AODNet [45], FAMED-Net [84], and RCAN [85], have been created following the launch of Dehaze-Net by Cai et al. [41], using data analytic approaches. The approaches [84-102] may be classified into two categories: (i) techniques that utilize the physical scattering model to estimate the transmission map and atmospheric light, and (ii) methods that directly learn the translation of haze-free images. Li et al. [45] introduced an end-to-end convolutional neural network model that learns about image quality from blurry pictures. Zhang and Tao [84] introduced a multi-scale dehazing network named FAMED-Net (rapid and accurate multi-scale end-to-end dehazing network) to quickly and effectively get details of haze-free photos. Wang et al. [85] employed a context aggression block to remove haze from images and enhance color precision successfully. Their approach involved maximizing the use of overall properties and improving the distinguishing capability of specific attributes in foggy photos. Dong et al. [92] introduced a multi-scale boosted dehazing network that integrates dense feature fusion inside the U-Net architecture.

There is an increasing prominence of dehazing techniques that use GANs (generative adversarial networks). These techniques effectively address the problem of uncertainty in previous knowledge. Chen et al. [90] employed the adversarial loss of the GAN to oversee the dehazing network, hence eliminating the requirement for prior knowledge such as ambient light. This method allows for the attainment of complete picture dehazing. Despite the successful outcomes in mitigating haze, the aforementioned learning-based systems are not commonly employed due to their need for supervised training using paired images, which are challenging to get in real-world scenarios. Li et. *al.* [96] presents an advanced image dehazing algorithm using an enhanced conditional GAN with an encoder-decoder architecture, incorporating VGG features and an L1-regularized gradient prior, trained on a synthesized dataset of indoor and outdoor scenes. Zhu et al. [102] introduced a CycleGAN, which has gained significant popularity in several computer vision applications. An important benefit of utilizing CycleGAN is its ability to eliminate the requirement for paired haze-free images throughout the training process [100]. Engin et al. [54] enhanced CycleGAN by including the cycle consistency loss and perception loss and trained the network with unpaired images. Nevertheless, the continuous use of CycleGAN to ambiguous pictures might lead to color aberration and reduced contrast. In addition, it neglects the consideration of restoring visual characteristics following the dehazing procedure. Hence, motivated by the benefits of this method that utilizes learning through competition and seeks to address its limitations, we present the efficacy of a two-step mapping strategy that utilizes a cyclic consistent generative adversarial network to enhance the performance of picture dehazing. Additionally, a new attention strategy is presented to specifically target the distinct features of various regions and channels, facilitating the effective processing of images with unequal fog distribution.

To create a dehazing model using GAN, a typical method entails creating a generator network that takes hazy photos as input and aims to generate clear, haze-free images. Concurrently, a discriminator network is trained to distinguish authentic high-quality photographs from those that are falsely generated. The generator and discriminator are trained simultaneously in an adversarial manner, with the generator attempting to trick the discriminator, while the discriminator aims to improve its capacity to distinguish between real and synthesized pictures.

Supervised dehazing networks, which frequently rely on paired data, can utilize adversarial loss as an extra supervisory signal. The idea of adversarial loss [50] may be broken down into two components: the main objective of the generator during training is to generate images that are recognized as genuine by the discriminator. The main goal of the discriminator is to effectively distinguish between the generated image and the authentic image included in the dataset. During the dehazing process, the adversarial loss serves to reduce the disparity between the generated image and the actual image, hence facilitating the optimization of the haze-free 𝐽 (𝑥) and transmission map 𝑡(𝑥) [100], as seen in Figure 4. The system consists of a generator and a discriminator. The generator is responsible for creating the physical parameters t(x) and A. Subsequently, the atmospheric scattering model is inverted to get a dehazed image. The discriminator ultimately differentiates between the dehazed image and the one that is completely clear of haze.

