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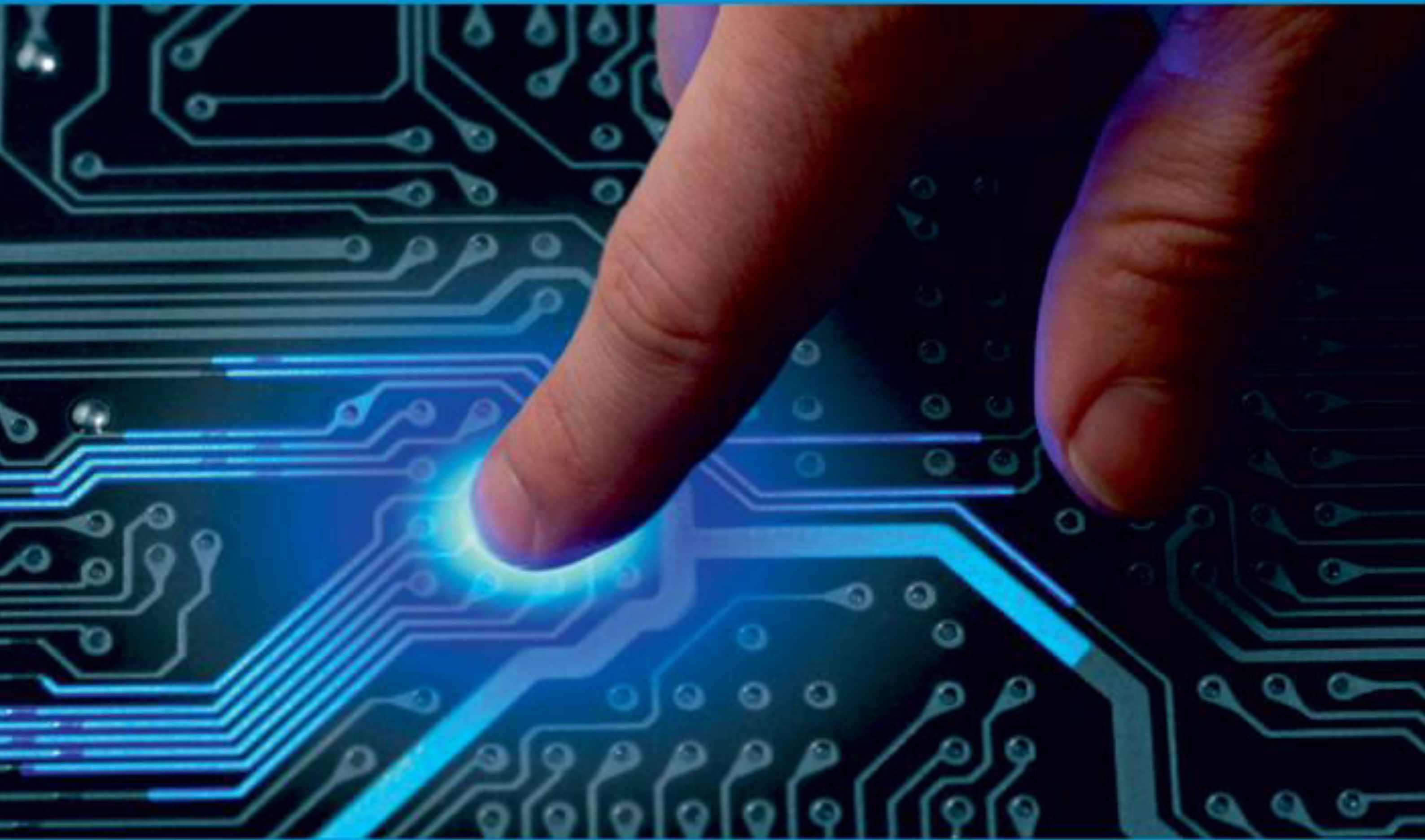

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Haze Removal for Remote Sensing Images using Residual Attentive Atmospheric Scattering Network

