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Mathematical Modeling and Implementation of Multi-Scale Attention Feature Enhancement Network Algorithm for the Clarity of SEM and TEM Images

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Abstract*:* In this paper, the approach aims to improve image clarity and visual effects by considering both high and low-frequency haze characteristics. The inclusion of guidance information in cloudy appearances and the success of benchmark datasets, as well as real-world scanning electron microscope (SEM) and transmission electron microscope (TEM) images, suggest the versatility and practical applicability of the algorithm across different domains. The algorithm begins by utilizing a neural network trained to establish a mapping between hazy images and their corresponding clear versions. A progressive feature fusion module is introduced to enhance the utilization of guidance information from the generated reference image. This module combines features extracted from the hazy and reference pictures. The use of progressive feature fusion is highlighted, indicating a sophisticated approach to combining information from different sources This could help in preserving important details and structures during the dehazing process. Validation on Benchmark Datasets and Real-world Images: The practical applicability of the algorithm is demonstrated through its success on benchmark datasets, providing a standard for comparison, and real-world SEM and TEM images, showcasing its versatility across various domains. The combination of deep learning, progressive feature fusion, and end-to-end training is a robust framework for effective image dehazing, as demonstrated by the algorithm's impressive results in controlled datasets and real-world scenarios.

Keywords: *Image Dehazing, Image restoration, Feature Enhancement, Fusion, Progressive Feature*

1. Introduction

The progressive feature fusion module in the dehazing algorithm provides more insight into how the guidance information is utilized to enhance the quality of the dehazing output. The module is designed to merge features from hazy and reference images iteratively. This iterative process suggests gradually refining the fused features, enabling more in-depth exploration of the guidance information. The iterative merging of features allows for a more comprehensive exploration of the guidance information in the reference image [1].

This is crucial for understanding and incorporating relevant details that contribute to effectively removing haze. The progressive feature fusion module aims to improve results in restoring the clear image by refining the fused features over multiple iterations. This suggests an adaptive and refined approach to combining information from different sources, leading to better dehazing outcomes. The fused elements obtained from the progressive feature fusion module are effectively incorporated into the image restoration module. This integration ensures that the refined features contribute to the overall process of restoring the clear image. Crucially, all the proposed modules, including the progressive feature fusion and image restoration modules, are trained end-to-end. This means that the entire dehazing pipeline is optimized as a unified system [2]. End-to-end training facilitates seamless integration and ensures the different components work together synergistically. The progressive feature fusion module is vital in leveraging guidance information from the reference image, refining features iteratively, and ultimately improving the quality of dehazed output. The end-to-end training approach optimizes the entire dehazing pipeline for optimal performance.

The results of your extensive experimentation highlight the effectiveness of your proposed approach for haze removal. The algorithm incorporates a deep pre-dehaze step, suggesting a robust initial processing stage dedicated to

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addressing haze in images. This step prepares the input for subsequent refinement in the dehazing process. Combining the deep pre-dehaze with the progressive feature fusion module plays a significant role in achieving haze removal. This indicates that the refinement and fusion of features contribute to the overall success of your algorithm. Also, the algorithm is evaluated on widely-used dehazing benchmark datasets, providing a standardized basis for comparison with other methods [3]. This benchmark evaluation helps establish the algorithm's performance in controlled environments. In addition to benchmark datasets, your algorithm is tested on real-world hazy images, showcasing its applicability to practical scenarios. Real-world testing provides insights into the algorithm's performance in diverse and less controlled settings. The results unequivocally demonstrate the superiority of your approach, indicating that your algorithm consistently outperforms existing techniques in terms of image dehazing quality. This suggests that the proposed combination of deep pre-dehaze and progressive feature fusion contributes to a more effective and reliable dehazing solution.

