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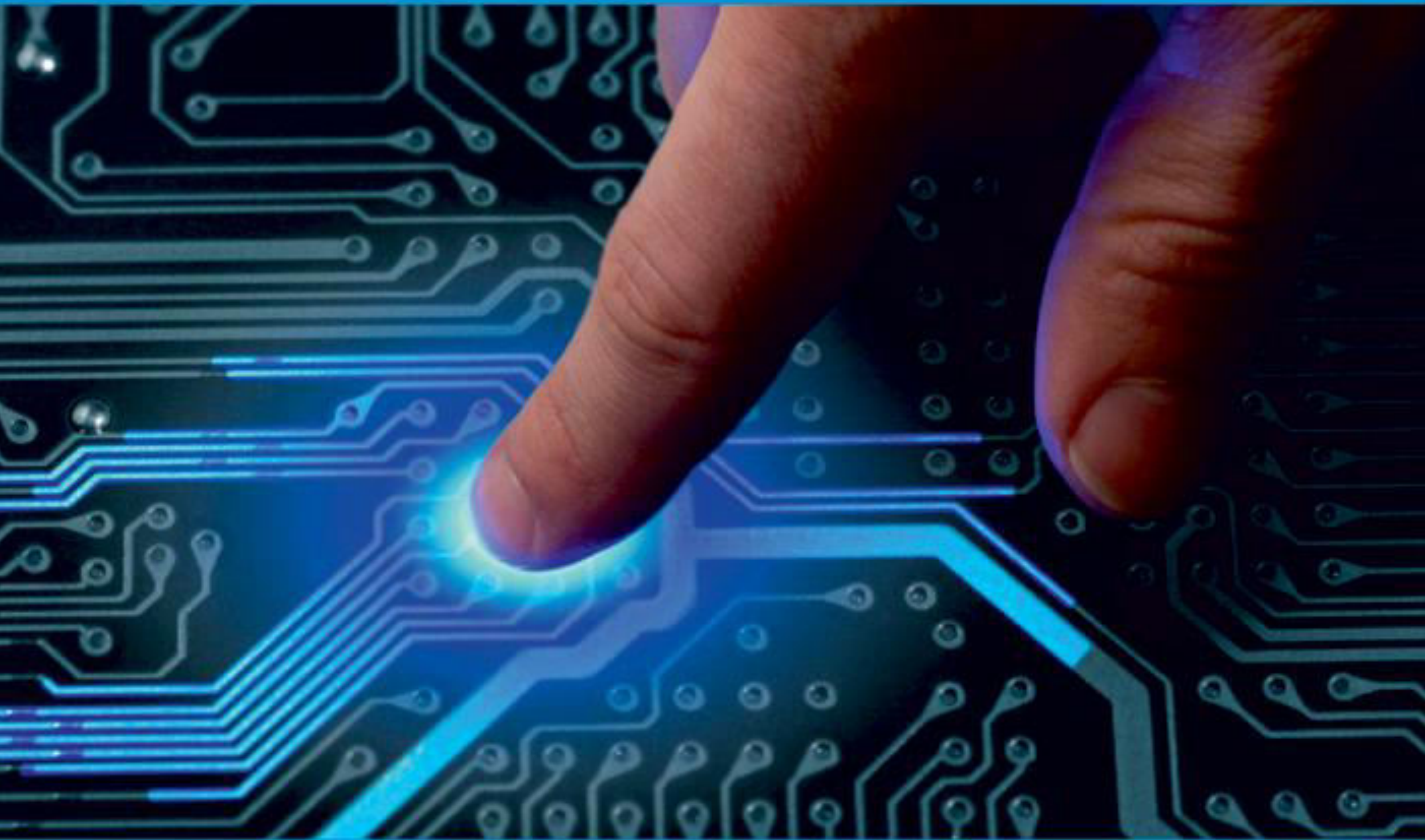

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Image Dehazing Using Computer Vision and Image Processing

