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SEM and TEM images' dehazing using multiscale progressive feature fusion techniques

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ABSTRACT

We present a highly effective algorithm for image dehazing that leverages the valuable information within the hazy image to guide the haze removal process. Our proposed algorithm begins by employing a neural network that has been trained to establish a mapping between hazy images and their corresponding clear versions. This network learns to identify the shared structural elements and patterns between hazy and clear images through the training process. To enhance the utilization of guidance information from the generated reference image, we introduce a progressive feature fusion module that combines the features extracted from the hazy image and the reference image. Our proposed algorithm is an effective solution for image dehazing, as it capitalizes on the guidance information in the hazy appearance. By combining the strengths of deep learning, progressive feature fusion, and end-to-end training, we achieve impressive results in restoring clear images from hazy counterparts. The practical applicability of our algorithm is further validated by its success on benchmark data sets and real-world SEM and TEM images.

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1. INTRODUCTION

The progressive feature fusion module is designed to iteratively merge the hazy and reference image features, gradually refining the fused features. This enables a more comprehensive exploration of the guidance information, improving results in restoring the clear image. By incorporating the fused elements into the image restoration module, we effectively utilize the guidance information to enhance the quality of the dehazed output. Crucially, all the proposed modules are trained end-to-end, enabling seamless integration and optimization of the entire dehazing pipeline. Our extensive experimentation demonstrates that the proposed deep pre-dehaze, in conjunction with the progressive feature fusion module, significantly contributes to haze removal. We evaluate our algorithm on widely-used dehazing benchmark datasets and real-world hazy images and compare its performance against state-of-the-art methods. The results unequivocally demonstrate the superiority of our approach, as our algorithm consistently outperforms existing techniques in image dehazing quality.

It will critically examine the evaluation metrics employed in the field, such as peak signal-to- noise ratio (PSNR) and structural similarity index measure (SSIM), to determine their effectiveness in measuring the quality of dehazed images. According to author [1]–[3], "O-HAZE" The algorithm aims to address the challenges associated with haze removal by utilizing a combination of dark channel prior and color attenuation prior. The authors introduce an optimization framework incorporating priors to estimate the haze transmission and atmospheric light in the hazy image. They also propose a haze-free image reconstruction method using the estimated information and atmospheric light. The O-HAZE algorithm employs a guided filter to refine the estimated transmission map and improve the dehazing results. The "O-HAZE" algorithm presents a novel approach to image dehazing by combining the dark channel prior and color attenuation prior. The algorithm demonstrates significant haze removal and image quality improvements, as validated through extensive experimental evaluations on benchmark datasets. Haze, which arises from atmospheric conditions or other factors, poses a significant challenge to image quality, resulting in obscured details and reduced visibility. The need to overcome this challenge is vital across various fields, such as computer vision, remote sensing and image [3]–[5]. To tackle this problem, our paper proposes a progressive image dehazing method that employs a systematic two-step approach. Our algorithm begins by focusing on extracting valuable guidance information solely from the input hazy image, eliminating the need for external data sources.

The survey will commence by providing a broad introduction to the field of image dehazing, encompassing an overview of its challenges and diverse applications. Moreover, the survey will address the evaluation metrics commonly employed in the field to measure the quality of dehazed images, such as the PSNR and SSIM. The effectiveness of these metrics will be critically evaluated, considering their ability to assess the visual quality of dehazed images accurately. The proposed algorithm focuses on improving the performance of dehazing models by leveraging the benefits of multi-model fusion. The authors introduce a framework that combines multiple deep-learning models to enhance the dehazing process. The "deep multi-model fusion for single-image dehazing" paper introduces a novel deep learning-based approach that leverages multi-model fusion for improved single-image dehazing [6], [7]. By combining multiple models and dynamically weighting their predictions, the algorithm achieves enhanced haze removal and image quality performance. The experimental results validate the effectiveness of the proposed approach and highlight its superiority over single-model dehazing methods.