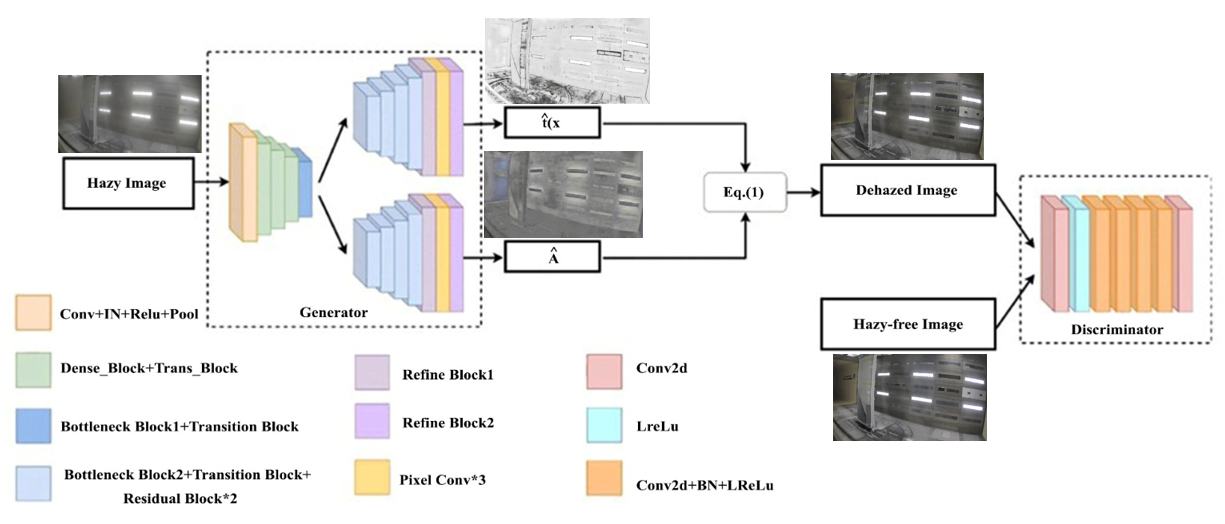


Figure 4: GAN based dehazing framework.

Developing a Generative Adversarial Network (GAN) for the purpose of removing haze from images is a challenging undertaking that may require the use of supportive methods like feature extraction, skip connections, or perceptual loss in order to improve the overall quality of the dehazed images. Ensure that the architecture and training settings are adjusted according to the unique dataset's features.

Here is a simplified explanation of the process:

**Data Preparation:** Gather a dataset of hazy images and their corresponding clear versions.

**Architecture Setup:** Design a generator network that takes hazy images and outputs dehazed images. Then, create a discriminator network that classifies images as either real (clear) or generated (dehazed). Finally, set up the GAN architecture where the generator and discriminator are connected in an adversarial manner.

**Training:** Train the GAN on the hazy-clear image pairs. The generator tries to generate realistic dehazed images to fool the discriminator. The discriminator tries to correctly classify between real and generated images.

**Loss Functions:** Define loss functions for both the generator and discriminator. The generator is typically trained to minimize the perceptual difference between the generated and real images. The discriminator is trained to correctly classify images and minimize the chances of being fooled.

**Optimization:** Use optimization techniques such as stochastic gradient descent to update the weights of the generator and discriminator.

