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Adaptive Haze Removal Utilizing Guided Filter-Infused Approximate DCP

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Abstract: In this project, we present a hybrid approach combining Adaptive Dual Combination Processing (ADCP) and the Guided Filter to enhance image quality, especially for haze-free image reconstruction. The proposed method is evaluated using two datasets, including publicly available ones from Kaggle, demonstrating its adaptability to various datasets with minimal modifications to the algorithm. The performance of the proposed method is quantitatively analyzed using two widely recognized metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Higher PSNR values indicate better image clarity, while SSIM values close to 1 represent a strong structural similarity between the reconstructed and original images. Experimental results show that our ADCP and Guided Filter combination significantly improves both PSNR and SSIM, resulting in better image quality restoration compared to traditional approaches.

Keywords:ADCP, Guided Filter, Image Quality Enhancement, PSNR, SSIM, Haze-free Image Reconstruction, Image Processing.

I. INTRODUCTION

To apply ADPC+guided filtering for remova of haze efficiently and compare with exiting ADPC or guided filter technique.

Objectives

1. To study individual ADPC and Guided filter techniques fo haze removal and their limitations
2. Apply hybrid technique ADPC+Guided filter and its advantages
3. Design using python and relevant libraries

Scope

Previous Journals Investigation and Present project Console

Advantages and Disadvantages compared to previous Base papers

Haze significantly degrades the quality and visibility of images, posing challenges in various image processing and computer vision applications. This project introduces a hybrid approach to haze removal by combining Adaptive Dual Combination Processing (ADCP) with a Guided Filter. Traditional methods often rely on either ADCP or Guided Filters alone, which may leave certain areas unsmooth or insufficiently clear. By integrating both techniques, the system enhances haze removal performance, particularly in terms of image clarity and structural integrity.

The proposed method is designed to work efficiently across different image datasets, including those available on Kaggle, and demonstrates strong adaptability with minimal adjustments. The effectiveness of the system is evaluated using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), two widely used metrics for image quality assessment. Higher PSNR and SSIM values achieved by the hybrid model confirm its superiority over standalone methods, especially in restoring visual detail and preserving the structure of haze-free images.

The entire system is implemented in Python, featuring a simple GUI built using Tkinter to facilitate user interaction. Users can upload hazy images through the interface, which then applies the hybrid algorithm to produce and display enhanced, clear outputs. Additionally, the system is robust, able to detect errors if invalid input files are uploaded. With the help of guided filtering, the final outputs show smoother transitions and improved transmission estimates, especially around image corners and fine details.

In conclusion, this haze removal project not only demonstrates the improved effectiveness of the

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ADCP+Guided Filter approach but also showcases the value of combining classical image processing techniques with adaptive enhancement for real-world usability. Its flexibility, performance, and user-friendly design make it a strong candidate for practical deployment in various image processing domains.

Previously only ADPC , guided filter or cnn are separately used , but in our application we combined ADPC+guided filter which works more efficient than individual techniques.

II. LITEARTURE SURVEY

Image dehazing has become a crucial task in the field of image processing, particularly for enhancing image clarity in adverse weather conditions. One of the earliest and most influential works in this area is by He et al. (2011), who introduced the **Dark Channel Prior (DCP)** method. This technique leverages the observation that in most non-sky patches, at least one color channel exhibits low intensity, allowing effective estimation of transmission maps. However, while DCP performs well in many cases, it can produce artifacts or poor results in bright or white regions.

To address the shortcomings of DCP, He et al. (2013) also proposed the **Guided Image Filter**, which is a fast and edge-preserving filtering technique. It has been widely adopted in various image restoration tasks, including dehazing, for refining the transmission maps generated by prior-based methods like DCP. The integration of guided filtering helps in maintaining structure and reducing halo effects near edges.

Zhu et al. (2015) proposed an alternative approach using the **Color Attenuation Prior**, which simplifies depth estimation through linear models. Similarly, Berman et al. (2016) introduced **non-local image dehazing**, which builds haze-lines in color space to estimate transmission. These approaches brought improvements but still faced challenges when applied to diverse image conditions and complex scenes.