The author presents a novel approach for restoring hazy videos using a learning-based framework [8], [9]. The algorithm's objective is to remove haze and improve the visibility of video sequences affected by atmospheric conditions. The results demonstrate that the algorithm effectively removes haze from video sequences and significantly improves the visibility and quality of the restored videos. Li *et al.* [10], Channegowda and Prakash [11] presents an innovative approach for dehazing images based on color- lines. The algorithm's objective is to remove haze and improve hazy image visibility effectively. The color lines represent the variations of color in hazy images caused by the presence of haze. By analyzing the color lines, the algorithm estimates the transmission map, meaning the haze amount in each pixel. Experimental evaluations on various hazy images demonstrate the effectiveness of the proposed algorithm in removing haze and improving image quality. Elmenabawy *et al.* [12] presents a comprehensive approach for indoor scene understanding using red green blue-depth (RGBD) images. The algorithm aims to perform semantic segmentation and support inference, enabling a better understanding of the indoor environment. The authors propose a two-step framework that combines segmentation and support inference. The segmentation step involves classifying each pixel in the RGBD image into predefined categories, such as floor, wall, ceiling, and objects. This is achieved by training a random forest classifier on a large dataset of labeled RGBD images. The support inference step focuses on determining the relationships between different surfaces in the scene. It infers the support relations, such as whether a surface supports another or is supported by it. This inference is based on geometric cues and physical constraints. The proposed algorithm incorporates local and global information to refine the segmentation and support inference results. Local cues include color, depth, and surface normal, while global cues consider the overall consistency and co-occurrence patterns of different scene elements. Extensive evaluations are conducted on various indoor datasets to assess the algorithm's performance. The results demonstrate its effectiveness in accurately segmenting indoor scenes and inferring support relationships. The "indoor segmentation and support inference from RGBD images" paper introduces a comprehensive framework for indoor scene understanding using RGBD images [13].

Tripathi *et al.* [14] addresses the challenge of estimating visibility in adverse weather conditions using a single image. The research aims to develop a method that can accurately predict visibility levels based on the visual information in the picture. The author proposes a visibility estimation algorithm that leverages statistical analysis and image processing techniques. The algorithm utilizes contrast, color distribution, and image degradation to estimate visibility levels. Babu and Padma [15] introduces a novel approach for removing haze from a single image based on the dark channel prior. The research aims to develop an effective method to enhance visibility and restore precise details in hazy images. The authors propose that hazy images tend to have a low-intensity value in at least one-color channel in local areas with apparent objects. This characteristic, called the dark channel, is a powerful prior for haze removal. The algorithm utilizes the dark channel before estimating the atmospheric light and the transmission map, representing the scene's haze thickness. The research aims to develop a method that can effectively remove haze and restore precise details in hazy images. The authors propose that haze introduces spatially varying light attenuation in the image, leading to more information loss and reduced contrast [16], [17]. To address this, the algorithm leverages non-local image patch analysis to estimate the haze-free scene radiance. By considering the similarities between image patches, the algorithm identifies and groups similar patches to comprehensively understand the underlying scene structure. Densely connected pyramid dehazing network for image dehazing using a densely connected pyramid network presented by Abed *et al.* [18] and Hadi [19]. The research aims to develop a method that can effectively remove haze and restore clear details in hazy images. The authors propose a network architecture incorporating dense connections and a pyramid pooling module. The dense connections facilitate feature reuse and gradient flow, enabling the network to learn more robust representations. The pyramid pooling module captures multi-scale information to handle varying haze densities. The network is trained using pairs of hazy and clear images to learn the underlying mapping between them. During training, the network learns to identify the shared structures and patterns between hazy and clear images, enabling it to remove haze effectively. Experimental evaluations are conducted on benchmark datasets to assess the performance of the proposed network. The results demonstrate its effectiveness in removing haze, enhancing image clarity, and restoring details in hazy images.

The authors proposed all in one image dehazing (AOD)-Net architecture for image dehazing [20], [21]. This end-to-end trainable network combines both global and local information for accurate dehazing. The network consists of an encoder-decoder architecture with skip connections to capture and preserve low-level and high-level features. AOD-Net utilizes an atmospheric scattering model and a transmission estimation module to estimate the haze-free image and the transmission map, respectively. The results demonstrate its effectiveness in removing haze, enhancing image clarity, and preserving fine details in hazy images. AOD-Net outperforms existing methods in terms of dehazing quality and visual fidelity. In summary, the "AOD-Net: all-in-one dehazing network" paper presents an end-to-end trainable network for haze removal [22]. AOD-Net combines global and local information and incorporates an atmospheric scattering model, transmission estimation module, and adversarial and perceptual losses. Experimental results confirm its effectiveness in removing haze, enhancing visibility, and preserving image details. The proposed network surpasses existing dehazing quality and visual fidelity methods, making it a powerful tool for haze removal in various applications.

