Enhancing Atmospheric Visibility in Satellite Images using Dehazing Methods

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Abstract

Image haze occurs due to the scattering of light by particles or molecules in the atmosphere. This phenomenon reduces visibility and degrades the quality of images, especially in outdoor scenes. Dehazing aims to remove or reduce this haze to reveal clearer and more visually appealing images. The study of dehazing techniques has a longstanding history in computer vision and image processing. Early approaches often relied on handcrafted filters and assumptions about the scene, making them limited in their effectiveness. However, recent advancements in computational techniques and deep learning have significantly improved dehazing algorithms, allowing for more accurate and robust haze removal. Clear visibility in images is crucial for various applications such as autonomous navigation, surveillance, remote sensing, and computer vision tasks. Haze obscures important details and reduces the effectiveness of these applications. Hence, the need for effective dehazing algorithms is essential in fields where accurate visual information is vital. The primary problem addressed by dehazing techniques is the removal of atmospheric haze from images. This involves estimating the underlying scene radiance and transmission map, which indicates the degree of haze in different parts of the image. The goal is to enhance visibility and recover details that are obscured by haze. Dehazed image enhancement represents a significant advancement in the field of image processing. It combines dehazing techniques with further enhancement processes to produce visually appealing results. This approach not only removes haze but also improves the overall visual quality of the image. It leverages advanced algorithms, often based on physical models of light scattering, to accurately estimate and remove haze from the image. Additionally, it may incorporate additional processing steps, such as contrast adjustment and color correction, to further enhance the result. This integrated approach addresses the limitations of traditional dehazing methods and provides a more comprehensive solution for improving image quality in hazy conditions.

1. Introduction

The implemented project focuses on dehazed Image Enhancement using the satellite image dehaze algorithm (SIDA). This technique aims to improve the visibility and quality of images captured under dehazed conditions, which are typically characterized by reduced brightness and contrast. By applying a series of mathematical operations and optimization techniques, the algorithm enhances the illumination levels of the image, thereby making objects and details more discernible. Enhancing images captured in dehazed environments is of significant practical importance across various domains. In surveillance, security, and law enforcement, it enables the extraction of critical information from poorly lit scenes. In medical imaging, it aids in improving the visibility of details in X-rays or other dehazed medical images. Furthermore, in photography and cinematography, it can be invaluable for salvaging underexposed or dimly lit footage. The project's significance lies in its potential to enhance the quality and utility of images in scenarios where adequate lighting is a challenge. 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.

2. Related Work

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.

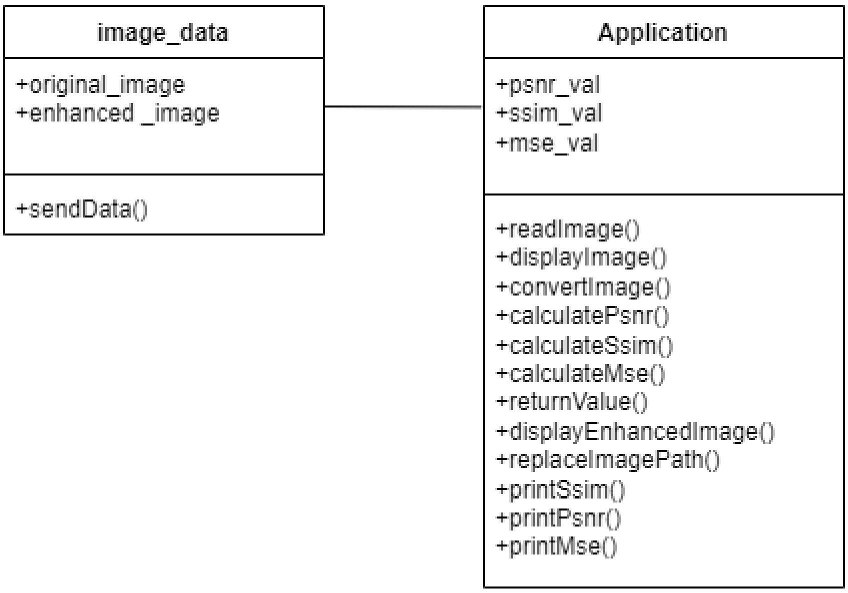
The atmospheric scattering model that is widely used for hazy image restoration is an underdetermined optical model that describes the physical process of radiation propagation in the medium. In order to solve the model, existing studies [1,2,3,4,5] have explored various haze-relevant priors through assumptions, observations, and statistics as complementary constraints to the atmospheric scattering model. However, these methods are based on priors of natural scene images, which are not well suited for RSIs. Therefore, researchers have attempted to uncover some latent priors of remote sensing hazy images to remove haze. Ning et al. [12] proposed a RSI dehazing algorithm based on a light-dark channel prior, which first utilizes the dark channel prior to remove haze and then uses the light channel prior to remove shadows. As an alternative to the dark and bright channel prior, Han et al. [13] proposed a RSI dehazing algorithm based on the local patchwise extremum prior and proved its feasibility and reliability. Zhu et al. [14] used a linear model trained by differentiable functions to estimate the scene depth and find the atmospheric ambient light based on depth information, and subsequently generated a color-realistic and haze-free image from the remotely sensed data using the atmospheric scattering model. Pan et al. [15] proposed a deformed haze imaging model by introducing a translation term and estimated the atmospheric light and transmission in the improved model through the dark channel, prior to achieving effective haze removal. Xu et al. [16] introduced the concept of "virtual depth" into RSIs and proposed a dehazing method that combines patch-wise and pixel-wise dehazing operators, in which dehazing operators are executed iteratively to progressively remove haze. Liu et al. [17] regarded haze as an additive veil, which can be represented by a haze thickness map, and proposed a haze distribution estimation algorithm to recover clear images effectively.

