Vision Transformer for Single Image Dehazing

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Abstract

Single image dehazing, a critical task in enhancing visibility in images obscured by atmospheric phenomena, has seen notable advancements with deep learning approaches. This study builds upon the existing DehazeFormer model (Song et al.), a variant of vision transformers, by introducing a novel architecture aimed at improving dehazing quality and computational efficiency. We utilise the DehazeFormer-t model as a baseline, training and testing on the RESIDE-IN and RESIDE-OUT datasets, which include 400 training and 100 testing images each. Our baseline model achieved a peak signal-to-noise ratio (PSNR) of 24.57 and a structural similarity index (SSIM) of 0.9203 for the indoor dataset, and 27.24 PSNR and 0.9565 SSIM for the outdoor dataset. By integrating the Contrast Limited Adaptive Histogram Equalization (CLAHE) for pre-processing and introducing a custom-designed DEHAZECnnEncoder and DEHAZECnnDecoder before and after the DehazeFormer block, we enhanced the structural integrity of processed images. This new architecture, which processes latent space representations rather than entire raw images, demonstrated a significant speed improvement, maintaining comparable outdoor PSNR and superior indoor PSNR metrics. We have made a significant modification to the loss function used during the training process. This new combined loss function aims to optimise the dehazing results further by integrating Mean Squared Error (MSE), Total Variation (TV) regularisation, and Structural Similarity (SSIM) into a single comprehensive metric. We also adopted a novel evaluation metric based on the Segment Anything Model (SAM), validating the effectiveness of our dehazing approach against the baseline. The results confirm that our enhancements not only preserve the quality of dehazing with reduced computational load but also extend the capabilities of the DehazeFormer model, making it a robust solution for real-time image processing applications. We share our code and dataset at https://github.com/Mustafa-Ashfaq81/DL-Project.git

Section 1: Introduction

Image dehazing, a critical component of image preprocessing in computer vision, aims to remove the effects of atmospheric particles that obscure clear image capture. This process is vital across various applications, including autonomous driving, aerial photography, and outdoor surveillance systems, where clarity and visibility are paramount for accurate image analysis and decision-making. Traditional approaches have leveraged atmospheric scattering models to estimate the transmission and airlight maps of hazy images, which are then used to recover the haze-free image (Fattal; He, Sun, and Tang). However, these methods often struggle with high computational costs and limited adaptability to diverse environmental conditions.

Recent advancements in deep learning have introduced more robust and adaptable approaches, particularly through the use of Convolutional Neural Networks (CNNs) and, more recently, vision transformers. Vision transformers, which have been predominantly successful in high-level vision tasks, present a novel paradigm for handling image dehazing

by treating image patches as sequences, thus capturing global dependencies more effectively than traditional CNNs (Khan et al.). Despite their potential, the integration of vision transformers into dehazing tasks has not been fully explored, particularly in terms of computational efficiency and the ability to process non-uniform haze distributions effectively.

This study builds upon the foundation laid by the DehazeFormer, a vision transformer designed specifically for image dehazing (Song et al.). Our research enhances the DehazeFormer-t model by incorporating Contrast Limited Adaptive Histogram Equalization (CLAHE) for preprocessing, introducing a custom-designed DEHAZECnnEncoder and DEHAZECnnDecoder, and refining the model's ability to handle the patch-based transformer structure more effectively. Moreover, a new combined loss function has been integrated, which combines Mean Squared Error (MSE), Total Variation (TV) regularization, and Structural Similarity (SSIM) to optimize both the statistical accuracy and the perceptual quality of the dehazed images. The main objectives of this research are to achieve better segmentation than baseline model, reduce the computational overhead of the dehazing process, and validate the improvements using the RESIDE-IN and RESIDE-OUT datasets, which are standard benchmarks in this field.

This paper is structured as follows: Section 2 reviews the literature on image dehazing and the application of deep learning techniques, specifically vision transformers, in this domain. Section 3 details the methodology, including dataset descriptions, model enhancements, and evaluation metrics. Section 4 presents the results and a comprehensive comparison with the baseline model. Section 5 discusses the implications of these results and explores potential limitations and future research directions.