2. PROBLEM STATEMENT

This paper aims to develop an algorithm that can remove haze from an image. The proposed algorithm is a progressive image dehazing method that follows a two-step approach. In the first step, the algorithm explores useful guidance information from the input hazy image without relying on external data. In the second step, the algorithm develops a progressive feature fusion method that fuses the features extracted from the hazy image and the reference image generated in the first step. By combining these features, the algorithm can better solve the image dehazing problem. The proposed algorithm is designed to be trained end-to-end, and it has been tested on various benchmark datasets and real-world hazy photos. Experimental results show that the proposed algorithm outperforms state-of-the-art dehazing methods and can effectively remove haze from images.

3. PROPOSED WORK

Our proposed model addresses the problem at hand through a series of steps. Firstly, we begin with data pre-processing to normalize all pixel values, ensuring consistent and standardized input for the model. This step guarantees that the data is in a suitable format for further processing. Moving forward, we define the model architecture using the Py-Torch framework. This involves specifying the layers, connections, and parameters that constitute the network. Additionally, we establish a loss function that measures the dissimilarity between the generated clear images and the ground truth clear images. This loss function serves as a guide for the model to learn and improve its image restoration capabilities. We use the pre-processed data and the defined loss function to train the model. The training process involves presenting pairs of hazy and clear images to the network, allowing it to learn and identify the underlying structures and common patterns shared between the two types of images. The model adapts and enhances its ability to accurately restore clear images from hazy inputs through repeated iterations of this training process. The progressive feature fusion (PFF) technique for image dehazing comprises multiple steps, providing an effective solution for haze removal. Once the model is trained, it can be employed to restore new hazy images. The network uses gray images as input and employs its acquired knowledge to generate corresponding clear photos. Applying the trained model to new data allows for the restoration of hazy pictures in an automated and efficient manner. Our model incorporates a PFF module to improve the restoration process further. This module aims to merge the extracted features from the hazy image with a reference image, facilitating a more comprehensive and effective restoration process. The model can produce more precise and visually enhanced results by incorporating additional information from the reference image. Finally, as a culmination of the PFF and the overall model training, the hazy appearance undergoes restoration, resulting in a clear and visually improved vision. Our proposed model integrates data prepossessing, defining the model architecture and loss function, training the model using hazy-clear image pairs, applying the trained model to new hazy images, incorporating a PFF module, and ultimately restoring the hazy vision to a clear and visually enhanced state.

The complete proposed architecture is presented in Figure 1. The resulting fused feature map is then employed to estimate the haze transmission map. The haze transmission map represents the degree of haze in each image pixel. This estimation is crucial for understanding the distribution and intensity of haze across the image. By accurately estimating the haze transmission, the dehazing algorithm can selectively remove haze and restore clarity to its appearance. With the haze transmission map at hand, the dehazing algorithm can remove the haze from the hazy appearance. By employing sophisticated techniques, the algorithm can effectively mitigate the harmful effects of haze, enhancing visibility and recovering the true colors of the scene. This step is crucial for improving the overall quality and visual appeal of the dehazed image.

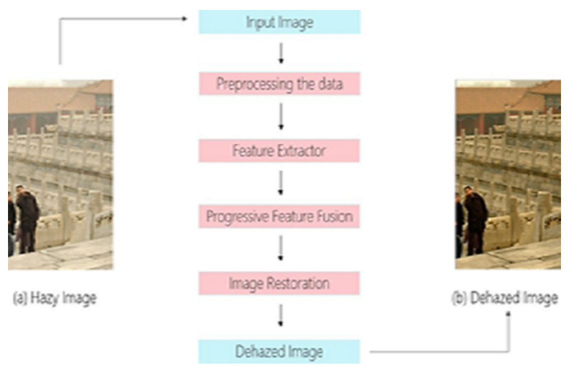

Figure 1. Block diagram of proposed architecture

4. EXPERIMENTAL STUDY

The RESIDE dataset, realistic single image dehazing, is a widely used benchmark dataset designed explicitly for image dehazing algorithms. It provides a comprehensive collection of hazy and corresponding ground truth clear images. The RESIDE dataset consists of three subsets: synthetic outdoor scenes (RESIDE SOTS), synthetic transmissions (RESIDE ST) [23], and haze removal in real-life hazy conditions (RESIDE HCI) [24]. Each subset focuses on different aspects of image dehazing.