The dehazing algorithms based on the physical model try to solve the physical process of image degradation by haze, but the atmospheric scattering model is an ideal and simplified model that ignores the differences between the imaging environment of RSIs and natural outdoor images. Therefore, this paper attempts to integrate the characteristics of remote sensing imaging into the atmospheric scattering model. With the significant breakthrough of deep neural network algorithms in various fields, an increasing number of deep learning-based haze removal algorithms have emerged. Ren et al. [18] trained a multi-scale deep neural network on a synthetic dataset, which obtains the coarse transmission map by the coarse-scale subnet and then refines it by the fine-scale subnet. Following the coarse-to-fine strategy in [18], Li et al. [19] proposed FCTF-Net, a two-stage dehazing neural network that effectively removes irregularly distributed haze in RSIs by combining attention mechanisms and standard convolution operations. To reduce the error amplification caused by separately estimating atmospheric light and transmission, Li et al. [20] reformulated the atmospheric scattering model and built an end-to-end lightweight neural network for efficient haze removal. By introducing an attention mechanism, Liu et al. [21] proposed GridDehazeNet, a multi-scale deep neural network based on a grid network that effectively alleviates the bottleneck issue and achieves good dehazing results. For visible RSI dehazing, Chen et al. [22] proposed a neural network with a nonuniform excitation module. It employs a dual attention block to extract locally enhanced features and deformable convolution to extract nonlocal features. The powerful feature extraction capability makes the network achieve a good dehazing effect. Chen et al. [23] proposed a hybrid high-resolution haze removal network, whose high-resolution branch can obtain precise spatial features, while the multi-resolution convolution branch can output rich semantic features. Regarding the nonuniform distribution of haze in RSIs, Jiang et al. successively proposed a dehazing network combining wavelet transform [24] and an asymmetric network with enhanced attention using k-means clustering and FFT [25]. To adapt flexibly to the specific haze condition in each image, Nie et al. [26] presented a haze-aware learning-based dynamic dehazing method using contrast learning, which can adaptively remove the diverse haze in RSIs. It is worth noting that deep learning-based and physics-based approaches are not separate, and some studies [27,28,29] tried to embed physical prior knowledge in deep learning models and achieved significant progress.

Despite the promising results demonstrated by deep learning-based dehazing algorithms, they heavily rely on the availability of large-scale training datasets, which may be challenging to acquire, especially for remote sensing applications. Additionally, the deployment of deep learning models for real-time applications can be hindered by their hardware requirements and computational complexity.

