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Artificial Intelligence Techniques for Image Dehazing: A Review

Gobinda Bauri[1,*], Arun Kumar Jhapate[2], Ritu Shrivastava[3]

Abstract

This review explores the application of artificial intelligence (AI) techniques for image dehazing, addressing the pervasive challenge of enhancing image quality in hazy or foggy conditions. Traditional dehazing methods and their role as a foundation for AI-based approaches are discussed. Deep learning-based methods, including single-image and multi-image dehazing, are examined, highlighting their strengths and limitations. Data-driven approaches, leveraging large-scale datasets and domain adaptation, are also investigated. Furthermore, the review outlines the challenges in real-time processing, robustness, explainability, and real-world deployment of AI-based dehazing solutions. As AI technology advances, it is expected that image dehazing will find practical applications across various domains, making it essential to overcome the existing challenges to fully unlock its potential.

Keywords: Artificial Intelligence, Dehazing, Image, Blur, Deep learning, Multi-Scale

INTRODUCTION

Image dehazing is a fundamental problem in computer vision and image processing, as it significantly impacts the quality and visibility of images captured under adverse atmospheric conditions such as haze, fog, or smog. Over the years, the development of artificial intelligence (AI) techniques has led to significant advancements in the field of image dehazing, offering powerful solutions for enhancing visual content affected by atmospheric obscurations.

In addition to discussing AI methods, this review delves into data-driven strategies, emphasizing the importance of large-scale datasets and domain adaptation in training and deploying effective dehazing models. Furthermore, the review highlights the ongoing challenges that AI-based image dehazing faces, such as real-time processing, robustness to diverse environmental conditions, the need for model explainability, and the ultimate goal of practical real-world deployment.

The ongoing evolution of AI technology and image dehazing techniques promises to revolutionize various domains, from photography to critical applications like autonomous vehicles, surveillance, and remote sensing. To unlock the full potential of AI-based image dehazing, it is

***Author for Correspondence**
Gobinda Bauri
E-mail: gobindabauri008@gmail.com

[1]Research Scholar, Department of Computer Science and Enginnering, Sagar Institute of Research & Technology, Bhopal, Madhya Pradesh, India
[2]Assistant Professor, Department of Computer Science and Enginnering, Sagar Institute of Research & Technology, Bhopal, Madhya Pradesh, India
[3]Associate Professor, Department of Computer Science and Enginnering, Sagar Institute of Research & Technology, Bhopal, Madhya Pradesh, India

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imperative to address these challenges, ultimately bridging the gap between research and practical, real-world usage.

Within the realm of image dehazing, AI-driven techniques represent a paradigm shift, offering innovative solutions that augment image quality and, in turn, the effectiveness of numerous applications. As we delve deeper into the various methodologies employed, it becomes evident that these AI approaches have the potential to tackle some of the most daunting challenges associated with hazy or foggy image data.

Traditional image dehazing methods, while valuable, often grapple with limited effectiveness in extreme conditions and the need for manual parameter tuning. The rise of deep learning-based techniques, however, has been instrumental in significantly improving dehazing performance. These techniques have the ability to automatically learn and extract relevant features from hazy images, making them adaptive to various degrees of atmospheric degradation.

Single-image dehazing models, based on convolutional neural networks, strive to estimate crucial factors such as the transmission map and atmospheric light directly from a hazy image. These models are lauded for their simplicity and effectiveness, particularly in moderately hazy conditions, making them suitable for real-time applications. Nonetheless, they do exhibit sensitivity to hyperparameters and may not consistently perform well under extreme haze.

Multi-image dehazing approaches leverage multiple hazy images or depth information to address the challenge of extremely dense haze. While these methods can yield improved results, they are more resource-intensive, which makes them less ideal for real-time applications and necessitates the availability of multiple images of the same scene.

Data-driven strategies play an instrumental role in the advancement of AI-based image dehazing. The availability of large-scale datasets containing hazy and clear image pairs has empowered researchers to train and fine-tune models more effectively. Nevertheless, the creation of such datasets poses challenges due to the need for hazy image acquisition in diverse real-world scenarios and potential dataset biases.