**Evaluation:** Evaluate the trained model on a separate set of hazy images to ensure it effectively removes haze.

1. Hybrid Methods

This paper focuses on reviewing the image dehazing methods based on GAN. However, there are lots of GAN-based aggregating models. A straightforward formulation based on a straightforward generative adversarial network (GAN) does not perform well in these tasks, and some structures of the estimated images are usually not preserved well. Motivated by an interesting observation that the estimated results should be consistent with the observed inputs under the physics models, Pan et *al.* [95] propose an algorithm that guides the estimation process of a specific task within the GAN framework. The proposed model is trained in an end-to-end fashion and can be applied to a variety of image restoration and low-level vision problems. Li et. *al.* [96] introduces an algorithm that directly restores clear images from hazy ones using a conditional generative adversarial network (cGAN). Unlike traditional methods that rely on hand-crafted features such as dark channels and color disparity and uses an end-to-end trainable neural network. We enhance the basic cGAN by employing an encoder-decoder architecture, incorporating VGG features, and adding an L1-regularized gradient prior to produce more realistic clear images. They also create a synthetic hazy dataset for training and evaluation. Extensive experiments show that our method outperforms state-of-the-art techniques on both synthetic and real-world hazy images. Bai et. *al.* [97] introduces a robust image dehazing algorithm that utilizes intrinsic information from the hazy image itself to guide haze removal. The algorithm initially applies a deep pre-dehazer to produce an intermediate image with clear structures, which is used as a reference. To effectively harness the guidance from this reference image, implement a progressive feature fusion module that integrates features from both the hazy image and the reference. The final image restoration module then takes these fused features to enhance the clarity of the image. The entire system is trained end-to-end. Dong and Pan [98] introduce a novel image dehazing approach based on a physics-driven feature dehazing network. Unlike typical end-to-end trainable dehazing methods, our network incorporates the physical model of haze formation into its design and operates in a deep feature space. Central to our method is the feature dehazing unit (FDU), which leverages the physics model to identify and utilize essential features for haze removal within the feature space. The FDU is integrated into an encoder-decoder architecture with residual learning, allowing the network to be trained end-to-end efficiently. The encoder extracts features, while the decoder reconstructs the clear image. Residual learning improves accuracy and simplifies the training process. Zamir et. al. [99] proposes an efficient Transformer model, called Restoration Transformer (Restormer), designed for image restoration tasks. While convolutional neural networks (CNNs) are adept at learning image priors from large datasets, they suffer from limited receptive fields and adaptability issues. Transformers, known for their success in natural language processing and high-level vision tasks, overcome these limitations but are computationally expensive for high-resolution images. Their Restormer model addresses this by optimizing the multi-head attention and feed-forward network components to capture long-range pixel interactions efficiently. This design allows it to handle large images effectively. Restormer achieves state-of-the-art results in various image restoration tasks, including image deraining, motion and defocus deblurring, and image denoising. Liu et. *al.* [100] introduces an iterative algorithm using deep CNNs to learn haze-related priors for image dehazing. Frame the dehazing task as minimizing a variational model, incorporating data fidelity and prior terms for regularization. By employing the classical gradient descent method with integrated deep CNNs, estimates iterative image priors for atmospheric light, transmission maps, and clear images effectively. This method blends the physical principles of image dehazing with the strengths of deep learning, resulting in clear images and accurate atmospheric light and transmission maps.

1. **Dataset for Dehazing**

Computer vision applications such as object recognition, picture segmentation, and image classification can benefit from the creation of accurate ground-truth labels by thorough annotation. Acquiring accurate and detailed labels, particularly for haze-free photos, from hazy photographs in real-world settings is extremely challenging. At now, there are mainly two approaches to obtaining a set of images, one with haze and one without haze. An effective strategy involves creating synthetic data utilizing ASM, such as D-HAZY [55], HazeRD [56], and RESIDE [59]. By adjusting several settings in ASM, researchers may easily create photos with different levels of haze density. To create a blurry image, four crucial elements are necessary: a sharp image, a depth map 𝑑(𝑥) that matches the content of the sharp image, ambient light 𝐴, and the atmospheric scattering parameter 𝛽.