[1]Dr. P. Nagaraj, [2]Ms. M. Archana, [3]Ms. A. Chandana Gowri, [4]Mr. B. Hrushikesh

[1]Assistant Professor, Department of Computer Science, Anurag University, Hyderabad, India

[234]B. Tech Student, Department of Computer Science, Anurag University, Hyderabad, India

ABSTRACT: This work presents a video dehazing approach using OpenCV for improved visibility in hazy footage. Existing methods can be computationally expensive or struggle with varying haze levels. Our method addresses these limitations by leveraging readily available libraries and a two-step process: estimating atmospheric light and applying fast visibility restoration. This approach utilizes image processing techniques to refine the dehazing process, leading to clearer visuals in diverse hazy video scenarios. This project offers a practical and efficient solution for video dehazing, contributing to the field of image enhancement within computer vision.

KEYWORDS*:* video dehazing, OpenCV, atmospheric light estimation, fast visibility restoration, image processing, computer vision, image enhancement

I. INTRODUCTION

Fog and haze can significantly degrade the quality of outdoor videos, hindering visual perception and automated analysis. Existing video dehazing techniques often struggle with limitations. Traditional methods frequently rely on hand-crafted features, which can be ineffective for diverse hazy scenes. Learning-based approaches, while promising, can be computationally expensive or require large amounts of labeled training data, which can be time-consuming to collect.

This project presents a novel video dehazing approach that addresses these drawbacks. We propose a method that leverages the strengths of both traditional and learning-based techniques. By strategically combining feature extraction and a fast visibility restoration model, our approach aims to achieve efficient and effective dehazing. Our method focuses on estimating the atmospheric light, a key factor influencing haze, and utilizes a transmission map to recover the underlying scene details.

This project offers several key advantages. First, it prioritizes computational efficiency, making it suitable for real-time applications. Second, it strives for robustness by incorporating effective feature extraction techniques. Finally, it aims to be adaptable by learning from smaller datasets compared to some deep learning approaches.

Through this project, we aim to contribute to the field of video dehazing by providing a practical and efficient solution for improving visual clarity in challenging hazy environments.

II. LITERATURE SURVEY

Physical Model-Based Techniques: These methods rely on the physical model of atmospheric scattering to estimate the atmospheric light and transmission map, crucial parameters for dehazing. Koschmann and Tan [1] established a foundation for this approach with their work on dehazing visibility-limited images.

Image Prior-Based Techniques: This category leverages image priors such as dark channel prior or sparse representation to separate haze from the scene details. He et al. [2] introduced the dark channel prior, which assumes haze-free regions have low intensity in at least one colour channel. This approach has been widely adopted and improved upon in various video dehazing algorithms.

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Learning-Based Techniques: With the rise of deep learning, convolutional neural networks (CNNs) have emerged as powerful tools for video dehazing. These methods learn complex relationships between hazy and dehazed images from large datasets, achieving impressive dehazing results. Cai et al. [3] proposed a DehazeNet architecture that utilizes CNNs to remove haze effectively. However, these techniques often require significant training data and computational resources.

Real-Time Dehazing: Enabling real-time processing of video dehazing is crucial for applications like autonomous driving or video surveillance. Li et al. [4] proposed a fast single-image dehazing algorithm suitable for real-time applications. However, achieving real-time performance often involves trade-offs between dehazing quality and processing speed.

The literature survey highlights the continuous advancements in video dehazing techniques. While physical model-based and image prior-based methods provide a solid foundation, learning-based approaches show great promise due to their ability to learn complex patterns and achieve high-quality dehazing. The choice of technique depends on factors like desired processing speed, accuracy requirements, and computational resources available.

