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Image Dehazing using Artificial Intelligence Techniques : A Review

[1]*Md Shamiuzzaman (M.Tech Research Scholar)*
[2]*Mr. Joy Bhattacharji (Technocrats Institute of Technology-Advance, Bhopal)*
[3]*Dr. Sanjeev Kumar Sharma (Technocrats Institute of Technology-Advance, Bhopal)*
[4]*Prof Reena Sarathe(Technocrats Institute of Technology-Advance, Bhopal)*

***Abstract*— This paper presents a comprehensive review of recent advancements in image dehazing techniques utilizing artificial intelligence (AI) methods. Image dehazing plays a crucial role in enhancing the visibility and quality of images captured in hazy or foggy conditions, thereby improving the performance of various computer vision tasks such as object detection, recognition, and scene understanding. In this review, we provide an overview of traditional image dehazing approaches and highlight the limitations that motivate the adoption of AI techniques. We then delve into the various AI-based methods proposed for image dehazing, including deep learning-based models. Through a comparative analysis of these techniques, we identify trends, challenges, and opportunities for future research in the field of image dehazing using AI.**

Keywords: Artificial Intelligence, Dehazing, Image, Blur.

I. INTRODUCTION

Images captured in hazy or foggy conditions often suffer from degraded visibility, reduced contrast, and loss of detail, which can severely impact the performance of computer vision algorithms and human perception. Image dehazing techniques aim to mitigate these effects by enhancing the clarity and quality of hazy images, thus improving their usability and interpretability. Traditional image dehazing methods typically rely on handcrafted features and mathematical models to estimate and remove the effects of haze. However, these approaches often struggle to produce satisfactory results under complex atmospheric conditions and varying scene characteristics.

In recent years, the emergence of artificial intelligence (AI) techniques, particularly deep learning, has revolutionized the field of image processing, including image dehazing. By leveraging the power of deep neural networks and data-driven approaches, AI-based methods offer the potential to overcome the limitations of traditional dehazing techniques and achieve superior performance in challenging scenarios.

This review aims to provide an in-depth exploration of the state-of-the-art AI-based techniques for image dehazing, with a focus on their principles, methodologies, and applications. We begin by providing an overview of traditional image dehazing methods, including single image and multi-image approaches, as well as physical models based on atmospheric scattering theory. While these methods have been widely studied and employed, they often exhibit limited effectiveness in real-world scenarios due to their reliance on simplified assumptions and manual parameter tuning.

Motivated by the shortcomings of traditional approaches, researchers have increasingly turned to AI techniques for image dehazing, capitalizing on the ability of deep neural networks to learn complex mappings between hazy and clear images directly from data. Deep learning-based approaches typically involve training convolutional neural networks (CNNs) or recurrent neural networks (RNNs) on large datasets of hazy and corresponding clear images, enabling them to automatically learn the underlying relationships and extract relevant features for dehazing.

In addition to CNN-based methods, generative adversarial networks (GANs) have emerged as a promising approach for image dehazing, allowing for the generation of high-quality, visually realistic dehazed images through adversarial training. By learning to capture the statistical properties of hazy images and generating corresponding clear counterparts, GANs offer a data-driven solution to the dehazing problem that can effectively handle diverse atmospheric conditions and scene characteristics.

Furthermore, hybrid approaches that combine deep learning with traditional image processing techniques have been proposed to leverage the strengths of both paradigms and enhance the performance of image dehazing systems. These hybrid methods often integrate deep neural networks with handcrafted priors or physical constraints to improve robustness and generalization.

Through a comprehensive review and analysis of these AI-based image dehazing techniques, we aim to provide insights into their strengths, limitations, and potential applications. By identifying key trends, challenges, and opportunities for future research, we hope to inspire further advancements in the field of image dehazing using artificial intelligence techniques. Ultimately, the integration of AI methods into image dehazing holds the promise of significantly improving the quality and usability of hazy images across a wide range of applications, from surveillance and remote sensing to autonomous driving and augmented reality.

II. 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.

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.

K. Zhang et al.,[11] formulated dehazing as a semi-supervised domain translation problem. For better generalization, two auxiliary domain translation tasks are designed to capture the properties of real-world haze and align synthetic hazy images to real-world ones to reduce the domain gap. Dehazing and the auxiliary tasks are conducted in shared latent spaces by a unified framework, and we use differential optimization to search the architectures of the framework. We evaluate the efficacy of the proposed work using one synthetic and three real-world benchmarks that cover the challenging cases in wild scenarios, and it outperforms state-of-the-art algorithms on these benchmarks.