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ABSTRACT: In this paper, we proposed a specialized solution for single remote sensing image dehazing which combines the haze density prior with deep learning technology. In the solution, the haze density prior HDM is extracted from the original hazy image at the first step and subsequently used as input of the network together with the original hazy image. The effectiveness of the HDM input has been further demonstrated through comparative experiments. A dense attentive dehazing network (DADN) is also presented in the solution, which composed of dense blocks and attention blocks (both spatial attention and channel attention) and directly learns the mapping from the input images to the corresponding haze-free image. The whole network contains an encoder-decoder architecture and has a discriminator at the end of the network, to further refine the dehazed results. A large-scale hazy remote sensing dataset was created as a benchmark, which contains both uniform and non-uniform, synthetic and real hazy remote sensing images. The experimental results on the created dataset demonstrated that DADN achieves better performances than the other prevailing dehazing algorithms, especially when it comes to a non-uniform haze distribution.

KEYWORDS: dehazing; remote sensing image; superpixel; heterogeneous atmospheric light;

I.INTRODUCTION

Remote sensing imagery finds broad utility across diverse fields. It delivers highresolution ground surface information, enabling researchers to classify, monitor, and forecast land use and cover types, while also facilitating the management and assessment of vital natural resources, including forests, grasslands, water bodies, and soil quality. Remote sensing images (RSIs) play a pivotal role in monitoring agricultural production conditions, encompassing factors, such as crop growth and pest infestation, thereby offering valuable insights for guiding agricultural decision making. Furthermore, these images are invaluable for tracking environmental concerns, including air pollution, water quality, soil contamination, as well as the occurrence and repercussions of natural disasters, such as floods and earthquakes. Moreover, RSIs hold significance in urban planning and management, spanning domains like traffic planning and community structure analysis. However, the efficacy of these visual applications crucially hinges upon the clarity and visibility of the input images. The degradation of RSIs arising from adverse atmospheric conditions can lead to a sharp decline in the algorithm performance of these downstream tasks, with haze emerging as the predominant atmospheric phenomenon among the various adverse conditions. To ensure the dependable operation of remote sensing vision systems, researchers have devoted substantial effort to solving the highly challenging problem of remote sensing haze image restoration.

The restoration of remote sensing haze images presents an inherently ill-posed problem, as it necessitates the simultaneous recovery of the dehazed image, the underlying atmospheric ambient light, and the depth-dependent transmission solely from a single hazy input. To tackle this challenge, researchers have endeavored to incorporate prior knowledge of haze images

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through observations, assumptions, and statistical methods [1–5], serving as supplementary constraints to render the problem well defined. However, these algorithms all rely on a common assumption, specifically that the transmission within local image patches remains constant, which is feasible in areas with smooth depth but fails in areas with abrupt depth changes, such as the intersection between the foreground and background of an image and its edges. Hence, when constructing local image patches, it becomes imperative to fully account for the structural information of the image. Existing haze removal algorithms frequently regard fixed-size rectangular regions within the image as local blocks. This oversimplification undermines the assumption that transmission remains constant within the same image patch, leading to incorrect transmission estimations. Notably, this issue becomes more serious as the size of the patch increases.

