Image Dehazing Techniques in Autonomous Driving Systems

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Abstract. With self-driving technology, safety under intricate conditions for vehicles is indispensable. Image dehazing as a key element of visual sensing for self-driving vehicles is indispensable under poor environmental conditions. In complex traffic scenarios, visual perception systems must accurately recognize obstacles, traffic signs, and lane structures to ensure driving safety. However, under adverse weather conditions such as fog, haze, or sandstorms, image quality can severely degrade, leading to diminished detection performance and potential safety risks. The paper reviews the progression of image dehazing for self-driving vehicles with classical methods, deep learning-based methods, and unsupervised learning-based methods. The classical methods show efficiency but cannot cope with instability under intricate conditions. Deep learning-based methods, particularly CNNs and Transformers, have registered remarkable progress with issues of computational costs and data adaptability. Unsupervised learning-based methods reduce reliance on labeled data with issues of training instability and incomplete reconstruction. The paper also explores image dehazing as an integration with object detection and multi-sensor fusion, with future directions on lightweight design, data generalization, and multi-modal fusion.

Keywords: Image Dehazing, Autonomous Driving, Deep Learning, Transformer, Multi-sensor Fusion.

1. Introduction

Given that self-driving technology evolves at a very high rate, the safety of vehicles within complex environments is a main challenge. Visual perception forms a main characteristic within self-driving systems that employ sensors such as cameras to supply environmental information. However, environmental variations throughout seasons, particularly those of seasons with fog, are a primary challenge to visual image quality obtained via cameras. Images obtained by seasons with fog are out of focus with low contrast values and influence decision-making and object recognition by systems [1]. As such, the extraction of clear visual information within blurry images is a primary challenge within fuzzy environments faced by self-driving systems [2].

Most of the conventional dehazing approaches are developed with physical modeling or statistical priors, for instance, Dark Channel Prior and Retinex theory. They model the light propagation process to eliminate haze. Although they are computationally fast and applicable to relatively easy scenes, they tend to have unstable performance under complex scenes and are not adaptive to different scenes [3]. Consequently, limitations of conventional approaches under harsh light conditions have encouraged researchers to develop more complex approaches.

Deep learning, particularly with advances of Convolutional Neural Networks (CNNs) and Transformer-based models, has achieved remarkable results for image dehazing technology in recent years. Deep learning approaches are able to learn automatically complex features and patterns from large datasets and remarkably enhance dehazing performance [4]. Additionally, with growing focus on unsupervised learning methodologies, dehazing models have increasingly found autonomy from hand-labeled data, which promotes their level of generalization and adaptability under realistic practical, real-world circumstances [5].

In self-driving vehicles, visual dehazing technology not only enhances visual quality but can also improve the reliability of perceptual systems under poor-weather conditions. The authors present a survey of recent advances in visual dehazing technology, discuss its uses in self-driving vehicles, and delineate its current technical challenges as well as future directions of research.

2. Image Dehazing Techniques: A Comprehensive Review

2.1. Traditional Physical Model-Based Dehazing Methods

Conventional image dehazing approaches are based primarily on atmospheric scattering models to mimic the propagation of light through a hazy atmosphere. Light within the atmosphere is subject to various factors, particularly scattering light, ambient light, and direct light. They all cause images to be blurry [4]. Figure 1 illustrates an outline of an atmospheric scattering model where light is subjected to sunlight, ambient light, and haze particles during its propagation and all cause the image to become blurry.

One of the common approaches is Dark Channel Prior (DCP). It considers that for any typical region of a non-hazy image, at least one-color channel will have a very low minimal value. Through estimating the image's transmission map, DCP eliminates haze and retrieves the image's clearness [4]. The benefit of this approach is its high-speed computation, which is desirable for real-time usage.

Another widely applied technique is Retinex Theory, which applies local contrast improvement to the image to approximate human eyes' adaptive brightness adjustment to make the image look sharper [4]. Retinex techniques mainly focus on adjusting the contrast, which is effective especially for low-contrast scenes.