Hence, we may classify the synthetic dataset into two separate stages. In the early stage, it is important to collect sets of distinct photos together with their corresponding depth maps. Highly accurate depth information is essential in order to generate a synthesized haze that closely mimics real-world haze. Figure 5 exhibits the unique image and its corresponding depth map taken from the NYU-Depth dataset [65]. During the second stage, the atmospheric light 𝐴 and atmosphere scattering parameter 𝛽 are assigned, either as preset values or by random selection. The D-HAZY dataset, extensively employed, is synthesized by assigning values of 1 to both 𝐴 and 𝛽. Researchers employ diverse values for 𝐴 and 𝛽 to augment the range of the produced images and so improve the overall flexibility of the trained model. For example, MSCNN [66] specifies that the values of A should fall between 0.7 and 1.0, and should fall between 0.5 and 1.5.

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|  |  |
| --- | --- |
| 1. Distinct image | 1. Depth map |

Figure 5: A distinct picture and its accompanying depth map.

A further approach is generating the blurred image by employing a haze generator, such as I-HAZE [57], O-HAZE [58], DenseHaze [60], and NH-HAZE [61]. The datasets utilized in the NTIRE 2018-2020 dehazing challenges [67-69] are derived from these generated datasets. Figure 6 exhibits four sets of samples, comprising both pictures with haze and images without haze. These examples are a subset of the datasets produced by the haze generator. The photos shown in Figure 6 (a) represent inside circumstances, whereas (b), (c), and (d) capture outside views. The three outdoor datasets display differences in the haze pattern. The haze in (b) and (c) is evenly distributed over the whole image, but the haze in (d) varies in intensity throughout the different landscapes. Moreover, the haze density in (c) is significantly higher than that in (b) and (d). These datasets, each possessing unique characteristics, provide useful insights for the advancement of dehazing algorithms. In order to reduce the intense haze levels in Dense-Haze, it is crucial to create dehazing models that have improved capacities to extract and recover features.

The main advantage of synthetic and produced haze is that it alleviates the difficulties faced during data collecting. However, the indistinct images generated via ASM or produced by a haze generator fail to faithfully represent the genuine formation of haze in the physical environment. Therefore, there is an inherent differentiation between artificial and genuine real-world data. Several research have recognized the constraints of created data and have attempted to construct datasets that faithfully depict the real environment, such as MRFID [62] and BeDDE [63]. However, the current real-world datasets are insufficient in terms of the number of occurrences compared to the synthetic dataset, such as RESIDE [59], because of the high costs and difficulties involved in gathering data. To facilitate the comparison of different datasets, we consolidate the properties of several datasets in Table 2.

|  |  |  |  |
| --- | --- | --- | --- |
| 1. Indoor Haze [57] | 1. Outdoor Haze [58] | 1. Dense Haze [60] | (d)Non-Homogeneous Haze [61] |

Figure 6: Samples of Haze Dataset: Hazy and the corresponding clear images.

Table 2: Dataset for image dehazing.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset | type | Numbers | Indoor/Outdoor | Pair/non-Pair |
| D-HAZY [55] | Synthetic | 1400+ | Indoor | Pair |
| HazeRD [56] | Synthetic | 15 | Outdoor | Pair |
| I-HAZE [57] | Haze-Generator | 35 | Indoor | Pair |
| O-HAZE [58] | Haze-Generator | 45 | Outdoor | Pair |
| RESIDE [59] | Synthetic & Real | 10000+ | Indoor & Outdoor | Pair & non-Pair |
| Dense-Haze [60] | Haze-Generator | 33 | Outdoor | Pair |
| NH-HAZE [61] | Haze-Generator | 55 | Outdoor | Pair |
| MRFID [62] | Real | 200 | Outdoor | Pair |
| BeDDE [63] | Real | 200+ | Outdoor | Pair |
| 4KID [64] | Synthetic | 10000 | Outdoor | Pair |