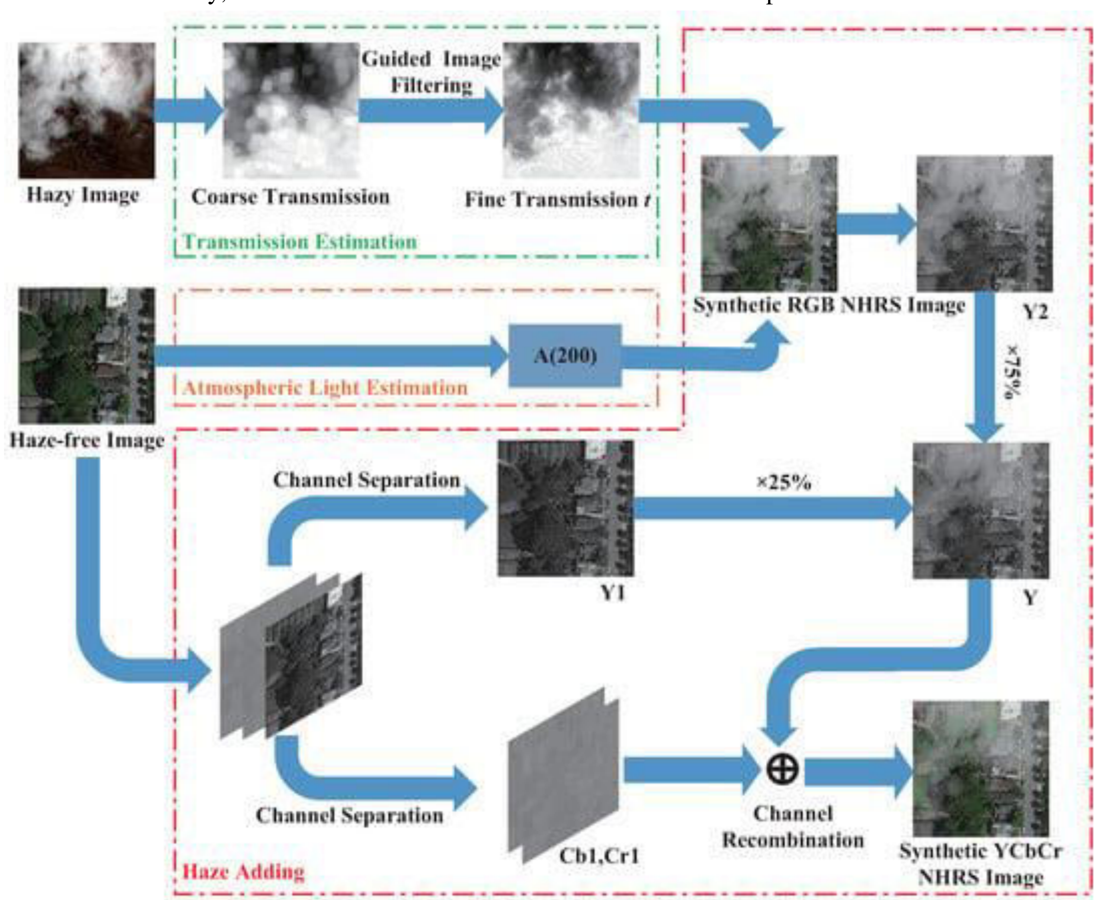

Fig 1: Remote Sensing Deep Dehazing

Given the problems inherent in existing physical model-based haze removal algorithms, this paper introduces an enhanced local image patch partitioning method using superpixels. Evaluating the color and brightness similarities among pixels, it clusters pixels with similar features together to build a superpixel, which preserves the structure information of the image as much as possible. Therefore, the patches are partitioned with arbitrary shapes relevant to the image content rather than fixed-size rectangles. Within each superpixel patch, all constituent pixels exhibit similar physical properties, allowing the atmospheric light and transmission to be rationally treated as constants in this local region. Furthermore, considering that the imaging space of RSIs is significantly broader than that of outdoor images taken near the ground, we believe that modeling the atmospheric ambient light in RSIs as a non-uniform distribution is more appropriate than a globally uniform one. This is because the temperature, pressure, and aerosol motion in the atmosphere can generate fluctuations of the atmospheric environment in the imaging space, so a globally non-uniform ambient light more closely matches the real world. In addition,

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since the natural outdoor images taken near the ground often exhibit limited depth of the scene, the transmission is often approximated as equal in the red, green, and blue channels of the image, ignoring its wavelength-dependent properties to simplify the model calculations. However, in RSI imaging, the emergent light reflected by scene objects traverses an extremely long distance, rendering the treatment of transmission maps of the RGB channels as being equal inappropriate. Consequently, this paper proposes a channel-separated transmission map estimation algorithm, which computes the respective transmissions of the RGB channels separately.

II.RELATED WORK

Extensive efforts have been dedicated to restoring degraded haze images over a significant period of time, resulting in the proposal of numerous remarkable algorithms one after another. In this section, we provide a concise overview of existing approaches for single image dehazing. It is important to acknowledge that many brilliant algorithms were originally designed for natural scenes, and it is only in recent years that dehazing techniques tailored for remote sensing scenes have been developed. The intrinsic disparities between remote sensing scenes and natural scenes render the dehazing algorithm designed for natural images ineffective when applied to RSIs.