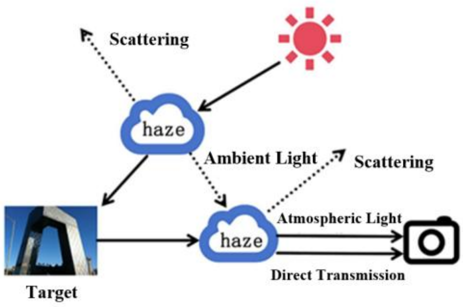

Figure. 1 Diagram of the atmospheric scattering model [4]

These classical approaches are computationally efficient and easy to apply and are therefore appropriate for real-time systems. But they suffer from the main demerits as well. For instance, they are based on assumptions, such, assumed to be of uniform illumination and limited variation of color distribution within the whole image. These assumptions are often violated under practical conditions such as strong lights, at nighttime, or with complex backgrounds [4]. They are additionally lacking good generalization capability as well. When applied to varying images or complex backgrounds, their dehazing performance becomes unstable and often contributes to distortion.

While such conventional approaches have such limitations, they are nonetheless useful in those situations where there is a need for real-time computation and limited computational resources are involved. As deep learning technology advances, data-driven image dehazing approaches are becoming increasingly successful with superior outcomes. Nevertheless, conventional approaches are useful under specific conditions where there is a need to accommodate real-time processing.

2.2. Deep Learning-Based Dehazing Methods

Deep learning-based methods have increasingly dominated image dehazing methods with the employment of Convolutional Neural Networks (CNNs) and Transformers, and brought new orientations to restoring images [4]. The workflow of the deep learning-based dehazing model architecture is shown in Figure 2, with a focus on key contributions of different models to the image processing workflow. Deep learning-based dehazing methods are capable of learning high-level features from large image datasets and restoring details and sharpness of images with learned patterns.

CNN-based approaches were amongst the first deep learning-based approaches proposed for image dehazing. LID-Net, for instance, applies a lightweight convolutional architecture and can be applied on embedded systems [4]. LID-Net operates on foggy images directly by multiple CNNs to reconstruct haze-free images. The benefit of this approach is that this method is capable of producing real-time dehazing even with limited computing capacity and is best applied on embedded systems for efficient processing.

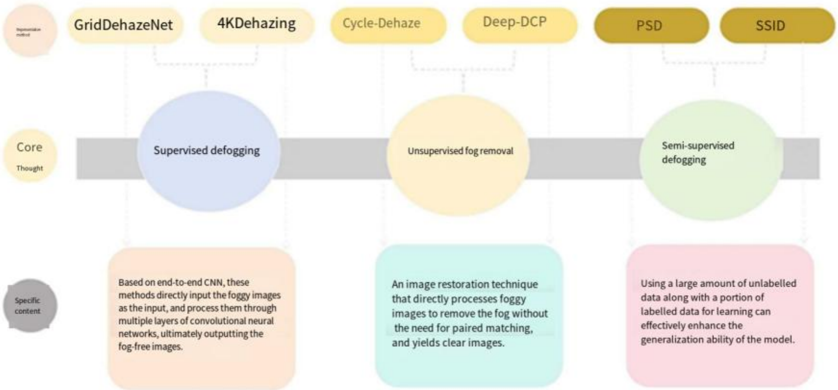

Figure. 2 Deep learning-based image dehazing structure [4]

Transformer-based Techniques are relatively new to the deep learning domain, with excellent performance on image processing tasks. TransWeather and DehazeFormer are two examples of this class of models, which utilize self-attention to handle long-range dependencies in an image and enhance dehazing performance for intricate scenes [6]. The benefit of using a Transformer is its capacity to learn global patterns as well as model long-range pixel dependencies and thus provide superior image restoration accuracy under highly structured and complex settings like city roads.

Although deep learning methods significantly improve image dehazing performance, they still face challenges. First, these methods require substantial computational resources, especially in Transformer models, where the large number of parameters results in high computational costs, suitable only for high-performance computing platforms [6]. Additionally, deep learning models typically require a large amount of labeled data for training, which can be a limitation in applications with limited labeled datasets.

Generally speaking, deep learning approaches, with their capacity to model on a global scale and train on massive datasets, have excellent image restoration performance and can adapt to varying scenes and intricate settings. Computational resource usage and data needs are nonetheless bottlenecks to present technology advancements, with future improvement centered on model efficiency optimization, computational overhead reduction, and enhanced generalization.

