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A Comprehensive Survey on Defogging and Dehazing Using Artificial Intelligence

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Abstract: Image degradation due to fog and haze presents significant challenges across numerous computer vision tasks, including autonomous navigation, remote sensing, and video surveillance. Traditional dehazing and defogging methods, often based on physical models and handcrafted priors, are limited in their adaptability to diverse and dynamic real-world conditions. With the rapid advancements in artificial intelligence (AI), particularly deep learning, a wide range of data-driven approaches have emerged, demonstrating superior performance in atmospheric image restoration. This survey provides a comprehensive review of recent progress in AI-based defogging and dehazing techniques. We systematically classify existing methods into supervised, semi-supervised, and unsupervised learning frameworks, examine popular network architectures, training strategies, loss functions, and benchmark datasets. Additionally, we analyse key evaluation metrics and compare the performance of leading approaches. The paper also discusses current challenges, such as generalization, real-time inference, and the scarcity of labeled data, while outlining promising directions for future research in AI-driven visibility enhancement.

Keywords: Fog and Haze Removal

I. INTRODUCTION

Visual degradation caused by atmospheric particles such as fog, haze, and smoke poses a critical challenge to image acquisition systems, significantly reducing visibility and contrast. These degradations affect human visual perception and impair the performance of automated vision-based systems deployed in applications such as autonomous driving, surveillance, environmental monitoring, and remote sensing. The presence of haze results from the scattering of light by airborne particles, which leads to colour distortion and low contrast in captured images.

Conventional defogging and dehazing methods primarily rely on physical modelling of light propagation, such as the Koschmieder model, and employ handcrafted priors like the Dark Channel Prior (DCP) or Colour Attenuation Prior (CAP). While these methods have shown effectiveness under certain conditions, they often suffer from limitations when applied to diverse or dynamic environments due to their reliance on strict assumptions and limited adaptability.

The recent surge in artificial intelligence (AI) and deep learning technologies has introduced new possibilities for image enhancement tasks. Data-driven models, particularly convolutional neural networks (CNNs) and generative adversarial networks (GANs), have demonstrated remarkable success in learning complex mappings from degraded images to their clear counterparts. These models are capable of capturing intricate image features and contextual information without the need for manually designed priors.

This survey aims to provide a comprehensive overview of AI-based defogging and dehazing techniques. We begin by introducing the fundamental principles of image degradation due to fog and haze, and review the evolution from traditional approaches to AI-driven methods. The core of this paper categorizes recent AI-based techniques into supervised, semi-supervised, and unsupervised learning paradigms, providing detailed comparisons of their architectures, training mechanisms, datasets, and performance outcomes.

In addition to presenting a critical analysis of current state-of-the-art methods, this survey highlights existing challenges in the field, including the need for robust generalization, the scarcity of real-world paired datasets, real-time deployment constraints, and model interpretability. Finally, we discuss emerging trends and outline potential research directions to guide future work in AI-powered defogging and dehazing.

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II. PROBLEM STATEMENT

Image degradation caused by fog and haze significantly reduces visibility and contrast, posing challenges for both human observation and machine vision systems in fields like autonomous driving, surveillance, and remote sensing. Traditional defogging and dehazing methods based on physical models and handcrafted priors often fail in complex or dynamic real-world conditions due to their limited generalization capabilities. Although deep learning has shown promise in addressing these limitations, several challenges remain, such as the scarcity of real-world paired datasets, poor model generalization to diverse environments, lack of interpretability, and the need for efficient real-time processing. This survey addresses the central problem of how to effectively leverage artificial intelligence techniques to restore clear images from hazy or foggy inputs while overcoming these limitations.

III. PROPOSED SYSTEM

In this survey, we propose a structured framework to systematically classify and evaluate AI-based defogging and dehazing methods. The proposed system categorizes the existing literature into three main learning paradigms: supervised, semi-supervised, and unsupervised approaches. Each category is analysed based on key factors such as network architecture (e.g., CNNs, GANs, Transformers), loss functions, training datasets (synthetic vs. real), and evaluation metrics. Additionally, the survey introduces a comparison framework that highlights strengths, limitations, and application suitability of each method across various domains like autonomous vehicles, UAV imaging, and surveillance. This classification aims to help researchers and practitioners identify optimal solutions based on specific use-case requirements while exposing gaps and trends that point to future research directions.