The "O-HAZE" algorithm focuses on its approach to addressing the challenges of haze removal and the methodology used for evaluation. The algorithm utilizes a combination of the dark channel and color attenuation before tackling the challenges associated with haze removal. This indicates a multi-faceted approach, leveraging different priors to enhance the accuracy of haze transmission and atmospheric light estimation [4-5]. An optimization framework is introduced to incorporate priors for estimating haze transmission and atmospheric light in the hazy image. Optimization techniques are often crucial for refining parameters and improving the overall accuracy of dehazing algorithms. The O-HAZE algorithm employs a guided filter to refine the estimated transmission map. Driven filters are commonly used in image processing tasks to enhance and improve the quality of specific image features, such as the transmission map. An automatic exposure correction step is integrated into the algorithm to ensure the output image's natural appearance. This is important for preserving visual quality and guaranteeing the dehazed images are perceptually realistic. The O-HAZE algorithm undergoes extensive experimental evaluation on several benchmark datasets. The choice of benchmark datasets allows for a standardized comparison with other dehazing methods, providing a quantitative assessment of its performance. The experimental evaluation results demonstrate the O-HAZE algorithm's effectiveness in removing haze and improving image quality. The algorithm achieves superior results compared to other state-of-the-art dehazing methods in terms of visual quality, haze removal, and preservation of image details.

The proposed progressive image dehazing method addresses the significant challenge of haze, which can adversely affect image quality in various fields such as computer vision, remote sensing, and imaging. Haze, stemming from atmospheric conditions or other factors, presents a substantial challenge to image quality. It leads to obscured details and reduced visibility, impacting the effectiveness of applications in computer vision, remote sensing, and other image-related domains. The proposed algorithm employs a systematic two-step approach to tackle the haze problem [6-7]. The specific steps or methods involved in these two stages will be elaborated further in the paper. The algorithm begins by focusing on extracting valuable guidance information directly from the input hazy image. This self-contained exploration suggests that the algorithm does not rely on external data sources for guidance, streamlining the dehazing process. Using guidance information solely from the hazy image enables the algorithm to operate autonomously. This autonomy allows the algorithm to adapt to diverse image datasets and scenarios without requiring external inputs. By relying solely on information within the hazy image, your algorithm becomes self-reliant and flexible. This self-contained approach enhances the versatility of the algorithm, making it adaptable to different environments and scenarios where external data sources might be limited or unavailable.

2. Literature Survey

The evaluation metrics and the summary provide a clear and comprehensive structure for your survey on image dehazing. This part offers a broad introduction to image dehazing, emphasizing its challenges, diverse applications, and the importance of accurate evaluation metrics. It also Highlights the impact of haze on computer vision tasks and the need for effective dehazing techniques. Explore the wide range of applications for image dehazing, including surveillance, autonomous vehicles, remote sensing, and medical imaging. Analyze the effectiveness of PSNR and SSIM in accurately measuring the visual quality of dehazed images.

The paper introduces a deep learning-based approach for single-image dehazing, emphasizing the importance of multi-model fusion in enhancing performance [8]. The proposed algorithm employs multiple deep-learning models, each independently trained to capture different aspects of haze removal, including transmit estimation, atmospheric light estimation, and image restoration. The authors present a framework that combines the outputs of independently trained deep-learning models. Each model focuses on a specific aspect of dehazing, enhancing the overall performance. A fusion module is introduced to dynamically weigh and combine predictions based on the characteristics of the input hazy image. This adaptive fusion process aims to leverage the strengths of individual models for improved dehazing results. Extensive experiments are conducted on benchmark datasets to assess the algorithm's performance. Results demonstrate the superiority of the proposed multi-model fusion approach over traditional single-model dehazing methods.