The image enhancement technique employed in dehazing methods fails to consider the physical degradation model of the hazy image. Instead, it focuses on enhancing the image quality by augmenting the image’s contrast and rectifying its color. To improve the visibility of degraded images affected by haze, Ancuti et al. [6] proposed a fusion-based approach. This approach effectively combines two intermediate results derived from the original image, which undergoes white balance adjustment and contrast enhancement. The fusion strategy considers the image’s brightness, chromaticity, and saliency, resulting in a dehazed image that exhibits enhanced visibility. Galdran et al. [7] introduced a novel variational image dehazing technique that incorporates a fusion scheme and energy functions. By minimizing the proposed variational formulation, the method achieves enhanced contrast and saturation of the input image. Retinex is a color vision model that simulates the human visual system’s ability to perceive scenes under varying illuminations. Galdran et al. [8] theoretically demonstrated that Retinex at inverted intensities is a feasible solution for image dehazing tasks. Although three image enhancement techniques—white balance (WB), contrast enhancement (CE), and gamma correction (GC)—were utilized, Ren et al. [9] innovatively adopted neural networks to learn how to fuse the results of these three enhancements rather than manually designing the fusion strategy to obtain clear haze-free images. Considering the dynamic range of the input image, Wang et al. [10] proposed a multi-scale Retinex with color restoration (MSRCR)-based single-image dehazing method. Li et al. [11] employed homomorphic filtering to enhance haze images on the basis of the observation that haze is highly correlated with the light component and is located mainly in the low-frequency part of the image. Note that the last two methods use the physical model of image degradation in addition to image enhancement techniques. Image enhancement-based dehazing algorithms sometimes suffer from over-enhancement, as they solely rely on the pixel information of the image and disregard the underlying physical degradation process of the haze images.

III.METHODS

he first column presents the synthetic hazy remote sensing images, the last column presents the ground truth images, and the other columns are the dehazed results of the different methods. DCP successfully removes most of the haze but tends to over-enhance the images, especially for the large white areas, since the DCP prior fails when color of the object is close to the atmospheric light. BCCR reveals the same problem of over-enhancement and leads to some color distortion (see the first two images), which is mainly due to the underestimation of the transmission matrices. The results of DCP and BCCR indicate the disadvantages of the prior-based methods, in that they can only obtain an accurate estimation when their assumptions fit perfectly.

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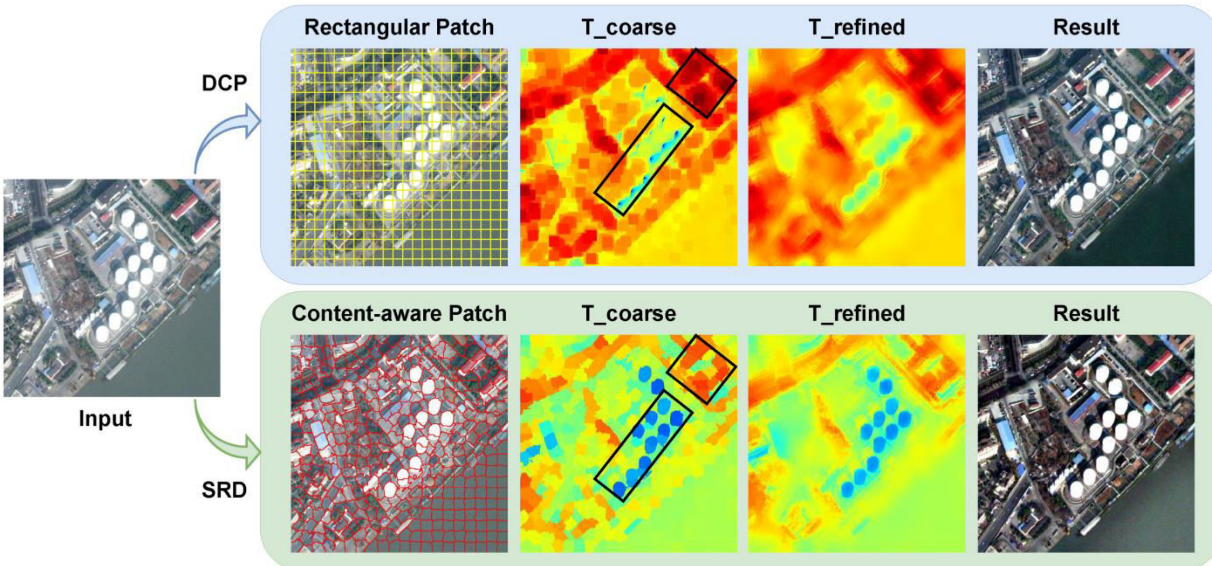