With the rise of deep learning, methods like **DehazeNet** (Cai et al., 2016) and **AOD-Net** (Li et al., 2017) introduced data-driven strategies that learn haze features directly from datasets. These networks showed improved performance over handcrafted priors by learning complex mappings between hazy and haze-free images. Ren et al. (2016) enhanced this further using multi-scale CNNs for better feature extraction, especially in varying haze densities.

However, traditional learning-based and deep learning methods often require extensive training data and computational resources. In contrast, hybrid methods like the one proposed in this project—combining **Adaptive Dual Combination Processing (ADCP)** with **Guided Filtering**—offer a balanced trade-off. By improving transmission estimates and refining the output with a guided filter, the proposed system achieves better **PSNR** and **SSIM** values, proving its effectiveness in quantitative evaluations.

Finally, Wang et al. (2004) introduced **SSIM (Structural Similarity Index)**, a widely accepted perceptual metric to evaluate the similarity between the original and processed images, while PSNR (Peak Signal-to-Noise Ratio) remains a traditional measure for image clarity. The use of both in the proposed system ensures a comprehensive performance evaluation.

III. PROPOSED METHOD

The proposed system implements a hybrid approach for haze removal from images by integrating Adaptive Dual Combination Processing (ADCP) with a Guided Filter. This combination leverages the strengths of both techniques to enhance image clarity, reduce noise, and preserve structural details effectively. The methodology is structured into several key steps, ensuring accurate haze removal and optimal performance across diverse image datasets.

1. Image Input and Preprocessing: Users begin by uploading hazy images through a graphical user interface (GUI) built using the Tkinter library in Python. The system validates the file type to ensure it is an image before proceeding. If a non-image file is uploaded, the system immediately throws an error. The selected image is displayed in the interface and prepared for processing.

2. Application of ADCP Algorithm: The first stage of the haze removal process involves the use of the ADCP technique. ADCP works by approximating the transmission map and atmospheric light to separate haze components from the image. Although ADCP is effective in removing haze, it sometimes fails to preserve smoothness at the edges or corners of the image.

3. Integration of Guided Filter: To overcome the limitations of ADCP, a Guided Filter is applied to refine the transmission map. The filter enhances edge-preserving smoothing, especially in areas with fine details or transitions. This step significantly improves the visual quality of the output by eliminating artifacts and ensuring a more natural look.

4. Performance Evaluation: The output images are evaluated using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). A higher PSNR indicates better visual clarity, while an SSIM value closer to 1 shows that the dehazed image closely matches the structure of the original haze-free image. This evaluation confirms the effectiveness of the hybrid model over standalone techniques.

5. Flexibility with Datasets: The methodology is designed to be adaptable across various datasets. It has been tested on multiple image collections, including Kaggle's haze image datasets (indoor and outdoor), and has shown consistent performance without the need for major adjustments. This flexibility makes the approach suitable for real-world deployment.

IV. RESULTS

Step by step results

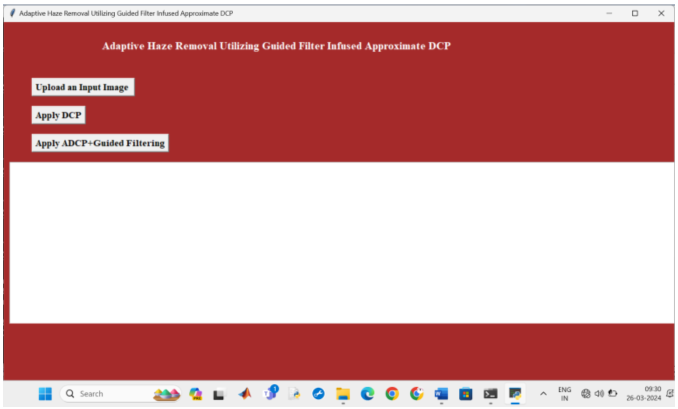

Fig. Proposed method GUI (Frontend)