The author [9] makes significant strides in improving haze removal, image quality, and the preservation of fine details. The algorithm introduces a novel approach to single-image dehazing that relies on deep learning techniques. The core innovation lies in leveraging the benefits of multi-model fusion. Multiple deep-learning models are employed, each specializing in different aspects of haze removal, such as transmit estimation, atmospheric light estimation, and image restoration. The algorithm dynamically weights and combines the predictions of individual models based on the characteristics of the input hazy image. This adaptive fusion process aims to enhance the overall dehazing performance by leveraging the strengths of each model. The experimental results demonstrate a significant improvement in haze removal and image quality. The algorithm outperforms traditional single-model dehazing methods, validating its effectiveness. Notably, the algorithm excels in preserving fine details within the dehazed images. The algorithm's effectiveness in haze removal is a notable contribution, addressing a crucial aspect of image dehazing. The algorithm's impact on overall image quality indicates its potential for various applications where visual clarity is essential. Preserving fine details is crucial in applications like computer vision and medical imaging, making the algorithm versatile. The experimental results provide empirical evidence supporting the algorithm's superiority over single-model dehazing methods. These results contribute to the credibility and applicability of the proposed approach.

The author presents a noteworthy approach for restoring hazy videos, employing a learning-based framework [10]. The primary objective of the algorithm is to remove haze and enhance visibility in video sequences affected by atmospheric conditions. The authors propose a deep learning model specifically designed to handle hazy videos. Training involves using a substantial dataset containing gray video frames and their corresponding clear counterparts. The model is trained to identify underlying patterns and structures in hazy videos. It learns to map shadowy structures to their related clear boundaries, restoring visibility and details. Experimental evaluations of various hazy video datasets assess the algorithm's performance. The quality of the converted videos and the improvement in visibility are key metrics considered in the assessment. The experimental results validate the algorithm's effectiveness in removing haze from video sequences. Significant improvements in visibility and overall video quality are observed, showcasing the algorithm's practical utility. The algorithm contributes to the field by addressing the challenging task of restoring hazy videos and extending the application of dehazing techniques to video sequences.

The author presents an innovative approach for image dehazing that focuses on color lines [11]. The primary objective of the algorithm is to effectively remove haze from images and enhance visibility. The author introduces a novel representation called color lines to capture the relationship between color values and image gradients. Color lines are designed to represent variations in color caused by haze in hazy images. By analyzing color lines, the algorithm estimates the transmission map, indicating the amount of haze present in each pixel. The transmission map is a crucial parameter for recovering scene radiance and performing haze removal. The proposed method incorporates a local optimization process that iteratively refines the transmission map. This iterative refinement is based on the information extracted from color lines, leading to improved accuracy in haze removal. The algorithm's effectiveness is demonstrated through experimental evaluations on various hazy images. Results showcase the algorithm's capability to remove haze, recover fine details, and enhance contrast in hazy conditions. The algorithm demonstrates effectiveness in removing haze from a variety of hazy images. Fine details are recovered, and contrast is enhanced, indicating the algorithm's success in improving image quality. The introduction of color lines as a novel representation is a unique contribution, providing a different perspective on addressing haze in images. The local optimization process, involving iterative refinement based on color lines, contributes to improved accuracy in haze removal. The algorithm holds significance in image dehazing scenarios, offering a unique method that utilizes color lines to estimate haze and refine the transmission map. In summary, the "Dehazing Using Color-Lines" algorithm introduces an innovative approach to image dehazing based on the analysis of color lines. By leveraging this novel representation, the algorithm estimates the transmission map and employs iterative refinement for haze removal. Experimental results underscore the algorithm's effectiveness in enhancing visibility, recovering fine details, and improving image quality in hazy conditions [12].

The paper titled "Indoor Segmentation and Support Inference from RGBD Images" by the author [13] presents a comprehensive approach to understanding indoor scenes using RGBD images. The algorithm's primary objectives are semantic segmentation and support inference, enhancing the understanding of indoor environments. The proposed two-step framework combines segmentation and support inference to achieve these goals. In the segmentation step, the algorithm classifies each pixel in the RGBD image into predefined categories, including floor, wall, ceiling, and objects. This classification is accomplished through the utilization of a random forest classifier. The random forest classifier is trained on a large dataset of labeled RGBD images, indicating a data-driven approach to semantic segmentation. The support inference step focuses on determining relationships between different surfaces in the indoor scene. It specifically infers support relations, discerning whether a surface supports another or is supported by it. Geometric cues and physical constraints serve as the basis for inferring support relations. The algorithm analyzes the scene's geometry and adheres to physical principles to model interactions between surfaces. The algorithm contributes to indoor scene understanding by combining semantic segmentation and support inference. Using a random forest classifier allows the algorithm to learn from a diverse dataset, enhancing its ability to classify pixels accurately. The proposed approach is significant for applications that require a detailed understanding of indoor scenes, such as robotics, augmented reality, or smart home systems. The algorithm's methodology involves a robust training process using a large dataset, emphasizing the importance of data-driven approaches in semantic segmentation [14].