Domain adaptation techniques further enhance the applicability of AI-driven dehazing solutions by transferring knowledge from synthetic or existing datasets to real-world scenarios. These methods bridge the gap between synthetic and actual hazy scenes and help AI models generalize better to the latter. However, domain adaptation can be a complex process, requiring domain-specific expertise and extensive data manipulations.

Literature Survey

S. Zhao et al. [1] Presented the benefits of prior-based and learning-based methods to dehazing by breaking the dehazing problem down into its component parts: visibility restoration and realness enhancement. This allows us to take use of both types of techniques simultaneously. To be more specific, we suggest a two-stage dehazing architecture called RefineDNet that is only lightly supervised. Prior to the visibility being restored, the first step that RefineDNet does is to switch to the dark channel. The basic dehazing findings from the first step are then refined in the second stage using adversarial learning using unpaired foggy and clear photos to increase the sense of realism in the image. We also present an efficient perceptual fusion technique to mix together the various dehazing outputs in order to produce results that are of a higher quality. Extensive trials support the claim that RefineDNet with the perceptual fusion has an exceptional capacity to remove haze and is also capable of producing outcomes that are aesthetically acceptable.

P. Purkayastha et al., [2] The Multi-Scale Fusion approach and the Retinex Algorithm are going to be combined in this image-dehazing study that has been proposed. The multi-scale fusion technique is going to need reflectance matrices to be extracted so that they may be included into the algorithm. The goal of the approach that has been suggested is to lessen the halo effect that may be seen in image-dehazing applications and other related efforts for very foggy pictures. In addition to this, it has been seen that the output quality is much better after using the unique approach that was presented.

P. Ling et al., [3] presented make the observation that the pixels that exhibit a linear relationship between their saturation component and the reciprocal of their brightness component in the corresponding hazy images that have been normalized by atmospheric light share the same surface reflectance coefficient in the local patches of haze-free images. These pixels can be identified by the presence of local patches of images that are free of haze. In addition, the saturation value of these pixels in the photos that are free of haze corresponds perfectly to the intercept of the line that is defined by the linear connection mentioned earlier on the saturation axis.

A. P. Ajith et al. [4] presented the Haze lines Prior approach. For the purpose of validating the suggested technique, the databases O-haze, I-haze, and FRIDA as well as several hazy real world photos without ground truth photographs are used. The performance of the algorithm is tested by the examination of the PSNR and SSIM values on a set of pictures consisting of ground truth and foggy conditions. The performance measures obtained by the recommended algorithm led to results that were superior to those produced by the approaches that were already in place.

M. Qasim et al., [5] Existing image dehazing algorithms for visible-band pictures either employ some kind of learning process to directly estimate the dehazed image or are dependent on previous assumptions to rebuild the transmission map. Both of these approaches are used to reconstruct the transmission map. Recently, performance comparisons of current popular picture dehazing algorithms employing spectral hazy images have been undertaken. These comparisons utilize chosen wavelength bands from photos with varying degrees of fog iness. According to the findings of the comparison, the performance of the various available approaches degraded with the selection of wavelength bands and fog intensity levels. Within the scope of this investigation, we develop an efficient spectral and prior-based image dehazing and enhancement network (SPIDE-Net) that demonstrates improved performance in comparison to other approaches when applying it to spectral hazy pictures obtained from varying wavelength bands and different amounts of fog density.

Z. Li et al., [6] presented real-world hazy photos, model-based single image dehazing methods restore haze-free images with crisp edges and rich details. However, when applied to synthetic hazy images, same techniques result in poor PSNR and SSIM values. Data-driven ones restore haze-free photos with high PSNR and SSIM values for synthetic hazy images but with poor contrast; for real-world hazy images, they may even leave some haze behind. Combining model-based and data-driven techniques has allowed the authors of this work to provide an innovative single picture dehazing solution. Both the transmission map and the atmospheric light are first estimated using model-based methods, and then the estimates are revised using dual-scale generative adversarial networks (GANs) based techniques.