To facilitate subjective evaluation, visual renderings of the dehazing results for each method on representative samples from the dataset should be included. These renderings will allow readers to visually compare the performance of the proposed method with the state-of-the-art techniques. The paper would benefit from including visual renderings of each comparison method on the dataset to provide a more comprehensive subjective evaluation. CVANet (Cascaded Visual Attention Network) [103] employs a series of attention mechanisms to focus on different aspects of the image, enhancing the dehazing process by prioritizing important regions. The cascaded structure allows the network to progressively refine its attention, resulting in clearer and more detailed outputs. Weighted Wavelet Visual Perception Fusion [104] uses wavelet transforms to decompose the image into different frequency components. By applying weighted fusion strategies, it combines the strengths of various dehazing techniques, effectively balancing detail preservation and noise reduction to achieve high-quality restored images. Inspired by the Retinex theory Retinex-Inspired Color Correction and Detail Preserved Fusion [105] approach separates the image into illumination and reflectance components. It applies color correction to the illumination and detail preservation techniques to the reflectance, merging them back to produce a clear and visually pleasing image with enhanced color accuracy and detail clarity. Including these visual comparisons will greatly enhance the subjective evaluation and provide a clearer understanding of each method's effectiveness in dehazing images.

1. **Experimental Evaluation**

Assessing the effectiveness of dehazing approaches based on GAN is a difficult undertaking, as it requires analyzing the extent to which a model accurately reflects a certain dataset. Significant progress has been made in comprehending the theory and applying Generative Adversarial Networks (GANs), leading to a diverse range of available GAN variations. However, the measurement of dehazing outcomes has not been given much focus, and there are still shortcomings in quantitative evaluation methods. This section presents the relevant and often used metrics [63] for evaluating the effectiveness of dehazing systems that rely on a GAN.

The numerical results are presented in Table 3, showing the average execution time (in seconds) of various state-of-the-art dehazing approaches on the synthetic test dataset. The dehazing outcomes of different approaches across all synthetic datasets will be evaluated using PSNR and SSIM measurements [106]. The majority of articles employ Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as metrics to assess the picture quality following the dehazing process. To calculate the PSNR, it is necessary to utilize Equation (7) in order to derive the mean square error (MSE).

(7)

Let x and y represent two photos that need to be assessed. The variables 𝐻 and 𝑊 represent the height and breadth, respectively. It is important to note that the dimensions of 𝑋 and 𝑌 must be same. The image's pixel location index is denoted by 𝑖 and 𝑗. The PSNR may be calculated using a logarithmic formula, as shown in Equation (8).

(8)

Where 𝑁 is equal to 8 for pictures with a bit depth of 8. The SSIM metric is derived from the association between human visual perception and structural information. Its calculation is specified by Equation (9).

(9)

where u𝑥, u𝑦, 𝜎𝑥, and 𝜎𝑦 denote the average and variability of 𝑋 and 𝑌, respectively; The symbol 𝜎𝑥𝑦 represents the covariance between two variables. The constants 𝐶1 and 𝐶2 are employed to provide numerical stability.

The dehazing outcomes for foggy photographs captured in real-world conditions are presented in Table 4, focusing on the restoration of contrast and color, particularly the retention of sharp edges. The original color is excessively intensified in DCP [82], and the dense regions of haze in the photos are inaccurately approximated. The colors produced by GCANet [88] and FFA-Net [97] exhibit excessive enhancement and are plagued by halo artifacts. The dehazed outcomes achieved using AOD [45] exhibit several remaining haze particles and result in minor color distortion. The outcomes of Cycle-Dehaze [52] exhibit inadequate clarity and pixel blurring. The Cycle-defog2refog algorithm [94] is unable to restore the visually pleasing environment without any haze. The approach of Kim et al. [78] has a commendable dehazing outcome, but with the drawback of color distortion. In comparison to alternative approaches.

Quantifying real-world hazy images is tough since it is challenging to get both hazy and haze-free photographs of the same place. In order to objectively analyze real-world foggy photographs and assess their performance in terms of lighting, color, and contrast recovery, we utilize the metrics contrast gain (*e*), percentage of saturated pixels (*σ*), and gradient ratio (*r̄*).