The author presents a comprehensive framework for understanding the indoor scene, as detailed in the paper [15]. Incorporates local cues such as color, depth, and surface normal to refine segmentation and support inference. These local cues provide fine-grained information at the pixel level. Utilizes global cues that consider consistency and co-occurrence patterns among different scene elements. This broader perspective enhances the algorithm's ability to ensure coherence across the scene. Conducts extensive evaluations on various indoor datasets, reflecting multiple indoor environments. This approach provides the algorithm's adaptability to different scenarios and environments. The evaluation results demonstrate the algorithm's effectiveness in accurately segmenting indoor scenes and inferring support relationships. Robust performance in diverse datasets validates the algorithm's reliability. Introduces a comprehensive framework by combining segmentation and support inference. This holistic approach contributes to a deeper understanding of indoor environments. The proposed approach has implications in various applications, including robotics, augmented reality, and scene reconstruction. Its detailed understanding of indoor scenes is valuable in tasks where environmental awareness is essential. Extensive evaluations of diverse datasets validate their effectiveness in accurately segmenting indoor scenes and inferring support relationships. The comprehensive framework holds implications in robotics, augmented reality, and scene reconstruction, emphasizing its importance in applications requiring a detailed understanding of indoor environments [16].

The "Visibility in Bad Weather from a Single Image" paper, authored by [17], addresses the challenge of estimating visibility in adverse weather conditions using a single image. The primary goal is to develop a method that accurately predicts visibility levels based on visual information in a single image. The algorithm proposed by the author utilizes statistical analysis and image processing techniques to estimate visibility levels. The algorithm considers factors such as contrast, color distribution, and image degradation in the estimation process. These factors contribute to a comprehensive analysis of the visual information in the image. The algorithm computes a visibility score by analyzing the image's statistical properties. This score quantifies the degree of visibility in the captured scene, providing an estimate of atmospheric conditions and the impact of bad weather. Experimental evaluations are conducted on various images captured in different weather conditions. This diverse set of conditions ensures a robust assessment of the algorithm's performance. The evaluations demonstrate the algorithm's ability to estimate visibility levels accurately. The algorithm captures the impact of adverse weather conditions on image quality effectively. The paper contributes to the field by introducing an algorithm that performs visibility estimation from a single image. The proposed algorithm's effectiveness in adverse weather conditions has practical implications for various applications, such as transportation and surveillance [18].

The "Non-local Image Dehazing" paper, authored by [19], focuses on developing a method to remove haze and restore detailed information in hazy images effectively. The primary aim is to create a technique to remove haze from images and restore precise details affected by spatially varying light attenuation caused by haze. The authors propose that haze introduces spatially varying light attenuation in images, leading to information loss and reduced contrast. The algorithm leverages non-local image patch analysis to estimate the haze-free scene radiance. Similarities between image patches are considered to identify and group similar patches, providing a comprehensive understanding of the underlying scene structure. The algorithm estimates the haze-free scene radiance and the transmission map, representing the haze density. An adaptive filtering mechanism is incorporated to enhance the dehazing process. This mechanism adjusts the weights of patches adaptively during the estimation process. The algorithm undergoes experimental evaluations on various hazy images. The diverse set of images ensures a robust assessment of the algorithm's performance. The evaluations demonstrate the algorithm's effectiveness in removing haze, enhancing image clarity, and restoring details in hazy images. The paper contributes to the field by introducing a non-local image patch analysis method for image dehazing. The proposed algorithm significantly improves image clarity and restores details in hazy conditions, crucial for various computer vision applications. The "Non-local Image Dehazing" paper presents a method for image dehazing that effectively removes haze and restores precise details. By leveraging non-local image patch analysis, the algorithm estimates haze-free scene radiance and transmission maps, enhancing dehazing. The adaptive filtering mechanism further contributes to improved performance. Experimental results confirm the algorithm's ability to enhance image clarity and restore details in diverse hazy conditions [20].