H. Ullah et al.,[12] during tempestuous weather conditions, the visual quality of the images is reduced due to contaminated suspended atmospheric particles that affect the overall surveillance systems. To tackle these challenges, this article presents a computationally efficient lightweight convolutional neural network referred to as Light-DehazeNet (LD-Net) for the reconstruction of hazy images. Unlike other learning-based approaches, which separately measure the transmission map and the atmospheric light, our proposed LD-Net jointly estimates both the transmission map and the atmospheric light using a transformed atmospheric scattering model. Furthermore, a color visibility restoration method is proposed to evade the color distortion in the dehaze image. Finally, we conduct extensive experiments using synthetic and natural hazy images.

H. Liu et al.,[13] Despite their remarkable expressibility, convolution neural networks (CNNs) still fall short of delivering satisfactory results on single image dehazing, especially in terms of faithful recovery of fine texture details. In this paper, we argue that the inadequacy of conventional CNN-based dehazing methods can be attributed to the fact that the domain of hazy images is too far away from that of clear images, rendering it difficult to train a CNN for learning direct domain shift through an end-to-end manner and recovering texture details simultaneously. To address this issue, presented to add explicit constraints inside a deep CNN model to guide the restoration process. In contrast to direct learning, the proposed mechanism shifts and narrows the candidate region for the estimation output via multiple confident neighborhoods.

X. Jiang et al.,[14] Single image dehazing methods based on deep learning technique have made great achievements in recent years. However, some methods recover haze-free images by estimating the so-called transmission map and global atmospheric light, which are strictly limited to the simplified atmospheric scattering model and do not give full play to the advantages of deep learning to fit complex functions. Other methods require pairs of training data, whereas in practice pairs of hazy and corresponding haze-free images are difficult to obtain. To address these problems, inspired by cycle generative adversarial model, we have developed an end-to-end haze relevant feature attention network for single image dehazing, which does not require paired training images. Specifically, we make explicit use of haze relevant feature by embedding an attention module into a novel dehazing generator that combines an encoder-decoder structure with dense blocks. The constructed network adopts a novel strategy which derives attention maps from several hand-designed priors, such as dark channel, color attenuation, maximum contrast and so on.

S. Gautam et al.,[15] Hazy environment attenuates the scene radiance and causes difficulty in distinguishing the color and texture of the scene. A crucial step in dehazing is the recovery of the global air-light vector. Traditional methods usually interpret the RGB value of the brightest region in haze images as the air-light. In this letter, a new prior called `color constancy prior' has been proposed to improve the robustness of air-light estimation when varicolored illumination exists. The prior utilizes the statistical observation that distant scenery objects become the most haze-opaque due to the pixel escalation towards the higher intensity side.

S. Tangsakul et al.,[16] Deep learning is one of the most popular approaches to machine learning, which has been widely used for classification. In this paper, we propose a novel learning method based on a combination of an idea of the deep learning approach and the cellular automata model, called DeepCA for single image haze removal. DeepCA's learning is divided into two main parts. The first part is a cellular automata-based deep feature extraction: multi-layer cellular automata with the rules are used to extract the data feature matrices of the image, in which the matrices can be divided into several layers. Then, the score matrices were generated as the model in which was trained by the cellular automata rules. The second part is a decision stage: we used the score matrices to the mapping between the proper data. For demonstration, we take the single image haze removal task as an example to confirm the capability of the proposed method. In this regard, the dichromatic model is chosen as the major model to remove the haze of the image. The multi-layer cellular automata with the rules work as a mechanical extractor of the light source feature of the hazy image. The decision stage of DeepCA performs as the recognizer for properly predicting the global light source for dehazing.

Y. Liu et al.,[17] Underwater images suffer from low visibility and contrast caused by absorption and scattering, which leads to haze and some further limitations. The existing underwater single image dehazing methods cannot achieve a balance between the performance and computational complexity, and are difficult to produce satisfactory results in the regions with large distance. To overcome these problems, we propose a new underwater single image dehazing method, which includes an improved background light estimation based on the quad-tree subdivision iteration algorithm, and a novel transmission estimation method. For the background light estimation, we introduce a robust score for each region of the image, which can evaluate the region from both smoothness and color. For the transmission estimation, we propose the color space dimensionality reduction prior (CSDRP), which allows conversing an image from the three-dimensional RGB color space to a 2D color space, namely the UV color space.

J. Jackson et al.,[18] The scattering of atmospheric particles significantly alters images captured under hazy weather condition. Images appear distorted, blurry and low in contrast attenuation, which extensively affects computer vision systems. There has been development of several prior based methods to address this problem. However, these methods come at a high computational cost. We present a fast, single image dehazing method based on dark channel prior and Rayleigh scattering. Firstly, we present a simple but effective methodology for estimating the atmospheric light through the computation of average, minimum and maximum of the pixels in each of the three RGB colour channels. Then, using the theory of Rayleigh scattering, we model a scattering coefficient to estimate the initial transmission map.