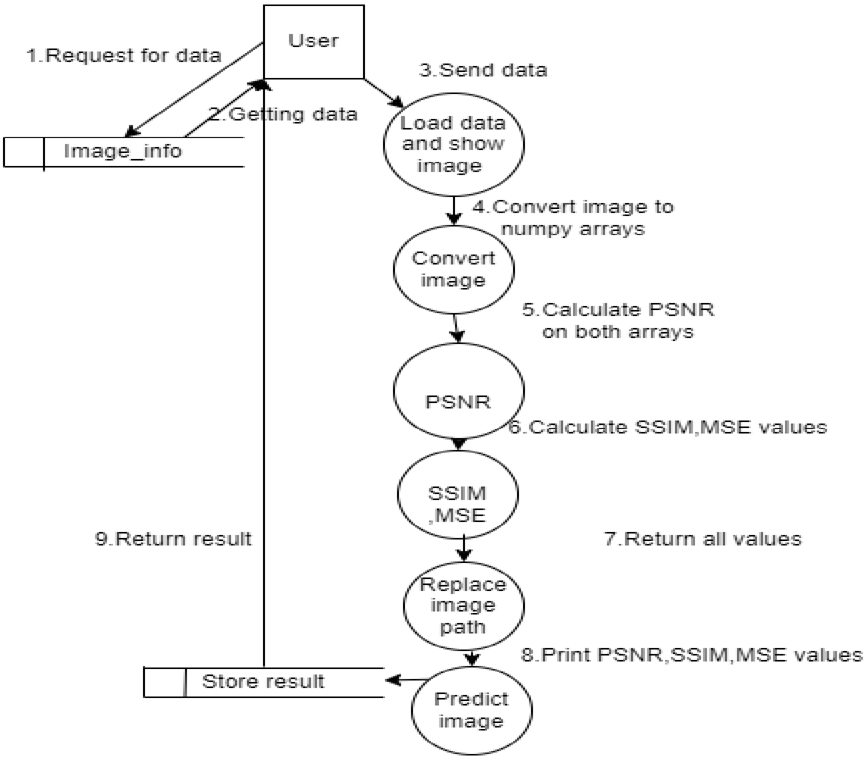
3. Proposed System Model

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML. The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.



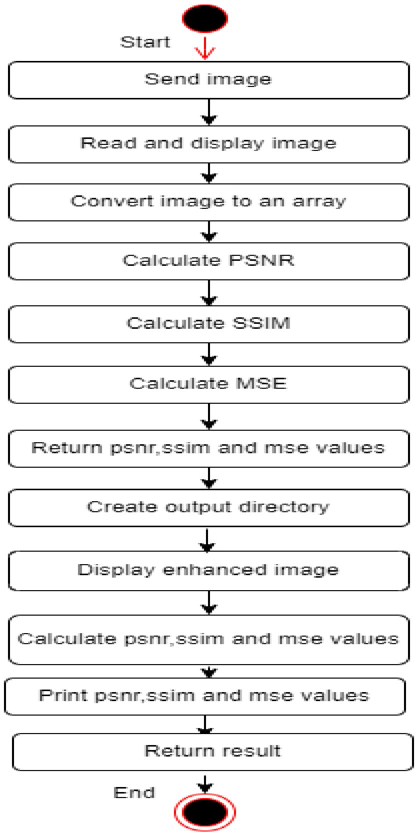
Data flow diagram

A Data Flow Diagram (DFD) is a visual representation of the flow of data within a system or process. It is a structured technique that focuses on how data moves through different processes and data stores within an organization or a system. DFDs are commonly used in system analysis and design to understand, document, and communicate data flow and processing.