The value of *r̄* is the geometric mean of the ratios between the visible gradients in the output image and the hazy image. *σ* is the proportion of pixels in the resulting image that are saturated, but were not saturated in the original hazy image. *e* represents the amplification of the contrast in the output compared to the input. Greater values of *r̄* and *e*, along with lower values of *σ*, correspond to superior performance. The findings are displayed in Table 4. The strong contrast increase achieved by AOD-net and Dehaze-net appears to be a result of oversaturation in the pictures, as seen by the elevated saturation percentage σ observed in these two approaches. Conversely, the low value of *σ* in Ma et al.'s technique is attributed to the lack of considerable contrast enhancement in the output picture compared to the input image. This results in a desired low value of *σ* but an undesirable low value of contrast gain *e*.

To evaluate efficiency, the experiment entailed computing the execution time on a simulated test dataset. The experiment employed synthetic datasets and modified images with size of 256 × 256 pixels as the input.

Table 3: Performance comparison of dehazing methods.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Methods | Execution time | Indoor | | Outdoor | |
| PSNR | SSIM | PSNR | SSIM |
| Deep Learning-Based Techniques | | | | | |
| He et al. [37] | 1.8 | 18.946 | 0.735 | 19.131 | 0.725 |
| Li et al. [45] | 0.15 | 15.950 | 0.738 | 18.096 | 0.715 |
| Chen et al. [90] | 0.33 | 20.40 | 0.868 | 24.961 | 0.861 |
| Kim et. al. [78] | 0.47 | 26.047 | 0.931 | 25.844 | 0.915 |
| GAN Based-Techniques | | | | | |
| Engin et. al. [54] | 0.29 | 17.014 | 0.747 | 18.042 | 0.781 |
| Qin et. al. [107] | 0.56 | 24.114 | 0.824 | 25.32 | 0.843 |
| Luo et. al. [108] | 0.72 | 26.335 | 0.890 | 26.984 | 0.904 |
| Ma et. al. [109] | 0.24 | 26.428 | 0.886 | 27.476 | 0.947 |
|  |  |  |  |  |  |

Table 4: Performance comparison of dehazing methods.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Methods | Indoor | | | Outdoor | | |
| Contrast gain, е | % of saturated pixels, σ | Gradient ratio, r̄ | Contrast gain, е | % of saturated pixels, σ | Gradient ratio, r̄ |
| Deep Learning-Based Techniques | | | | | | |
| He et. al. [37] | 2.66 | 0.04 | 2.03 | 1.85 | 0.05 | 1.77 |
| Li et al. [45] | 2.06 | 0.05 | 2.98 | 2.21 | 0.03 | 1.91 |
| Chen et al. [90] | 2.54 | 0.17 | 2.39 | 2.42 | 0.03 | 2.02 |
| Kim et. al. [78] | 2.84 | 0.04 | 3.02 | 2.24 | 0.03 | 2.29 |
| GAN Based-Techniques | | | | | | |
| Engin et. al. [54] | 2.40 | 1.14 | 2.21 | 1.76 | 1.26 | 1.18 |
| Qin et. al. [107] | 2.88 | 0.28 | 3.01 | 2.37 | 0.23 | 2.26 |
| Luo et. al. [108] | 2.94 | 0.06 | 3.25 | 2.46 | 0.04 | 2.18 |
| Ma et. al. [109] | 3.10 | 0.03 | 2.89 | 2.48 | 0.01 | 2.32 |

1. **State-of-the-Art GAN-Based Dehazing**

Reviewing on various literature it is noteworthy that the efficacy of GAN-based dehazing methods is contingent upon several factors, including the caliber of the training data, network architecture, hyperparameters, and the intricacy of the haze conditions. Although these techniques have the potential to yield visually pleasing outcomes, their success is subject to these aforementioned considerations. The advantages and disadvantages of the state-of-the-art GAN-based dehazing techniques are given Table 5.