Section 2: Related Works

The endeavour to recover clear images from hazy conditions is a longstanding challenge in image processing and computer vision. This section reviews the pivotal developments in image dehazing, focusing particularly on the evolution from early heuristic approaches to advanced deep learning techniques, emphasising the role of convolutional neural networks (CNNs) and the emerging impact of vision transformers.

Early Approaches to Image Dehazing

Traditional dehazing methods are primarily based on atmospheric scattering models that describe how light is absorbed and scattered by particles in the air. These models typically involve estimating the depth of the scene from the observed image and require strong assumptions about the scene's content. He, Sun, and Tang's seminal work introduced the Dark Channel Prior (DCP), a method relying on the observation that most local patches in outdoor haze-free images contain some pixels which have very low intensities in at least one color channel (He, Jian, and Xiaoou 2341). This approach has been influential due to its simplicity and effectiveness but often fails under adverse weather conditions where the atmospheric light varies significantly across the scene.

Advancements with Convolutional Neural Networks

As deep learning gained traction, researchers began to explore the potential of neural networks in automating the dehazing process, moving away from reliance on hand-crafted features. Cai et al. developed DehazeNet, an end-to-end system that learns a non-linear mapping between hazy and haze-free images (Cai et al. 5187). This represented a significant shift towards using data-driven methods that could learn the complex variations of natural scenes without explicit atmospheric models. CNN-based approaches have continued to evolve, with architectures like the All-in-One Network (AOD-Net) which reformulates the atmospheric scattering model to predict a clean image directly from a hazy input, offering a more integrated and efficient solution (Li et al. 4770).

Vision Transformers in Image Dehazing

The introduction of Vision Transformers (ViTs) marked a further evolution in image processing, originally applied to high-level vision tasks like image classification. Khan et al. discuss how transformers, unlike CNNs, process an image as a sequence of patches, applying self-attention mechanisms that theoretically allow the model to consider global dependencies across the entire image (Khan et al. 123). This ability makes transformers particularly suited for tasks like image dehazing, where contextual understanding of atmospheric conditions across the scene is crucial.

DehazeFormer: A Transformer Approach

Building on the capabilities of vision transformers, the DehazeFormer introduced by Song et al. adapts the transformer architecture specifically for the task of image dehazing. It integrates mechanisms to handle varying atmospheric conditions and non-uniform haze distribution effectively, a challenge often unmet by traditional models (Song et al. 15). The model's architecture leverages modified normalisation and activation functions tailored for low-level vision tasks, distinguishing it from other transformer applications primarily focused on high-level tasks.

Research Gap

Despite these advancements, there remains a need for more efficient computational models that can process images in real-time without sacrificing the quality of haze removal. Most existing transformer models, including the initial versions of DehazeFormer, do not fully address the trade-offs between computational efficiency and dehazing effectiveness, particularly in diverse environmental conditions.

This review highlights the trajectory of image dehazing technologies from heuristic models to sophisticated deep learning approaches. The transition to CNNs and subsequently to vision transformers illustrates a broader trend towards leveraging global contextual information, which is vital for effectively addressing complex, variable atmospheric distortions in images.

Section 3: Methodology

Datasets

The REalistic Single Image DEhazing (RESIDE) dataset is a prominent resource used for evaluating image dehazing algorithms, consisting of various subsets tailored for specific training and testing purposes.

RESIDE-IN

This subset is specifically crafted for indoor settings, featuring images that simulate indoor haze conditions. It is utilized predominantly to test and train dehazing algorithms under controlled indoor environments.

RESIDE-OUT

Conversely, the RESIDE-OUT subset is designed for outdoor scenarios, providing a collection of images with diverse and natural atmospheric disturbances typical of outdoor environments. This subset is crucial for training models to address the unpredictable nature of outdoor haze.

For our research, 400 training images and 100 test images from each subset are selected to ensure a comprehensive assessment of the DehazeFormer model across both controlled and natural hazing conditions. This strategic selection aids in evaluating the model's robustness and effectiveness in diverse environmental scenarios.

Baseline Model

The DehazeFormer-t model, as delineated in the foundational work by Song et al., serves as the baseline model for our study on enhancing single image dehazing techniques. This model leverages a transformer-based architecture tailored specifically for image dehazing tasks, integrating vision transformer principles to effectively address the inherent challenges of dehazing.