2.3. Unsupervised/Contrastive Learning-Based Dehazing Methods

Along with the emergence of image dehazing technology, unsupervised learning is increasingly becoming a new focus of research. The main benefit of unsupervised learning approaches is to lower the reliance on hand-labeled data and thereby ease data annotation difficulties and high data costs [5]. Compared to supervised learning with paired clear and hazy images, unsupervised learning often trains models by building positive and negative samples with image transformations.

One of the conventional approaches is UCL-Dehaze, which is built on unsupervised learning and contrastive learning. The approach produces positive and negative samples within the same image with different transformations to guide the model to learn dehazing representations [7-10]. The primary idea is to enable the model to learn to distinguish hazy and clear images by a paradigm of contrastive learning without using manually tagged clear images. The advantage of this method is its ability to train the model with a massive set of unlabeled data to reduce its reliance on high-quality labeled data and grant more flexibility during training [5].

Yet, with all the remarkable benefits of unsupervised learning to decrease labeling data requirements and enhance flexibility in training, there are several demerits too. Firstly, as there are no explicit target images to train on, training may become unstable and render incomplete detail restoration [5]. This is particularly a concern with high-security usage (like automotive obstacle detection systems), as even a restored image remains blurry to make decisions on system accuracy. Hence, although unsupervised dehazing solutions are very flexible with haze elimination, they are yet to be optimized for practical usage, particularly high-precision usage [11-13].

In summary, unsupervised/contrastive learning-based dehazing methods enhance training flexibility and model adaptability by reducing the dependence on labeled data. However, due to training instability and incomplete detail restoration, they have not yet fully replaced supervised methods, especially in applications that require high precision, where further improvements and optimizations are necessary.

3. Image Dehazing in Autonomous Driving Systems: Integration Applications

Dehazing technology for pictures is necessary to enhance the self-driving vehicles' perception function during unfavorable environmental conditions. Hazy days can cause blurred visual images, which affects object detection, path tracking, and decision-making capabilities of self-driving vehicles. From this point forward, image dehazing becomes an indispensable technology to enhance system reliability as well as safety. Image dehazing for self-driving vehicles is typically embedded with object detection and multi-sensor fusion technology to enhance perception.

Application to object detection is one of the main applications of image dehazing. The PED-YOLO model is among those models that apply image dehazing to objects for object detection. The model initially applies multi-scale dehazing processing to the received image and outputs the image to the YOLO detector to detect objects. The algorithm enhances object detection performance under rainy conditions by simultaneously training dehazing as well as detection tasks [14-17]. Image dehazing enhances not only image clarity but also target feature salience and consequently enhances object detection systems under adverse environmental conditions.

Furthermore, multi-sensor fusion is imminent as a component of autonomy for vehicles, especially with image dehazing. Autonomous vehicles typically carry several sensors, such as radar, LiDAR, and cameras to supply data. Via data fusion of those data, a more comprehensive understanding of the scene can be derived by the system [10]. Image dehazing forms a pre-processing improvement step under this situation by improving camera-visible image quality to supply sharper data to subsequent multi-sensor fusion. The fusion not only improves the system's resilience but also its flexibility under harsh environments.

Nonetheless, with increasingly popular multi-sensor data fusion technology comes growing security threats as well. Adverse hackers might interfere with data from one sensor and thus interrupt decision-making by the whole system. For instance, interference with visual data from cameras might blur out images, which will be detrimental to object recognition and the accuracy of path planning [11]. Towards this end, science professionals have introduced multi-modal collaborative training plans which entwine feature alignment and adaptive weighing strategies to improve the system's anti-interference ability [18].

By integrating image dehazing with object detection and multi-sensor fusion technologies, self-driving vehicles are not only capable of advancing image quality during bad weather but can enhance all-around perception as well to present more trustworthy data to guide decisions. The joint use of those technologies contributes significantly to ensuring self-driving vehicles' safety and accuracy, especially under complicated and dynamic scenes.

4. Challenges and Future Directions

Although dehazing technology for images has significantly improved with its application on self-driving vehicles, its practical implementation is challenged by several problems. The following are the main challenges encountered with current technologies, with solutions and prospects as recommendations for future study.