Fig 2: Remote Sensing image analysis

Since these priors are statistically achieved based on natural images, when it comes to remote sensing images, they may not fit and can lead to unsatisfactory dehazing results. FVR retains much of the haze and leads to obvious color distortions and artifacts, at the cost of saving time. The results of AOD-Net are not clear enough and tend to become dimmer than the ground truth. DCPDN achieves much more pleasing results for this uniform hazy dataset. However, unlike AOD-Net, DCPDN tends to lighten the dehazed results (see the last image), mainly caused by the inaccurate estimation of the atmospheric light. In contrast, the developed method, which avoids the estimation of intermediate parameters (transmission and atmospheric light) and directly measures the distortion of the clear image rather than that of the intermediate parameters, obtains the most pleasing results, with color and structural details that are the closest to the true haze-free images, verifying the advantage of the proposed network structure. The proposed SRD algorithm achieves a good dehazing effect with little increase in the computational overhead, and it demonstrates superior processing speed in comparison to the HL, HTM, and IDeRs algorithms when subjected to equivalent testing conditions. The time cost of the SRD algorithm is primarily devoted to the division of image patches by the superpixel technique, as well as to the calculation of the local maximum and minima within each patch to estimate the coarse atmospheric light and the channel-separated transmission. Fortunately, our method exhibits good parallelism because the computations within each superpixel patch are independent of each other and can be implemented concurrently. Moreover, within any given image patch, the operations of finding the maximum and minimum values can also be independently executed as well.

IV.RESULT ANALYSIS

In this study, we proposed a dense attentive dehazing network (DADN) which combines physical prior and deep learning technology to learn the mapping between the original input images and the corresponding haze-free image directly. Specialized designed for single remote sensing image dehazing, we propose to first extract an HDM from the original hazy image, which can be regarded as a haze density prior, and subsequently combine the HDM with the original hazy image as input of the network for a better description of the non-uniform haze distribution in hazy remote sensing images. Meanwhile, both spatial and channel attention blocks are carefully constructed in the network to recalibrate the extracted feature maps, thus allowing more adaptive and efficient training. To make sure that the estimated dehazed result is undifferentiated from the corresponding clear image, we further utilize a discriminator at the end of net, to refine the output.

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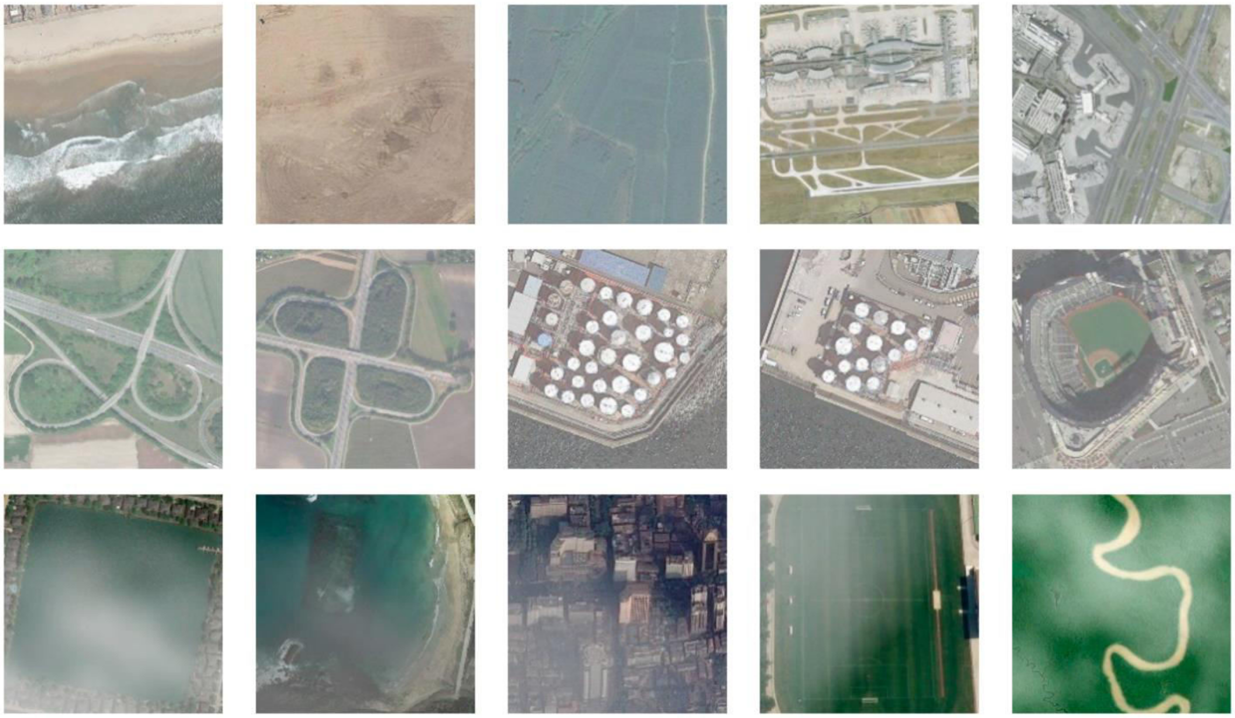