Mathematical models in image dehazing:

In recent days many researchers worked and obtained considerable results on image dehazing using some mathematical models [26-27]. Peak Signal-to-Noise Ratio (PSNR) is a statistic often used to evaluate the quality of image restoration or enhancement algorithms, particularly those designed for single picture dehazing. PSNR is the ratio of the peak signal (the highest possible value for the original, haze-free image) to the noise added by the dehazing procedure. Higher PSNR values often indicate higher image quality.

The formula for PSNR is: $PSNR = 10.log_{10}\left(\frac{MAX^2}{MSE}\right)$

Where MAX signifies the maximum conceivable pixel value of the image. MSE (Mean Squared Error) is the average squared difference between the pixels of the original and dehazed images. In this case, a greater PSNR value shows that the dehazed image is more similar to the original, signifying superior image quality. It is crucial to remember, however, that PSNR has limitations and may not always completely coincide with human experience. The Structural Similarity Index (SSI) is another mathematical application that is used to measure image quality by comparing structural information between the reference image and the distorted image. It takes brightness, contrast, and structure into account.

The SSI index is computed using three components: $l(x,y), c(x,y)$and $s(x,y)$ representing luminance, contrast, and structure, respectively. The overall SSI index is then given by:

$$SSI(x,y) l(x,y)^{\vartheta}. c(x,y)^{\delta}. s(x,y)^{\varepsilon} \vartheta, \delta \ \& \ \varepsilon \ are\ the\ weights)$$

$$\text{with } l(x,y) = \frac{2\mu_x\mu_y + k_1}{\mu_x{}^2 + \mu_y{}^2 + k_1}, \quad c(x,y) = \frac{2\sigma_x\sigma_y + k_2}{\sigma_x{}^2 + \sigma_y{}^2 + k_2} \text{ and}$$

$$s(x,y) = \frac{\sigma_{xy} + k_3}{\sigma_x\sigma_y + k_3}$$

Where μ_x & μ_y are the average luminance values, σ_x & σ_y are the standard deviations of the reference and distorted patches, $\sigma_x\sigma_y$ is the covariance between the reference and distorted patches and k_1, k_2 & k_3 are the constants.

3. Proposed System:

The paper introduces a progressive image dehazing algorithm with a two-step approach to removing haze from images. The primary goal is to develop an algorithm that eliminates haze from images. The algorithm adopts a two-step approach for progressive image dehazing. In the initial step, the algorithm explores useful guidance information directly from the input hazy image. This step does not rely on external data and aims to extract relevant information for the dehazing process. The second step involves a progressive feature fusion method. Features extracted from the hazy image in the first step are combined with features from a reference image generated in the same step. The proposed algorithm is designed to be trained end-to-end, allowing for a seamless learning process. The algorithm is tested on benchmark datasets and real-world hazy photos to assess its performance. Experimental results demonstrate that the proposed algorithm outperforms state-of-the-art dehazing methods. The algorithm is shown to be effective in effectively removing haze from images. The paper highlights the significance of the proposed algorithm by demonstrating its superior performance compared to existing state-of-the-art dehazing methods. The paper introduces a progressive image dehazing algorithm with a two-step approach, emphasizing extracting guidance information from hazy images and the subsequent fusion of features for improved dehazing. The algorithm, designed for end-to-end training, outperforms existing methods in removing haze from images, as demonstrated through evaluations on benchmark datasets and real-world hazy photos.