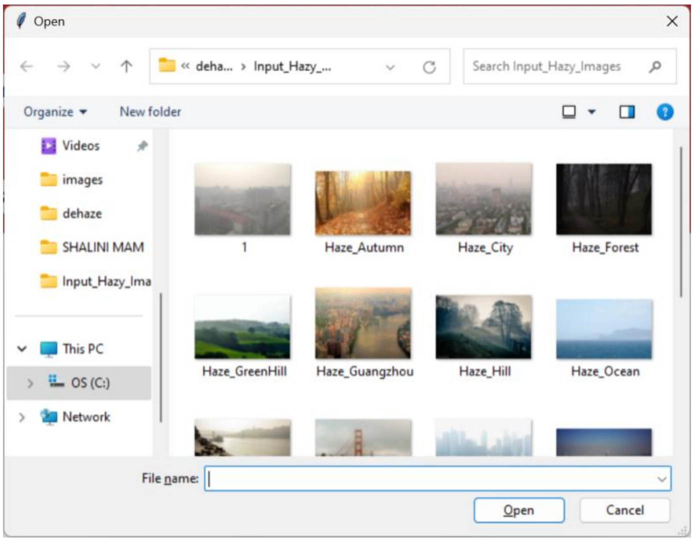

Fig. when we click on first button, it will ask image from user

The selected image from user is displayed. And remaining algorithms will be applied on selected image.

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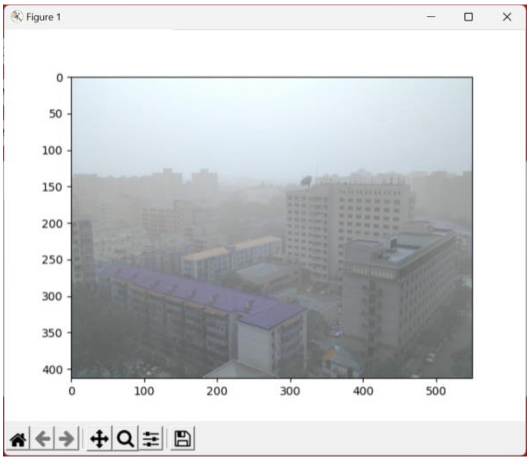