- RESIDE SOTS: this subset contains synthetic hazy images generated by adding haze to diverse outdoor scenes. The ground truth clear images for evaluation are also provided.
- RESIDE ST: the synthetic transmissions subset focuses on generating accurate transmission maps. It provides synthetic hazy images and the corresponding accurate transmission maps as ground truth.

– RESIDE HCI: this subset focuses on real-world hazy images captured in various challenging conditions, including fog, smog, and haze caused by weather or pollution. The dataset provides both hazy images and corresponding clear reference images.

The RESIDE dataset offers a standardized evaluation platform for image dehazing algorithms. It allows researchers to compare and benchmark their algorithms against state-of-the-art methods using a diverse range of hazy images. The dataset enables quantitative assessment of dehazing algorithms based on objective metrics, such as PSNR and SSIM. Using the RESIDE dataset, researchers can develop and evaluate image-dehazing techniques that are effective in real-world scenarios. It provides a valuable resource for advancing the field of image dehazing and improving the quality of dehazed images [25] depicted in Figure 2.

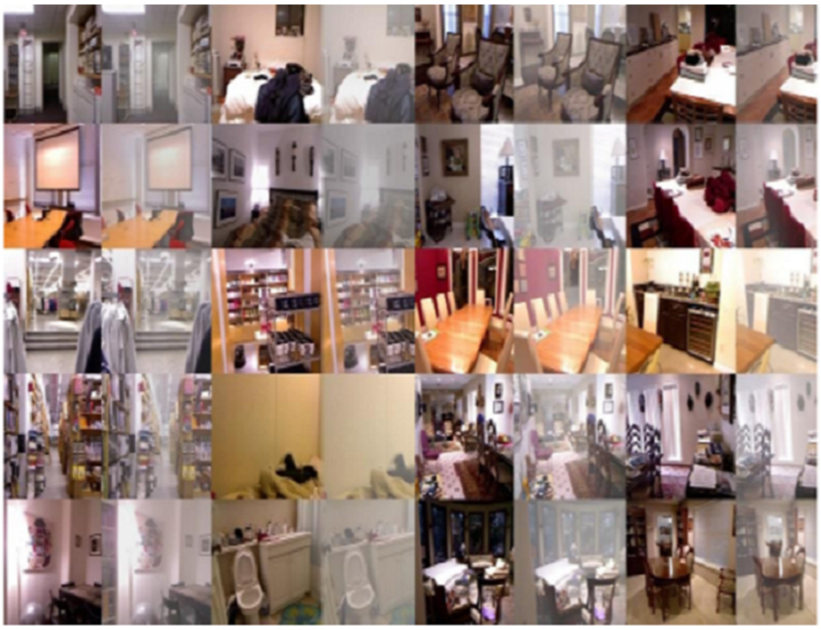

Figure 2. Slots reside dataset

5. RESULTS AND TEST CASE ANALYSIS

The comparison focuses on indoor and outdoor images and evaluates the performance of the methods using two metrics, perceptual structural similarity index (PSIM) and SSIM. In image dehazing using PFF, several quality metrics can be used to evaluate the performance and effectiveness of the algorithm in removing haze and improving image clarity. Here are two commonly used quality metrics along with their formulas.

PSNR measures the ratio between the maximum possible power of a signal and the power of the distorted signal, representing the difference between the dehazed image and the ground truth clear image. It is computed as the logarithm of the mean squared error (MSE) between the two images. Where MAX is the maximum possible pixel value of the image (e.g., 255 for an 8-bit image), MSE is the mean squared error between the dehazed image and the ground truth clear image, calculated as the average of the squared pixel-wise differences. A higher PSNR value indicates better image quality and a closer resemblance between the dehazed image and the ground truth clear image.