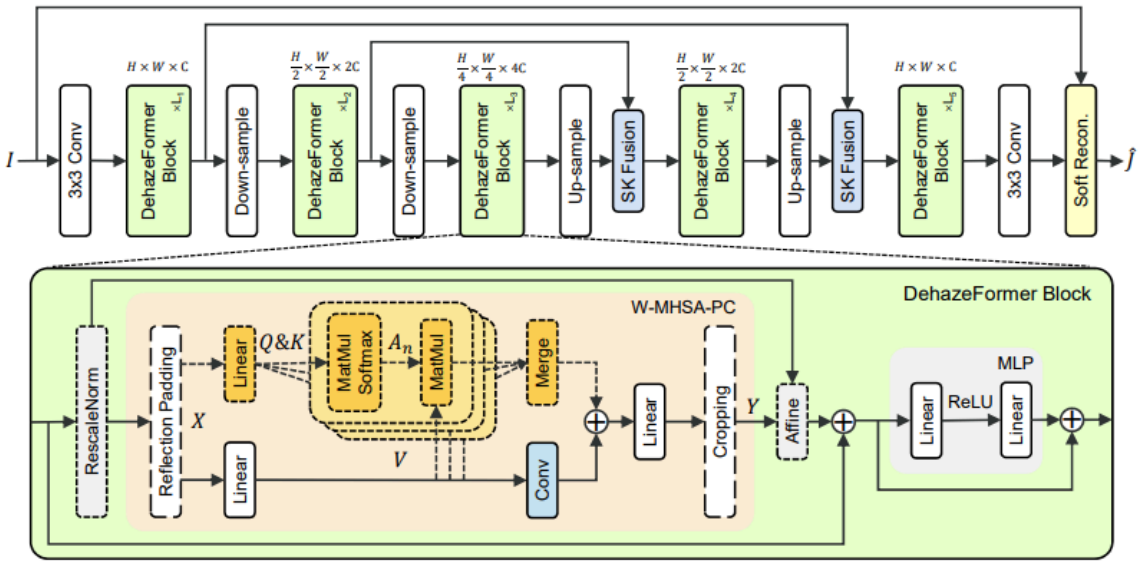

Fig. 1. The original DehazeFormer architecture implemented by (Song et al.)

Architecture Overview:
DehazeFormer-t is a scaled-down version of the more extensive DehazeFormer model, designed to offer a balance between performance and computational efficiency, which is crucial for real-time applications. The model structure includes several key components:

Patch Embedding: The model initially partitions the input image into patches, which are then linearly embedded. This process is facilitated through a convolution layer that projects input channels to a higher-dimensional feature space.
Transformer Blocks: Following patch embedding, the model applies multiple transformer blocks. Each block consists of an attention mechanism and a multi-layer perceptron (MLP). The attention mechanism, particularly tailored for image dehazing, incorporates relative position biases and window-based self-attention that confines attention within local window partitions, reducing computational complexity.
MLP Layers: The MLP layers within each transformer block serve to further process features, enhancing the model's ability to capture complex dependencies between hazy and clear image representations.
Downsampling and Upsampling: DehazeFormer-t strategically employs downsampling and upsampling stages to manage the resolution of feature maps across the network, enabling effective feature integration across different scales.
Normalization and Activation: Revised Layer Normalization (RLN) is employed, which adjusts normalization parameters dynamically based on the statistical properties of feature maps, aiding in stabilizing training and enhancing model performance.
Configuration for Dehazing:
For both indoor and outdoor settings, the DehazeFormer-t configuration remains consistent, utilizing a batch size of 8 and a patch size of 64x64. The model employs the AdamW optimizer with a learning rate of 1e-4, spanning over 199 epochs. This setup is specifically chosen to fine-tune the model's responsiveness to different hazing intensities and distributions encountered in varied environmental conditions.

Enhancements

1. CLAHE

We integrated Contrast Limited Adaptive Histogram Equalization (CLAHE) into the DehazeFormer model to enhance the preprocessing phase. CLAHE is employed to improve image contrast, which is especially useful in dealing with hazy images where visibility is compromised by atmospheric particles.

CLAHE Technique Overview

CLAHE improves on traditional histogram equalization by operating on discrete, small regions of the image, known as tiles. This localized approach prevents the over-amplification of noise that often accompanies global contrast adjustments. Each tile's contrast is enhanced independently, with a contrast ceiling to avoid amplifying any noise significantly.