Selected input image by user

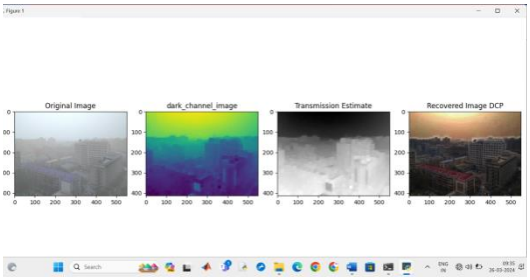


Fig. ADCP image results

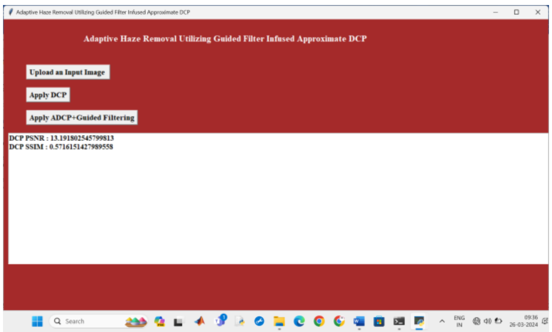


Fig. Perfomance Metrics for ADPC

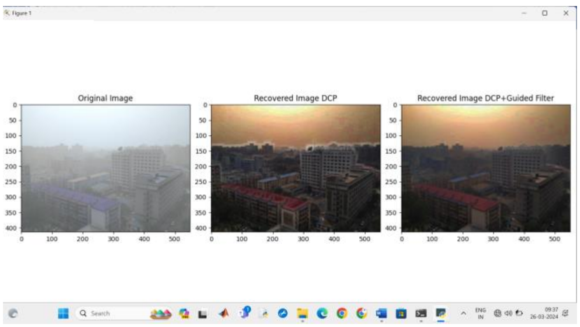


Fig. a) input image b) ADPC image c) ADPC+Guided filter image

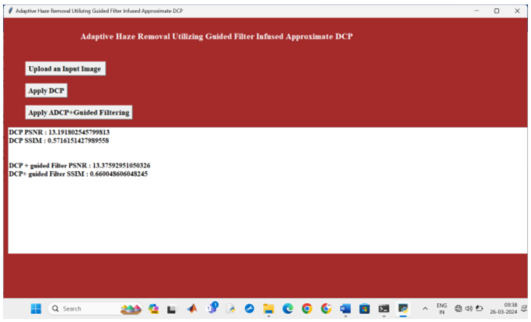
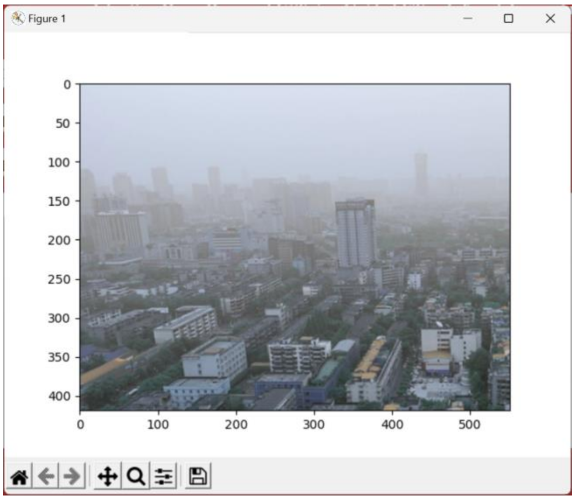


Fig. Perfomance analysis of ADPC+Guided filter

We can see in above results that first by applying ADPC , haze is removed but at corner there is no smoothness , that smoothness is added by guided filter by improving transmission estimate.

Similarly you can test more images



Input Image

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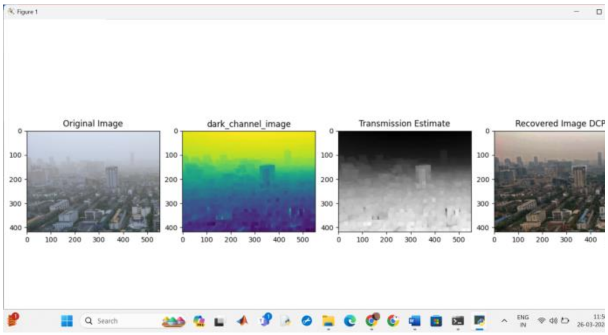

Fig. ADPC steps results

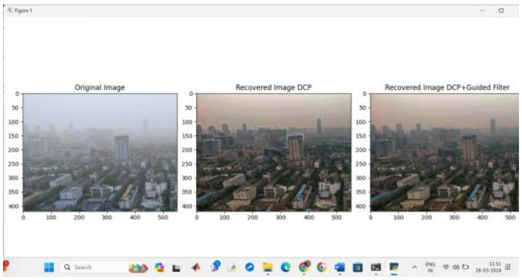

Fig. a) original image b) ADPC c) ADCP +Guided filter

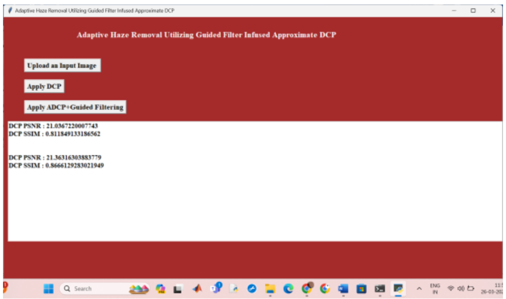

Fig. Performance Analysis

V. CONCLUSION

The proposed system effectively demonstrates a hybrid approach for haze removal by combining Adaptive Dual Combination Processing (ADCP) with a Guided Filter. This integration leverages the strengths of both techniques, enabling the removal of haze while preserving image details and enhancing visual quality. The use of performance metrics such as PSNR and SSIM confirms that the system achieves superior clarity and structural similarity when compared to standalone dehazing methods.

Through experimental evaluation on diverse datasets, the system has shown adaptability, robustness, and accuracy. The guided filter significantly improves the transmission map refinement, especially in edge regions, contributing to smoother and more natural results. Moreover, the user-friendly interface and real-time processing capabilities make this solution practical and accessible for real-world applications.

In conclusion, this project not only addresses the limitations of existing dehazing techniques but also presents a scalable and efficient solution suitable for further development. Future enhancements may include the integration of deep learning techniques and real-time video dehazing, paving the way for broader implementation in fields such as surveillance, autonomous driving, and remote sensing.

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