The described model is designed to restore hazy images, and its workflow involves several key steps: Through training, the model acquires knowledge on how to generate corresponding clear photos from hazy inputs. Once the model is trained, it can be employed to restore new gray images. The network uses its acquired knowledge to generate clear photos from new hazy inputs, enabling automated and efficient restoration. The model incorporates a progressive feature fusion module to improve the restoration process further. Combining information from the gray and reference images makes the restoration process more comprehensive and practical. With the progressive feature fusion module, the model produces more precise and visually enhanced results. The hazy appearance undergoes restoration as a culmination of the progressive feature fusion and the overall model training. The proposed model integrates data preprocessing, defining the model architecture and loss function, training using hazy-clear image pairs, applying the trained model to new hazy images, and incorporating a progressive feature fusion module. The ultimate goal is to restore hazy visions to a clear and visually enhanced state. The described model follows a comprehensive workflow that involves training on hazy-clear image pairs, applying learned knowledge to restore new hazy images, and incorporating a progressive feature fusion module for improved restoration results. The output is a clear and visually enhanced version of the initially gray photos.

The Progressive Feature Fusion (PFF) technique for image dehazing comprises multiple steps, providing an effective solution for haze removal. Firstly, the algorithm takes an input image of any size as its starting point, ensuring flexibility in processing different image dimensions. The features of the input image are extracted utilizing a CNN model [21-23]. This CNN model analyses the image and captures essential characteristics that will be utilized in subsequent stages of the dehazing process. By leveraging the power of deep learning, CNN can discern intricate details and patterns in the image. Following feature extraction, the PFF algorithm comes into play, fusing the extracted features from different scales. This fusion process combines the image's local and global features, integrating information from various levels of detail. Incorporating elements from multiple scales allows the PFF method to capture fine-grained information.