4.1. Computational Costs and Resource Constraints

Although deep learning-based methods, particularly those using Transformers, are highly effective for image dehazing tasks due to their excellent feature extraction and learning abilities, they are too computationally expensive to apply directly on limited-resource platforms like onboard platforms. Transformer-based models often come with large parameter counts, which incur high computational costs to maintain such large parameter volumes during computations and are not efficient with fast decision-making requirements for on-vehicle platforms with limited computational resources [14].

Solution: Future projects will focus on finding lightweight networks to improve the model's computational efficiency and ensure their utilization on embedded platforms. The lightweight deep learning models are able to reduce the number with lowered computational needs and are more suitable for limited resource conditions. Additionally, hardware acceleration as well as model quantization may play an essential role in solving this issue [14].

4.2. Domain Gap between Synthetic and Real Data

Most current image dehazing models are trained on synthetic hazy images. Although synthetic data can be quickly trained on to provide large sample numbers, there are differences between synthetic data and true scene images. The differences usually cause inferior model performance on practical sites [15]. Synthetic data could fail to include all possible complexities and illumination changes encountered on true scene hazy days, and as such, generalize poorly.

As a solution to this issue, scientists have proposed data augmentation strategies and unsupervised learning methods to enhance model generalization performance. Data augmentation can synthesize additional environmental conditions and haze states during training and make the model generalize to various states seen in practice more easily. Besides that, unsupervised learning methods reduce reliance on labeled real-world data and allow the model to learn internal image features and improve adaptability [15]. These solutions are able to decrease domain differences between synthetic data and real data and improve model performance under applied conditions.

4.3. Lack of Standardization in Multi-Modal Sensor Fusion

While multi-modal sensor fusion has been a significant trend in autonomous driving systems, particularly under complex environmental conditions where the perception capacity of a single sensor usually fails to satisfy system requirements, data from multiple sensors is combined to enable a more comprehensive and high-fidelity environmental perception. There is not yet a unified fusion modeling under current multi-modal sensor fusion technology, which presents much space for improvement on multi-source data synchronization and robustness [6]. The sensors differ from one another with different characteristics and accuracies, and integration of differences during fusion to ensure data accuracy and consistency is a primary challenge under current technology.

The next step for research is to design unified protocols and standards to enable optimal multimodal data fusion approaches. If standardized, not only will data from various sensors become more compatible with each other, but the system in practical use will also be more stable and reliable. Strong fusion algorithms and cross-sensor synchronization schemes will also be essential to enhance system performance [6]. As deep learning advances, the ways we can utilize deep learning-based models to enhance multi-modal sensor data fusion are another significant area to study.

4.4. Future Directions

With the advancements of autonomous driving technology, image dehazing and sensor fusion technology are confronted with new challenges and opportunities. Future studies will concentrate on enhancing model efficiency, adaptability, and system robustness to comply with requirements. When considering resource constraints, designing a lightweight network architecture will lower model computational overhead and enhance its deployment efficiency on embedded platforms and onboard hardware. Simplifying network architecture with hardware acceleration will allow these models to maintain dehazing performance and enhance processing speed and efficiency.

Additionally, with increasingly complex and varied future driving scenarios, adaptive structure design will be of key significance to future advancements. The model will slowly adapt its structure by varying environmental conditions to improve both accuracy and stability under changes of varying weather and illumination. At the same time, extending multi-sensor data fusion approaches and cross-domain generalization will play a crucial role in making the system able to adapt to complex driving scenes better, which will improve the system's resilience to various types of uncertainties.

5. Conclusion

This paper introduces image dehazing technology to autonomous driving visual sensing and outlines the essential function of dehazing technology to improve system performance as well as safety. Ever since deep learning came to this domain, image dehazing methods have progressed markedly, especially under harsh conditions. However, deep learning-based methods are susceptible to issues of computational costs, limited capabilities, and data mismatches.

By comparing classical physical models, deep learning approaches, and unsupervised learning approaches, this paper presents an overall outlook on using image dehazing technology for self-driving vehicles. All approaches have their own benefits and shortcomings: classical approaches are superior for real-time performance and computational efficiency, but deep learning approaches are superior under complex conditions, but have to overcome shortcomings with respect to computational cost and adaptability to data.

Future image dehazing technology studies will focus on designing a lightweight network structure, data generalization performance, and multi-sensor fusion. The above study directions will help to promote the stable application of image dehazing technology on practical self-driving systems and improve system performance under harsh environmental conditions.

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