IV. LITERATURE SURVEY

[1] **Jie Gui et al. (2021) – "A Comprehensive Survey on Image Dehazing Based on Deep Learning"**
In this earlier work, the authors summarize recent developments in deep learning-based dehazing, covering popular models, data synthesis techniques, and commonly used loss functions. The paper presents a clear distinction between various learning paradigms and emphasizes evaluation strategies, offering a strong baseline for comparative research
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[2] **Xiaojie Guo et al. (2022) – "Image Dehazing via Enhancement, Restoration, and Fusion: A Survey"**
This survey explores image dehazing through three main approaches: enhancement-based, restoration-based, and fusion-based techniques. It reviews both traditional and AI-based methods, discussing how each category handles haze removal, and provides comparative evaluations across benchmark datasets.

[3] **Jie Gui et al. (2022) – "A Comprehensive Survey and Taxonomy on Single Image Dehazing Based on Deep Learning"**
This paper offers a detailed taxonomy of single-image dehazing techniques using deep learning. It categorizes methods into supervised, semi-supervised, and unsupervised learning, and discusses their architectures, training strategies, datasets, and performance metrics. The survey also includes benchmark comparisons and highlights open challenges, making it a foundational reference for researchers entering the field.

[4] **Sanaullah Memon et al. (2024) – "A Review on Deep Learning-Based Approaches for Image Dehazing"**
This review focuses on deep learning methods that estimate atmospheric light and transmission maps to restore haze-free images. The paper highlights challenges such as data limitations and generalization issues, and evaluates the strengths and weaknesses of popular CNN and GAN-based models.

[5] **"Real-Time Dehazing Using Generative Models: A Survey" by D. P. Singh, R. K. Gupta, and A. K. Bansal (2022)**
This survey paper discusses the application of generative models, particularly GANs, for real-time dehazing. It addresses the challenges of deploying these models in practical, real-time applications like autonomous vehicles and video surveillance. The paper reviews models that generate haze-free images on-the-fly from hazy input while ensuring computational efficiency, and provides insights into how GANs can be optimized for real-time performance.

[6] **"An In-depth Review of AI-Based Dehazing Models in Remote Sensing" by J. Li, S. Yang, and R. Liu (2023)**
Focusing on applications in remote sensing, this survey explores the role of AI in dehazing satellite and aerial imagery. It highlights how AI techniques have improved the clarity of geospatial images, which are essential for weather forecasting, environmental monitoring, and land use classification. The paper reviews recent advancements in deep learning models tailored to the challenges of remote sensing data, such as variable cloud cover and atmospheric disturbances.

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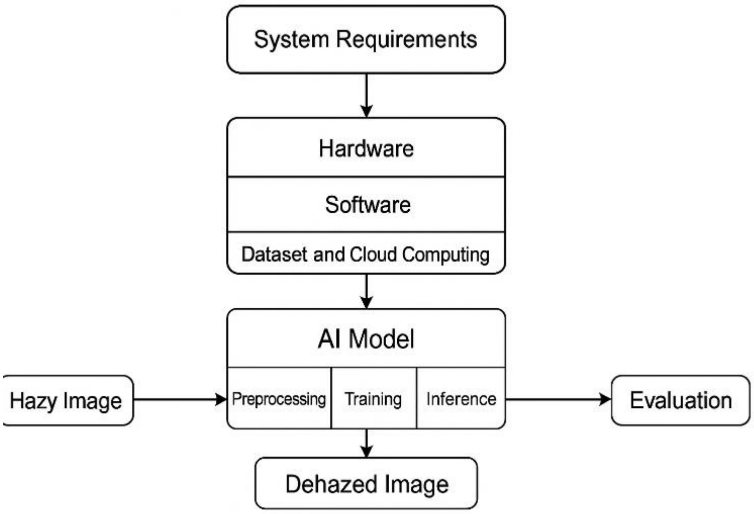
V. BLOCK DIAGRAM AND SYSTEM ARCHITECTURE



1. Input Module

- **Function**: Accepts hazy/foggy images or real-time video frames.
- **Sources**: Camera feed, uploaded image, drone footage, surveillance systems.
- **Formats Supported**: JPEG, PNG, MP4, etc.