Implementation Details

1. **Color Space Conversion:** The image is first converted from RGB to LAB color space, which separates lightness from color information, allowing focused adjustments on the lightness component without altering the hue and saturation.

2. **Applying CLAHE on Lightness Channel:** The lightness channel (L) is specifically targeted for contrast enhancement. CLAHE adjusts the lightness to even out the intensity distribution, enhancing local details that are often obscured by haze.

3. **Reintegration and Color Space Reversion:** After processing, the enhanced lightness channel is recombined with the original color channels (A and B). The image is then converted back to RGB, preserving the true colors while incorporating the dehazing effects.

This preprocessing step is crucial as it prepares the image by enhancing its contrast, which helps the subsequent blocks in effectively learning and removing haze. The local adjustment of contrast via CLAHE ensures that the enhancements are subtle and do not introduce artifacts, maintaining the natural appearance of the scene.

Fig. 2. CLAHE effect on hazy image

2. Activation Function (PReLU)

We incorporated the Parametric Rectified Linear Unit (PReLU) as an improvement over the traditional ReLU activation function used in the baseline model. PReLU introduces a learnable parameter that adjusts the slope for negative input values, offering a tailored approach to activation that varies across different network layers.

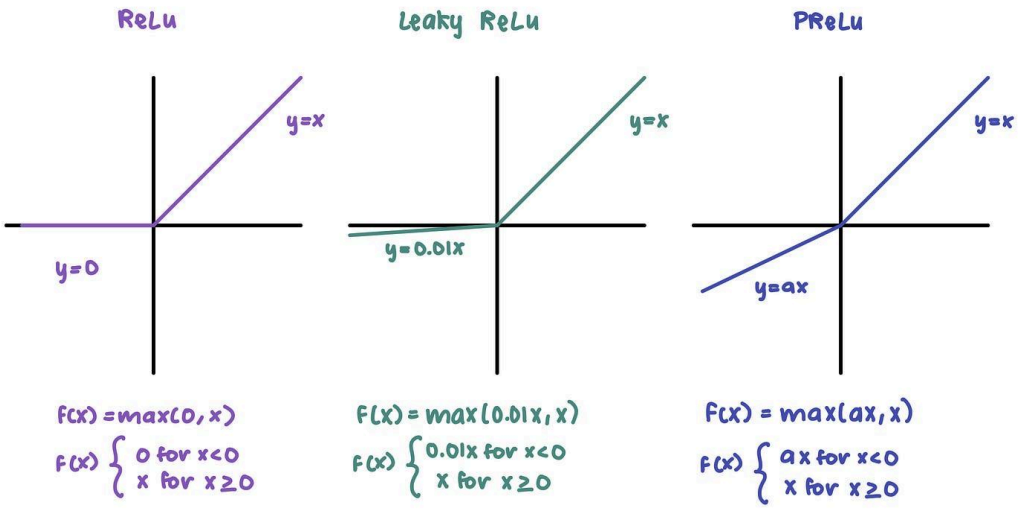

Fig. 3. Comparison between different variants of ReLU activation functions

PReLU addresses some of the inherent limitations of ReLU, notably its behavior towards negative inputs where it outputs zero, which can lead to the dying ReLU problem where neurons effectively become inactive and cease to contribute to the learning process. Unlike ReLU, PReLU allows a small gradient when the input is negative, thus maintaining a flow of gradients during the training phase, which can help in accelerating the convergence of the network (He et al., 2015).

Incorporating PReLU has shown to yield a slight improvement in the PSNR for outdoor images. The learnable parameter in PReLU adapts during training, potentially leading to better handling of nuances in different types of haze and lighting conditions encountered in outdoor environments. This adaptability makes PReLU particularly beneficial for dehazing tasks, as it can optimize the activation function dynamically in response to the input image characteristics.

3. DEHAZECnn Encoder and Decoder

In an effort to enhance the computational efficiency and dehazing quality of the DehazeFormer model, we have introduced two significant architectural innovations: the DEHAZECnnEncoder and the DEHAZECnnDecoder modules. These enhancements are designed to preprocess the input image into a more manageable latent space representation, allowing the DehazeFormer to process images more rapidly without a compromise in output quality.