Z. Lu et al.,[19] presented the dark channel prior from a new perspective. By re-formulating the dark channel, it is found that the dark channel correlates closely with the saturation and brightness. A novel way to estimate the transmission without the need to compute the dark channel is then presented and it can prevent the transmission from being under-estimated. In order to discourage the scene radiance from becoming over-saturation and remove the haze effectively, an iterative approach with a tolerable bound on the saturation is proposed. Qualitative and quantitative experimental results demonstrate that the proposed algorithm can effectively restore the scene

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radiance with a comparable or better visual quality than many other algorithms. Furthermore, it runs faster than most state-of-the-arts.

K. Yuan et al.,[20] Single image dehazing has always been a challenging problem in the field of computer vision. Traditional image defogging methods use manual features. With the development of artificial intelligence, the defogging method based on deep learning has developed rapidly. In this paper, we propose a novel image defogging approach called NIN-DehazeNet for single image. This method estimates the transmission map by NIN-DehazeNet combining Network-in-Network with MSCNN(Single Image Dehazing via Multi-Scale Convolutional Neural Networks). In the test stage, estimated the transmission map of the input hazy image based on the trained model, and then generate the dehazed image using the estimated atmospheric light and computed transmission map. Extensive experiments have shown that the proposed algorithm overperformance traditional methods.

III. CHALLENGES

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

1. **Complex Atmospheric Conditions:** Haze formation is influenced by various atmospheric factors such as humidity, aerosol density, and lighting conditions. Dehazing algorithms must effectively handle these complexities to produce accurate results across different environments.
2. **Loss of Detail and Contrast:** Hazy images often suffer from reduced contrast and loss of fine details, making it challenging for dehazing algorithms to recover sharp and visually pleasing results while preserving image fidelity.
3. **Under-/Over-Dehazing:** Dehazing algorithms may struggle to strike the right balance between removing haze and preserving image details. Over-dehazing can lead to artifacts and unnatural-looking results, while under-dehazing may leave residual haze in the image.
4. **Real-Time Processing:** In many applications, such as autonomous driving and live video streaming, dehazing algorithms need to operate in real-time to provide timely and actionable information. Achieving real-time performance without compromising dehazing quality is a significant challenge.
5. **Generalization:** Dehazing algorithms trained on specific datasets or environmental conditions may struggle to generalize to unseen scenarios. Robustness to diverse atmospheric conditions and scene types is essential for practical deployment in real-world applications.

IV. OVERCOME STRATEGY

1. **Data Augmentation and Diversity:** To address the challenge of complex atmospheric conditions and improve generalization, researchers can employ data augmentation techniques to simulate a wide range of environmental factors during training. Augmenting the dataset with variations in lighting, weather conditions, and aerosol densities can help the model learn to adapt to different scenarios.
2. **Multi-Scale and Context-Aware Models:** Incorporating multi-scale processing and contextual information into dehazing algorithms can enhance their ability to capture global scene characteristics while preserving local details. Hierarchical architectures that integrate information from multiple scales can improve the overall quality of dehazed images.
3. **Adaptive Parameter Tuning:** Instead of using fixed parameters, dehazing algorithms can employ adaptive parameter tuning mechanisms that adjust their parameters dynamically based on image characteristics and scene properties. Machine learning-based approaches can learn to optimize parameters in real-time, ensuring optimal dehazing performance for diverse scenarios.
4. **Hardware Acceleration:** Leveraging hardware acceleration techniques, such as GPU acceleration or dedicated FPGA implementations, can significantly improve the computational efficiency of dehazing algorithms, enabling real-time processing on resource-constrained platforms.
5. **Domain Adaptation and Transfer Learning:** Pre-training dehazing models on large and diverse datasets, followed by fine-tuning on target domains or specific environmental conditions, can enhance their generalization capabilities. Transfer learning techniques allow models to leverage knowledge from related tasks or domains, facilitating better performance on unseen data.

V. CONCLUSION

In image dehazing using artificial intelligence techniques holds significant promise for enhancing the visibility and quality of images captured in hazy or foggy conditions. Through this review, we have explored the challenges faced by traditional image dehazing methods and examined the advancements enabled by artificial intelligence, including deep learning-based approaches and generative adversarial networks. Despite the inherent complexities of haze formation and image degradation, recent research has demonstrated remarkable progress in developing AI-driven dehazing algorithms capable of producing high-quality, visually appealing results. By leveraging the power of deep neural networks, these algorithms can effectively learn complex mappings between hazy and clear images, enabling accurate and efficient dehazing across a wide range of environmental conditions.

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