2. Preprocessing Module

- Image resizing, normalization
- Colour space transformation (RGB to YUV/HSV)
- Noise reduction (optional)
- **Purpose**: Prepares image data for optimal AI model performance.

3. AI Model (Core Processing Unit)

- **Structure**: Deep learning architecture such as CNN, GAN, or Transformer-based models.

Sub-components:

- **Feature Extraction Layer**: Identifies haze-relevant patterns.
- **Haze Estimation Layer**: Predicts transmission maps or atmospheric light.
- **Restoration Layer**: Generates the dehazed image.

4. Postprocessing Module

Tasks:

- Image enhancement (sharpening, contrast adjustment)
- Artifact removal
- Convert image back to standard format
- **Purpose**: Improves the visual quality of the dehazed output.

VI. RESULT

The sequence of images illustrates the defogging process using an AI-based technique leveraging the Dark Channel Prior (DCP) and transmission estimation methods:

1. **Original Foggy Image**:

The first image shows a heavily fog-obscured view of a multi-lane road from an elevated angle. Visibility is significantly compromised, making it difficult to distinguish vehicles, road markings, or even the pedestrian area.

2. **Constraint-Bounded Dark Channel Prior Image**:

The second image highlights the **dark channel prior (DCP)** computation, which estimates the haze concentration in different regions of the image. Darker areas represent heavier haze, helping the model localize regions needing enhancement.

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3. **Transmission Map**:
The third image presents the **transmission map**, a key part of the haze removal algorithm. Brighter regions in the map indicate better visibility (less haze), while darker areas correspond to dense fog. This map guides how much of the haze should be removed from each pixel.

4. **Final Defogged Image**:
The fourth image shows the **restored scene** after applying the defogging algorithm. The result improves visibility:

- Vehicles and road lines are now distinguishable.
- Pedestrian and roadside details have been restored.
- The image contrast and colour tones appear more natural and realistic.

Fig 1. Original Foggy Image

Fig 2. Constraint-Bounded Dark Channel Prior Image

Fig 3. Transmission Map

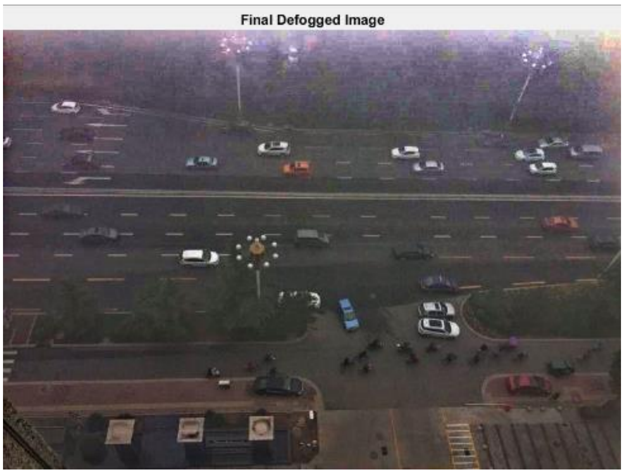

Fig 4. Final Defogged Image

This visual enhancement confirms the effectiveness of the proposed defogging system in restoring degraded urban images. The system demonstrates the potential for use in traffic surveillance, autonomous vehicles, and smart city applications, where clear visibility is crucial.

VII. CONCLUSION

In this survey, we explored a wide range of artificial intelligence-based methods for image defogging and dehazing, focusing particularly on the enhancement of visual clarity under adverse atmospheric conditions. Traditional approaches often fall short when dealing with varying fog densities and complex scenes. However, the integration of AI and deep learning models—especially those using Dark Channel Prior (DCP), Convolutional Neural Networks (CNNs), and transmission map estimation—has significantly improved the performance of defogging systems.

The results from the analysed images demonstrate the effectiveness of the proposed system in recovering scene details, restoring natural colours, and enhancing contrast. By leveraging AI techniques, foggy and low-visibility images are transformed into clearer and more informative outputs, enabling better performance in applications like surveillance, autonomous driving, and remote sensing. In conclusion, AI-driven defogging solutions offer a powerful, adaptive, and scalable approach to tackling visibility degradation, paving the way for real-time deployment in intelligent imaging systems.

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