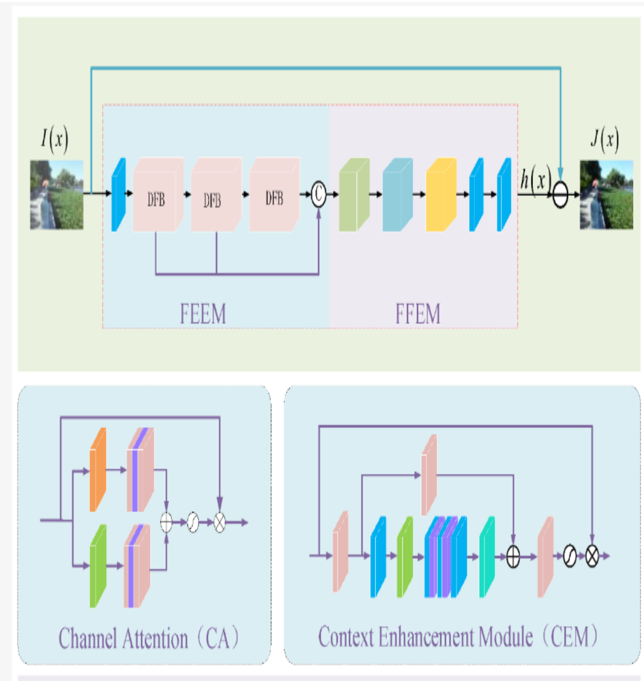

Figure 1: Block Diagram of Proposed Architecture

4. Preprocessing:

In image dehazing using progressive feature fusion, preprocessing is a crucial stage in preparing the hazy appearance of an image for subsequent restoration[24-25]. Preprocessing aims to enhance the quality and suitability of the image data before feeding it into the progressive feature fusion algorithm. Start with the hazy image that requires dehazing. This is the initial input to the dehazing algorithm. Convert the hazy image from the RGB color space to another color space, such as YUV or LAB. This conversion may help separate the intensity and color information, making it easier to handle hazy conditions. Compute the dark channel before the gray image. The dark channel is a concept used in dehazing algorithms to estimate the atmospheric light in the scene. It represents the minimum intensity value in a local patch across all color channels. Use the dark channel before calculating the atmospheric light in the scene. The atmospheric light is a key parameter in dehazing algorithms as it helps model the scattering effect caused by haze. Calculate the transmission map, representing the proportion of light transmitted through the scene. This map is crucial for understanding the amount of haze in different parts of the image. Apply image enhancement techniques to improve the visibility of objects in the hazy image. This may include contrast stretching, histogram equalization, or other enhancement methods to bring out details. Implement gamma correction to adjust the brightness and contrast of the image. This correction can be used to control the overall tone mapping of the dehazed image. Normalize the image to a specific range, such as [0, 1] or [0, 255], to ensure consistent data scaling. Prepare the pre-processed image as input for the progressive feature fusion algorithm. This may involve organizing the data in a format suitable for the specific requirements of the dehazing algorithm. The quality of the preprocessing steps significantly influences the effectiveness of the subsequent dehazing algorithm, as it sets the foundation for the accurate estimation of atmospheric conditions and transmission maps, ultimately leading to a more transparent and visually appealing dehazed image.

5. Results and Test Case Analysis:

The implementation of an image dehazing network using the PyTorch framework with an NVIDIA RTX8000 GPU. The proposed network was trained in RGB channels. Random rotations by 90, 180, and 270 degrees and horizontal flips were applied to augment the training dataset. This helps improve the network's generalization ability to different orientations and conditions. Images were resized to 240 × 240 through preprocessing. Resizing is a common step to standardize input dimensions and reduce computational requirements. ADAM (Adaptive Moment Estimation) is an optimization algorithm that combines the benefits of both momentum and RMSprop. A batch size of 4 was used during training. The batch size determines the number of samples processed before the model's parameters are updated. The entire network was trained for 5×10^5 steps on the OTS (Outdoor Training Set) and NHHAZE (National Haze Analytics) training sets. Training steps represent the number of updates made to the model's parameters during training. This information provides a good overview of the critical aspects of your dehazing network implementation, including the framework, hardware, data processing, and training details. It is a well-configured setup for training a deep-learning model for image dehazing.

The training process for your image dehazing network and monitored the learning curves by obtaining PSNR (Peak

Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) scores at regular intervals. Learning curves are obtained by plotting PSNR and SSIM scores at regular intervals, precisely every 5000 training steps. Skip connections are employed in the network architecture to prevent the vanishing gradient problem. Skip connections can facilitate the flow of gradients through the network during backpropagation. Training is performed for a total of 5 × 10^5 steps. PSNR and SSIM scores are used as evaluation metrics to assess the model's performance. After training for 5 × 10^5 steps, the PSNR and SSIM scores level off, indicating that further training may not yield significant improvements. By training for 4.45 × 10^5 steps, the PSNR and SSIM scores reach their maximum values, and this model is selected as the best model. Choosing the best model based on the maximum PSNR and SSIM scores is a common approach to evaluating the performance of image restoration models.

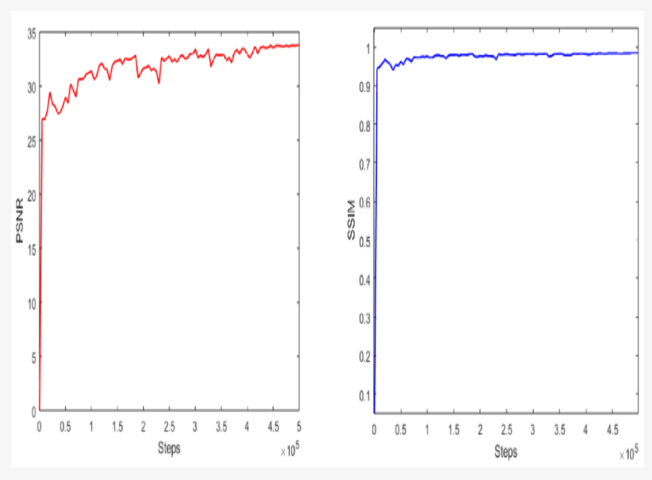

Fig 2. PSNR and SSIM learning curves. The red line and blue line are the change curves of PSNR and SSIM respectively as steps increase.