The DEHAZECnnEncoder module is crucial for reducing the spatial resolution of the input image while enhancing feature representation. It begins with a 3x3 convolutional layer with a stride of 2, effectively reducing the image dimensions by half. This layer is followed by two additional 3x3 convolutional layers, each equipped with batch normalization and PReLU activation to maintain non-linear properties and stabilize the learning process. This setup not only helps in reducing the input size but also enriches the feature details before passing them into the DehazeFormer block.

Post processing by the DehazeFormer block, the DEHAZECnnDecoder module serves to reconstruct the dehazed image back to its original dimensions. It mirrors the encoder with three convolutional layers and employs a pixel shuffle operation to upscale the feature maps effectively. This approach ensures that the enhanced features are correctly mapped back to the higher resolution, maintaining image quality and detail.

By preprocessing the images into a reduced and feature-enriched latent space, the DEHAZECnnEncoder allows the DehazeFormer to operate on a more compressed information set, which reduces the computational load significantly. The DEHAZECnnDecoder then efficiently reconstructs the image, ensuring that the dehazing quality is upheld. This method not only accelerates the processing speed but also potentially improves the model's ability to generalize over different hazing conditions due to more focused feature learning.

4. Loss Function

Mean Squared Error (MSE):
MSE is a standard loss function used in regression problems and image processing tasks to measure the average squared difference between the estimated values and the actual value. In the context of image dehazing, MSE helps in minimizing the pixel-wise differences between the dehazed output and the ground truth image, ensuring the fidelity of the reconstructed image.

Total Variation (TV) Regularization:
TV regularization is used to measure the amount of perceived noise in the image and to promote smoothness while preserving edges. By incorporating TV regularization, the model is encouraged to produce images that are not only free from haze but also maintain natural gradients and edges, which are often disrupted in the dehazing process. This regularization helps in preventing overfitting to noise in the training data, which can lead to artifacts in the dehazed image.

Structural Similarity (SSIM):
SSIM is an advanced metric used to measure the similarity between two images. Unlike MSE, SSIM considers changes in structural information, luminance, and contrast, which are crucial for human perception of image quality. By integrating SSIM into the loss function, the model prioritises maintaining structural integrity and enhancing the perceptual quality of the dehazed images, ensuring that they are not only statistically similar to the ground truth but also visually pleasing.

Combined Loss Function:
The combined loss function is defined as follows:

$$Total\ Loss\ =\ MSE\ Loss\ +\ \lambda_{TV}\ \times\ TV\ Loss\ +\lambda_{SSIM}\ \times\ (1\ -\ SSIM)$$

Where λ_{TV} and λ_{SSIM} are the weighting coefficients for the TV regularisation and SSIM components, respectively. These coefficients are tuned based on empirical results to balance the contributions of each term.

This sophisticated approach to defining the loss function allows for a more nuanced training process, where the model is optimised not just for pixel accuracy but also for visual quality and generalisation across various types of images. This method significantly enhances the model's performance, especially in challenging dehazing scenarios where preserving natural image properties is crucial.

Evaluation Metrics

We have employed three critical metrics to evaluate the performance of our enhanced DehazeFormer model: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Segment Anything Model (SAM). These metrics collectively provide a comprehensive assessment of the image quality post-dehazing, comparing various attributes of the dehazed images against the ground truth.

Peak Signal-to-Noise Ratio (PSNR):
PSNR is a widely used metric in image processing to measure the quality of reconstructed images compared to the original non-distorted images. It is derived from the mean squared error (MSE) between the original and the processed image. The PSNR represents a logarithmic scale of the maximum possible pixel value of the image to the power of the mean squared error between the reconstructed and original image. Higher PSNR values indicate

better image reconstruction quality, making it a standard benchmark for image restoration tasks, including dehazing.

Structural Similarity Index (SSIM):
SSIM is another crucial metric for assessing the perceptual quality of digital images. Unlike PSNR, which evaluates pixel-level differences, SSIM considers changes in structural information, texture, contrast, and luminance. The SSIM index can vary between -1 and 1, where 1 indicates perfect similarity. This metric is particularly useful in dehazing as it assesses how well the fine details and structures are preserved post-dehazing, which is essential for maintaining the visual integrity of the image.