Fig 3: Result analysis

To further validate the effectiveness of each module of the network, we conducted experiments on a network without the HDM (DADN_noHDM), a network without the discriminator (DADN_noDISCRI), and a network without the attention blocks (DADN_noRCSAB). The results are presented in **Figure 13** and **Table 6**. DADN_noHDM and DADN_noRCSAB fail to detect the non-uniform haze, and obvious vestiges of haze remain, especially in the last two images, indicating that models without the HDM prior and RCSAB lack the ability to mine high-level haze-relevant features, and thus fail to remove all the non-uniform haze. Meanwhile, for the PSNR and SSIM criterion in **Table 6**, the proposed DADN method considerably outperforms DADN_noHDM and DADN_noRCSAB, which demonstrates that the haze density prior of the HDM and the attention module (RCSAB) are important and effective in the detection and removal of the non-uniform haze existing in remote sensing images. For the visual effects, DADN_noDISCRI and DADN are the most competitive methods, with vivid color, clear structure, and most of the non-uniform haze removed, while for the qualitative results, DADN outperforms DADN_noDISCRI, with the PSNR improved by 0.5. The qualitative results on the large-scale test data further validate the effectiveness of the proposed discriminator. Furthermore, a comparison on average consuming time (per image) is conducted. As we can see, our module makes obvious improvement in dehazing performance only with the cost of less than 0.06 s increase in time (per image), which is acceptable.

V.CONCLUSIONS

In this article, we present a novel haze removal algorithm specifically for RSIs, namely SRD, which is developed based on the distinctive imaging characteristics inherent to RSIs. Firstly, the imaging space of RSI is extremely large, so the assumption of globally uniform atmospheric light distribution is not tenable. To address this issue, we propose a global non-uniform atmospheric light estimation algorithm utilizing the maximum reflection prior. Secondly, the imaging distance of RSI is very far, which makes the transmissions of each color channel of the image unequal. Therefore, we introduce a channel-separated transmission estimation method. Our estimations of both atmospheric light and transmission are based on local image patches. However, existing dehazing algorithms divide the image into local patches using fixed-size rectangles,

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which tends to result in the loss of crucial structural information and undermines the availability of haze-relevant priors. Consequently, we introduce a superpixel-based patch division strategy, which can preserve the structure and color information of the input image, ensuring that pixels within each local patch exhibit similar imaging behavior. Furthermore, we validate the proposed SRD algorithm on a large number of real-world and synthetic haze RSIs, and the comparison experiments with existing state-of-the-art algorithms suggest that the dehazed images by SRD exhibit enhanced natural color fidelity, well-defined structural contours, and overall improved visual quality. The quantitative assessment based on both full-reference and noreference IQAs demonstrates that SRD has superior dehazing performance. Moreover, our parameter analysis experiments affirm the robustness of the SRD method and its potential to yield promising dehazing results, even when applied to outdoor natural images.

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