Table 5: Advantages and disadvantages of the state-of-the-art GAN-based dehazing techniques

|  |  |  |
| --- | --- | --- |
| Methods | Advantages | Disadvantages |
| Engin et. al. [54] | Offers significant advantages in terms of practical training with unpaired data, avoiding atmospheric model estimation, and improving visual and quantitative performance through advanced loss functions. Its ability to handle high-resolution images and robust performance across multiple datasets highlight its effectiveness | Challenges related to training complexity, potential quality loss in upscaling, generalization to diverse conditions, and implementation difficulty. |
| Qin et. al. [107] | A robust and innovative approach to single image dehazing, leveraging feature fusion and attention mechanisms to achieve significant improvements in performance. The network's ability to treat different features and pixels unequally, bypass less important information, and adaptively learn feature weights contributes to its effectiveness. | The complexity and computational demands of the network, coupled with the need for careful training and validation, pose challenges that need to be addressed for practical deployment and generalization across diverse conditions. |
| Luo et. al. [108] | Addressed a significant medical problem, using GANs for high-quality image restoration, and supporting both human and computer-aided diagnosis. The two-stage network approach simplifies training and reduces hyperparameters, potentially leading to better performance. | Challenges on data collection, GAN training complexity, the need for extensive clinical validation, and high computational costs. |
| Ma et. al. [109] | Presents significant advantages in terms of unpaired image learning, attention-enhanced feature processing, and robustness to complex haze distributions. It addresses common limitations of requiring paired data and improves the perceptual quality of dehazed images. | Careful consideration of these factors: training complexity, computational cost, evaluation metrics, generalization, is essential for effective implementation and deployment in practical applications, |

1. **Challenges and Scopes**

Generative Adversarial Networks (GANs) are a type of artificial intelligence model used in the fields of machine learning and computer vision to perform a range of tasks including image dehazing. A GAN consist of two neural networks, namely a generator and a discriminator, that work together in a competitive way to produce data that is both realistic and of high quality [110-119]. .0

Though the GAN models show improved dehazing performance, however, each model faces substantial challenges during the training phase, requiring careful tuning of hyperparameters and a substantial investment of computing resources. Moreover, the training of the GAN requires a substantial quantity of top-notch data, and obtaining a varied and representative dataset for dehazing might pose a challenge. A significant obstacle arises from the intricate nature of foggy situations and the varied circumstances under which haze might manifest. To be useful in real-world applications, GAN-based dehazing models must possess the ability to generalize well over a range of weather conditions, lighting settings, and scene complexity. Currently, the GAN model is used to remove haze in photos has shown promising results in academic research, it is essential to evaluate the performance for real-time scene dehazing for practical situations such as vehicle navigation in foggy and rainy weather conditions.

**8. Conclusion**

In this paper, we explored the landscape of GAN-based dehazing models, aiming to identify and analyze state-of-the-art techniques in the field. We began by discussing the basic concepts of haze formation and the principle of dehazing process. This explanation set the stage for an in-depth examination of various GAN-based dehazing methods, where we detailed the architectures and functions of generators and discriminators, employed loss functions, and the specific training strategies that enhance model performance. Our review encompassed a wide range of synthetic and real-world datasets that are commonly utilized to train and evaluate dehazing models. We conducted a comparative analysis of the dehazing models, meticulously detailing the evaluation metrics used to assess their effectiveness. This comparison provided insights into the strengths and weaknesses of various models, highlighting their relative performance across different scenarios and datasets. Furthermore, we identified and discussed several challenges inherent in GAN-based dehazing. These challenges include the acquisition of high-quality paired datasets, the instability and complexity of training GAN models, issues related to generalization and computational resources required. In light of these findings, we also outlined promising directions for future research.

**Data Availability**

The works used publicly available datasets mentioned in references [55-64].

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