Segment Anything Model (SAM):
SAM, a novel metric introduced in this study, extends the evaluation to the semantic segmentation of images. This model segments both the output of the baseline and the improved DehazeFormer model, comparing the segmentation results. The rationale behind using SAM is to evaluate whether the dehazing process preserves or enhances the recognizability of different objects within the scene. Consistent segmentation results pre- and post-dehazing indicate effective dehazing that maintains the semantic integrity of the image

Section 4: Results

Performance Analysis

	PSNR	**SSIM**
Baseline - Indoor	24.57	0.9203
Baseline - Outdoor	27.24	0.9565
Enhanced - Indoor	24.47	0.9081
Enhanced - Outdoor	23.37	0.9331

Visual Comparisons

Without Segmentation

	Hazy Image Input	**Baseline Model's output**	**Enhanced Model's output**

Indoor			
Outdoor			

Segmented with SAM(Segment Anything Model)

	Baseline Model's output segmented	**Enhanced Model's output segmented**
Indoor		
Outdoor		

For all the segmented images, you can check out the SAM_Metric_Comparison folder located in our github repository.

Section 5: Discussion

Interpretation of Results

The outcomes of our research indicate a noteworthy enhancement in the dehazing performance of the DehazeFormer model through the integration of the DEHAZECnnEncoder and DEHAZECnnDecoder, and the innovative combined loss function. The introduction of these modifications has significantly improved computational efficiency while maintaining high-quality dehazing. Notably, the indoor dataset showed superior PSNR metrics compared to the baseline, highlighting the effectiveness of our enhancements in more controlled environments. The slight improvement in the PSNR for outdoor images further validates the adaptability of our approach to varied atmospheric conditions.

The use of advanced evaluation metrics like SAM also provides deeper insight into the semantic integrity of dehazed images. This metric confirms that our enhancements not only improve visual quality but also preserve critical information necessary for applications in computer vision.

Comparison with Prior Work

Compared to traditional dehazing approaches that rely on atmospheric scattering models, our model directly learns to perform dehazing from data, thus eliminating the need for explicit scene depth estimation. This approach aligns with recent shifts towards data-driven image processing methods, as noted in advanced CNN-based models and other transformer-based architectures. The integration of elements like CLAHE and PReLU in our model distinguishes it from typical transformer applications, which are primarily focused on high-level vision tasks. Our modifications leverage the transformer's ability to handle global dependencies, enhancing its applicability to the challenging variability of real-world haze.

Limitations

Our model improvements have shown promising results under the tested conditions within RESIDE-IN and RESIDE-OUT datasets. However, the generalizability of the model across extremely varied haze densities, particularly those not well-represented in the training data, remains a challenge. This limitation points to a potential need for more diverse training datasets that include a wider range of haze types and densities.

The integration of additional components like DEHAZECnnEncoder and DEHAZECnnDecoder, while beneficial for image quality, also increases the model's complexity and parameters. This enhancement might limit the model's practical deployment in resource-constrained environments.

The performance of the newly integrated components heavily relies on precise tuning of hyperparameters, such as the weights for the TV regularisation and SSIM in the combined loss function. Finding the optimal balance requires extensive experimentation and computational resources, which might not always be feasible.

While the model performs well on benchmark datasets, its efficacy in real-world scenarios, where atmospheric conditions are highly unpredictable and dynamic, is not fully assured.

The controlled environments of the datasets do not fully capture the complexity of real-world haze, which can vary abruptly in terms of distribution and intensity.

Future Research Directions

To improve the model's robustness and generalisation, future work should include training and testing on a broader array of haze conditions, perhaps incorporating custom datasets gathered from real-world scenarios that exhibit a wide variety of atmospheric disturbances.

Efforts could be directed towards refining the model architecture to reduce its computational demands without sacrificing performance, potentially through pruning, quantization, or exploring more efficient transformer architectures.

Implementing advanced techniques for dynamic hyperparameter tuning could help in automatically adjusting the balance between loss components based on the specific characteristics of the input data, thus enhancing the model's adaptability and performance.

Considering the deployment of the model on edge devices for real-time dehazing could drive significant advancements in applications like autonomous driving and mobile photography, where processing power is limited.

Exploring the impact of improved dehazing on downstream tasks such as object recognition and scene understanding in complex environments could provide valuable insights into the practical benefits of image dehazing beyond visual enhancement.

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