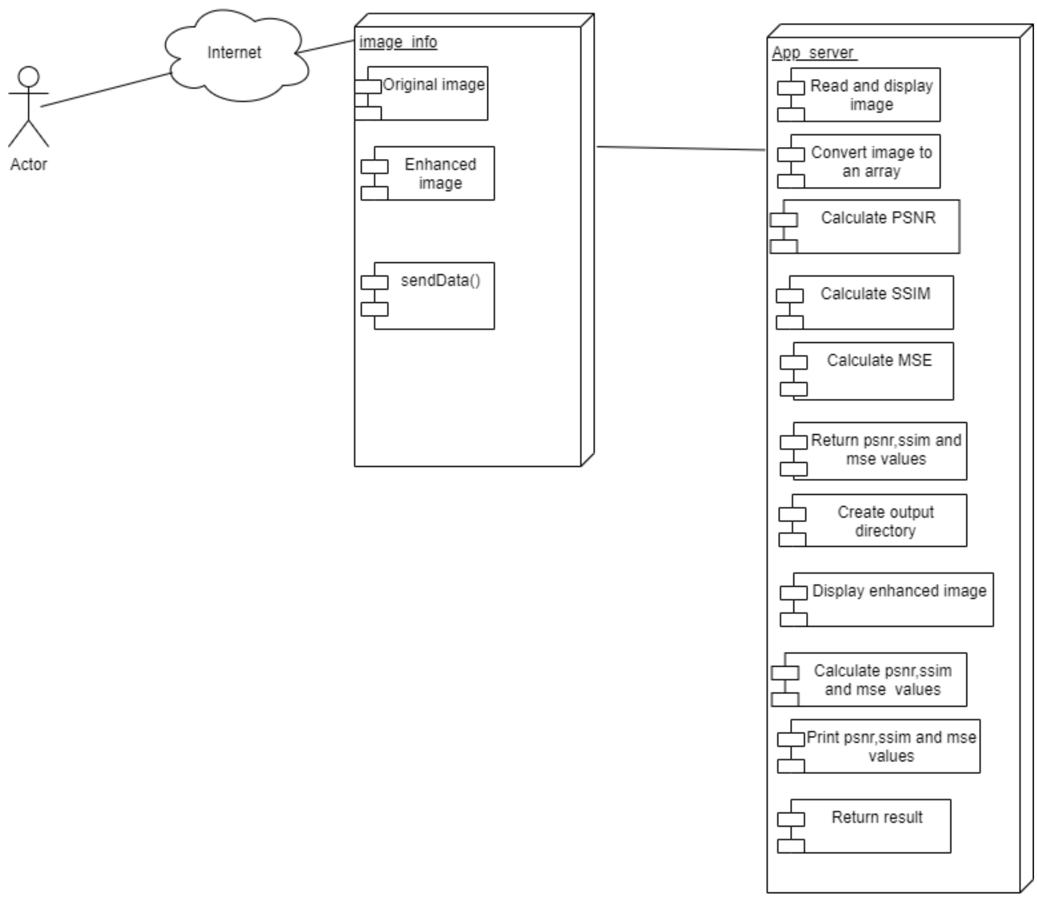


Activity diagram

Activity diagram is another important diagram in UML to describe the dynamic aspects of the system.



Deployment diagram: The deployment diagram visualizes the physical hardware on which the software will be deployed.



4. Results and Discussion

Figure 1 shows a collection of original images that are taken in hazed conditions or have poor lighting quality. These images serve as the input to the proposed image dehazement model. These images are the input images that the model will process to improve their visibility and quality. The purpose of this figure is to provide a visual representation of the types of images that the model is designed to enhance.

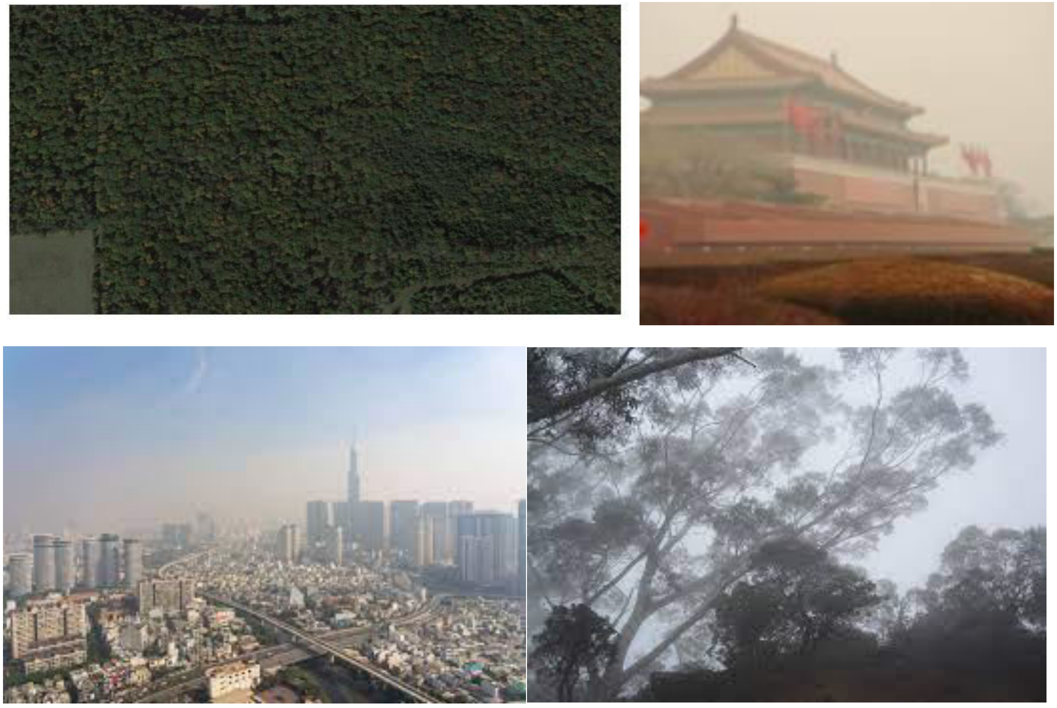


Figure 1: Sample dehazed images fed to the proposed model.

5. Conclusion

The implemented SIDA project has demonstrated its effectiveness in significantly improving the visibility and quality of hazed images. Through the application of the SIDA algorithm, the script successfully enhances images by intelligently adjusting their illumination levels. The inclusion of image quality metrics, including PSNR, SSIM, and MSE, provides a quantitative assessment of the enhanced image's fidelity compared to the original. Moreover, the script offers a high degree of customization, allowing users to fine-tune algorithm parameters to suit specific scenarios. The visualization component enables users to visually inspect the original and enhanced images, aiding in intuitive assessment. Additionally, the capability to save the enhanced image to a designated output folder enhances convenience in managing results. However, for future iterations, there is potential to further optimize processing speed and potentially integrate deep learning models for more advanced enhancement techniques. The incorporation of noise reduction techniques and automatic parameter tuning could also enhance the algorithm's performance and user-friendliness. Additionally, exploring multi-modal image enhancement and accommodating various types of image degradation would expand the algorithm's applicability across diverse scenarios. Overall, this project provides a robust foundation for enhancing images in dehazed conditions, with ample opportunities for future enhancements and adaptations.

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