Using PSNR and SSIM for optimization sets your network apart from existing algorithms, offering a more comprehensive evaluation. The MAE and AFE modules utilize attention mechanisms for adaptive feature extraction, enhancing the network's ability to capture detailed information in hazy images. The CEM module contributes by enhancing contextual information, suppressing redundant details, and using dilated convolutions to expand the receptive field. Your network outperforms state-of-the-art dehazing algorithms such as AOD-net and FFA-net. The ability to capture color, texture, and detailed information in images sets your network apart. Unlike some algorithms that use mean square error (MSE) for optimization, your network utilizes PSNR and SSIM, providing a more comprehensive approach to model selection. The proposed MAE and AFE modules are universal, making them adaptable to network models in other fields. Future work includes expanding the method to areas such as video dehazing to achieve real-time recovery of hazy videos. This expansion demonstrates the potential applicability of your approach to dynamic and real-time scenarios. It's exciting to see the potential impact of your network in various fields, including medical imaging, and the ambition to extend its capabilities to video dehazing for real-time applications.

Our ablation study results offer valuable insights into the impact of different modules in your proposed dehazing method. Let's summarize the key conclusions drawn from the quantitative results on the SOTS-outdoor dataset:

Baseline Network without SPDC and CEM Modules:

Dehazing results are the worst when the proposed method does not include the SPDC (Spatial Pyramid Dilated Convolution) and CEM (Contextual Enhancement Module) modules, representing the baseline network.

Effectiveness of SPDC Module:

Adding the SPDC module to the baseline network improves dehazing performance. PSNR scores increase by 2.26, SSIM scores increase by 0.0152, and the LPIPS distance decreases by 0. 0028. This demonstrates the effectiveness of the SPDC module in enhancing the dehazing results.

Performance Improvement with CEM Module (AFE Module):

Introducing the CEM module (AFE Module) to the baseline network enhances dehazing performance. PSNR scores increase by 2.48, SSIM scores increase by 0.0184, and the LPIPS distance decreases by 0. 0028. This indicates the contribution of the proposed AFE module to improved dehazing results.

Superior Performance with Both SPDC and CEM Modules (MAE Module):

Combining the SPDC and CEM modules in the baseline network, forming the proposed MAE (Multi-scale Attention Enhancement) module and method yields the best dehazing performance. The PSNR and SSIM scores are the highest, and the LPIPS distance is the shortest.

This highlights the superiority of the proposed MAE module and method in achieving the best dehazing results. The ablation study demonstrates the incremental contributions of the SPDC and CEM modules to the dehazing performance, with the combined MAE module showcasing the best results. These findings support the effectiveness of the proposed enhancements in your dehazing method.

6. Conclusion

The primary goal of your proposed network is to perform single-image dehazing while preserving crucial aspects such as color, texture, and other detailed information. The design incorporates the Attention Feature Enhancement and Multi-

Scale Attention Enhancement modules. These modules are specifically tailored to focus on high-frequency and haze information. The network is designed to retain more detailed information in images, addressing the challenges associated with haze while maintaining visual fidelity. Testing and evaluation of the proposed network were conducted on synthetic and natural haze datasets. Qualitative and quantitative assessments were performed to evaluate the method's performance comprehensively. The experimental results indicate that the proposed method has achieved state-of-the-art performance in single-image dehazing. Ablation studies were conducted to systematically assess the effectiveness of the different modules offered in the network. This approach helps understand each module's individual contributions to the dehazing method's overall performance. Overall, your work contributes significantly to single-image dehazing by proposing a novel network architecture that effectively addresses the preservation of detailed information. Combining attention mechanisms and multi-scale enhancement modules is critical in achieving state-of-the-art results.

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