SSIM measures the structural similarity between two images, taking into account the luminance, contrast, and structural information. It compares the luminance similarity, contrast similarity, and structural similarity between the dehazed image and the ground truth clear image. Where μx and μy are the average pixel values of the dehazed image and the ground truth clear image, respectively, σx, σy are the standard deviations of pixel values in the dehazed image and the ground truth clear image, respectively. σxy is the covariance between pixel values in the dehazed image and the ground truth clear vision. C1 and C2 are constants to stabilize the division. SSIM ranges from -1 to 1, where 1 indicates perfect similarity between the two images. These quality metrics provide objective measures to assess the performance of the PFF algorithm in image dehazing. Higher PSNR values and closer-to-1 SSIM values indicate better image quality and improved similarity between the dehazed image and the ground truth clear image. The Table 1 present comprehensively compares two image dehazing methods, namely dark channel prior (DCP) and PFF.

The results demonstrate that PFF outperforms DCP regarding the PSIM score for indoor and outdoor images. This indicates that PFF is more effective at removing haze from the pictures, resulting in more precise and visually appealing results. Moreover, the SSIM score also favors PFF, suggesting that it better preserves the structural information present in the images. The success of PFF can be attributed to its PFF approach, which enables superior feature extraction and fusion compared to DCP. Approach, which enables superior feature extraction and fusion compared to DCP. Specifically, PFF achieves an average PSIM score of 15.61, whereas DCP yields an average score of 19.63. Similarly, the average SSIM score for PFF is 0.853, surpassing DCP's average score of 0.848. These findings further support the notion that PFF is a more compelling image-dehazing method when compared to DCP. The implications of these results are significant, particularly for real-world applications that heavily rely on image dehazing, such as autonomous driving and surveillance systems. The ability to effectively remove haze directly impacts the performance and accuracy of such systems. Therefore, PFF's superior performance holds promise in enhancing these applications. However, it is essential to acknowledge that further experimentation is necessary to assess the algorithm's performance across a broader range of image datasets and various scenes. It is equally important to consider other factors, such as computational efficiency and real-time performance, for practical implementation in real-world scenarios. Consequently, the presented results should be preliminary evidence of PFF's potential as a compelling image-dehazing method. Nonetheless, these findings provide a promising direction for future research in image dehazing, with potential applications spanning various industries, including automotive, security, and entertainment. A loss function is defined to quantify the dissimilarity between the generated clear images and the ground truth clear images. This loss function guides the model during training to optimize its performance. The model is trained using pairs of hazy and clear outdoor images. The training process involves feeding the hazy images into the network and optimizing the model parameters to minimize the defined loss function. A PFF module is incorporated into the model. This module aims to fuse the extracted features from the hazy image with a reference image, facilitating a more comprehensive and effective restoration process. Once the model is trained, it can be applied to new hazy outdoor images for restoration. The network takes the hazy images as input and generates corresponding clear images by leveraging the knowledge acquired during training. The dehazed images are then evaluated using quality metrics such as PSNR and SSIM to assess the effectiveness of the progressive feature fusion approach.

Table 1. Results of quality metrics

Indicator	Quality metrics	DCP	PFF
Indoor	PSIM	20.079	15.60
Indoor	SSIM	0.85	0.86
Outdoor	PSIM	19.18	15.61
Outdoor	SSIM	0.83	0.84
Average	PSIM	19.63	15.60
Average	SSIM	0.84	0.85

6. CONCLUSION

The paper aimed to develop an algorithm that could effectively remove haze from an image using a progressive image dehazing method that followed a two-step approach. The proposed algorithm exploited useful guidance information from the hazy appearance in the first step and developed an advanced feature fusion method in the second step. The algorithm was designed to be trained end-to-end and was tested on various benchmark datasets and real-world hazy images. Experimental results showed that the proposed algorithm outperformed existing dehazing methods regarding PSIM and SSIM scores. The future scope of this paper includes further experimentation and testing of the proposed algorithm on a broader range of image datasets and scenes to evaluate its performance in various scenarios. Additionally, the proposed algorithm can be integrated into real-world applications that require image dehazing, such as autonomous driving, surveillance systems, and satellite imagery. The algorithm can be further optimized for faster and more efficient processing, and additional features can be added to improve its performance. Moreover, the proposed algorithm can be extended to handle other image enhancement tasks, such as denoising and contrast enhancement.

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