W. Imai et al., [7] presented the quality of photographs shot outdoors in bad weather is directly impacted by floating air particles. This is especially true when the weather is overcast. Methods of haze reduction are an essential component in ensuring the photos retain their high quality. Eliminating the haze that was present across the whole picture is the most challenging aspect of the haze removal process. There have been a lot of different suggestions made for CNN-based solutions to get rid of the haze, and these may be broken down into two categories. There are two ways to do this: the first is to employ a multi-scale structure, and the second is to stack layers. The first method results in a degraded picture because part of the original information included in an image is lost, whereas the second method results in an increase in the computing complexity of an image since the resolution is not decreased.

M. -H. Sheu et al., [8] presented the haze simulation equation serves as the foundation for the dehazing algorithms, which work to eliminate haze and restore the original picture feature maps. This is accomplished by calculating the intensity coefficient of the atmospheric light source as well as the scattering coefficient of the atmosphere. However, the coefficient prediction isn't very accurate, which causes artifact noise in the picture that is generated after dehazing. The use of deep learning methods in computer vision applications is expanding, and this is partly due to the increased need to battle noise and interference in the foggy image.

Y. Bie et al.,, [9] Dehazing a picture using remote sensing (RS) is a difficult operation since there are many different types of haze that drastically affect the image quality. Recent learning-based algorithms have achieved remarkable performance for RS dehazing; nevertheless, older methods are restricted in their applicability due to the fact that they only use datasets that are completely labeled and include less prior-guided information. In this letter, we investigate the Gaussian and physics-guided dehazing network, also known as the GPD-Net, with the goal of improving the generalization ability in real-world conditions and obtaining hazy features more effectively. A unique global attention mechanism (GAM) is engaged in the process of extracting features from various haze distributions.

Z. Li et al.,, [10] Due to the breadth of its potential applications, model-based single picture dehazing has received a significant amount of research. Two difficulties that are intrinsic to model-based single picture dehazing include ambiguity between object radiance and haze as well as noise amplification in sky areas. In order to solve the former difficulty, the authors of this study suggest a dark direct attenuation prior, also known as a DDAP. In order to lessen the morphological artifacts brought on by the DDAP, a fresh approach to hazy line averaging has been suggested. This will make it possible for a weighted guided image filter to have a smaller radius, which will further lessen the morphological abnormalities while still maintaining the picture's fine structure.

Challenges

Some of the key challenges of AI techniques for image dehazing include:

- *Lack of training data:* AI-based dehazing methods require a large amount of training data to learn how to effectively remove haze from images. However, collecting and annotating high-quality dehazing data is a challenging and expensive task.
- *Overfitting:* AI-based dehazing models can be prone to overfitting, which can lead to poor performance on unseen data. To address this challenge, researchers are developing new techniques to regularize dehazing models and improve their generalization ability.
- *Computational complexity:* AI-based dehazing models can be computationally complex, especially for high-resolution images. This can make them impractical for real-time applications. Researchers are working on developing new, more efficient algorithms for AI-based dehazing.
- *Robustness to variations in haze conditions:* AI-based dehazing models need to be robust to variations in haze conditions, such as haze density, haze type, and illumination. This can be challenging, as haze conditions can vary widely in real-world images.
- *Hallucination:* AI-based dehazing methods can sometimes hallucinate artifacts in the dehazed image. This can happen when the model does not have enough information to accurately recover the original scene. Researchers are developing new techniques to reduce hallucination artifacts in AI-based dehazing methods.

CONCLUSION

In conclusion, the application of artificial intelligence techniques to image dehazing is a rapidly evolving field with immense potential. While substantial progress has been made, significant challenges persist, such as achieving real-time processing capabilities, ensuring the robustness of AI models in diverse environmental conditions, and making the models interpretable for practical use.

These challenges need to be addressed to fully unlock the potential of AI-based image dehazing techniques across a wide range of applications, from enhancing photographs to enabling critical functions in autonomous vehicles, surveillance, and environmental monitoring. As we explore the various facets of this technology, it becomes clear that AI-driven image dehazing is on the cusp of reshaping the way we perceive and utilize visual data in the face of adverse atmospheric conditions.

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