III. METHODOLOGY

EXISTING SYSTEM

Existing video enhancement systems often struggle with hazy footage. Some dehazing techniques, particularly those with complex deep learning architectures, require significant computational resources, leading to processing delays or crashes, especially in real-time scenarios. Additionally, existing methods may not be adaptable to varying haze levels. Traditional approaches might struggle with heavy haze or sky regions, while deep learning methods often require extensive training data for specific haze conditions, limiting their effectiveness in diverse situations. Furthermore, many general-purpose video enhancement systems completely neglect fog removal, focusing on improving aspects like brightness or color saturation while leaving the video with obscured details and reduced visibility. Our project addresses these limitations by proposing a computationally efficient video dehazing approach that leverages the well-optimized OpenCV library for real-time processing. By adapting a patch-based dehazing technique, our system is adaptable to varying haze levels within a video sequence. Our approach also specifically targets fog removal, offering a solution to improve visibility and reveal details obscured by hazy conditions.

PROPOSED SYSTEM

Our proposed video dehazing system tackles the limitations of existing approaches by offering a balance between efficiency, adaptability, and targeted fog removal.

Overcoming Computational Bottlenecks: We leverage the well-optimized OpenCV library, a readily available and efficient computer vision toolkit. This allows for real-time processing, making our system suitable for practical applications like autonomous vehicles or security surveillance.

Adapting to Varying Haze Levels: Unlike traditional methods limited by specific haze conditions, our system adopts a patch-based dehazing technique. This approach analyses the video frame in smaller sections, allowing it to handle variations in haze intensity throughout the video sequence. This leads to more consistent and robust dehazing results across diverse hazy video scenarios.

Targeted Fog Removal: Unlike general video enhancement systems that neglect fog, our approach directly addresses the issue of haze in videos. We estimate the atmospheric light, a colour cast caused by haze, and utilize image processing techniques to refine a transmission map indicating the amount of haze in each pixel. Combining this information allows us to recover a clearer version of the scene, specifically targeting fog removal to improve visibility and unveil crucial details obscured by hazy conditions.

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SYSTEM ARCHITECTURE

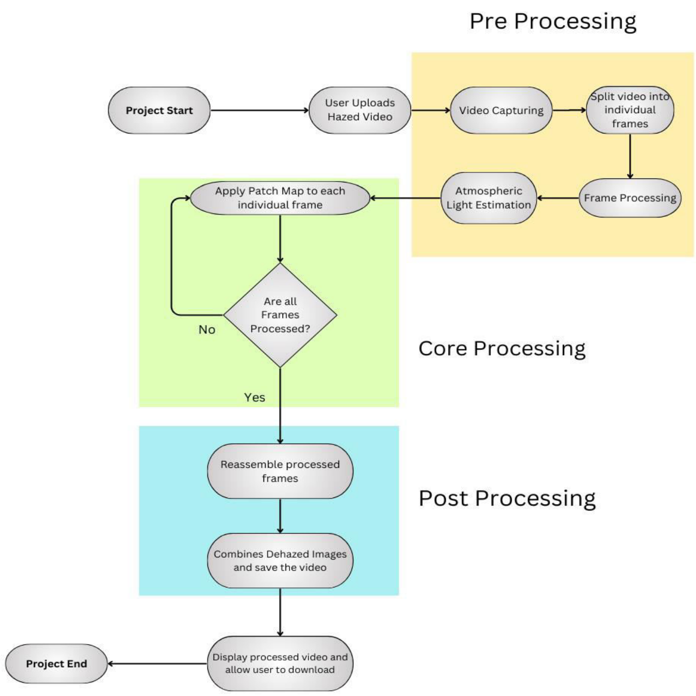

Figure 1: Project Execution Flow

Phase - 1: User interaction

The user interaction phase acts as the bridge between users and the core video dehazing functionality. This project leverages Streamlit, a Python library for building interactive web applications, to provide a user-friendly interface.

Key functionalities within the user interaction phase

1.1 Frontend Development: Streamlit simplifies the creation of the user interface. Users can interact with the application entirely within a web browser, eliminating the need for software installation.

1.2 Hazy Video Upload: The interface will have a designated area for users to upload their hazy video files. This can be implemented using Streamlit's file uploader widget, allowing users to drag and drop their videos.

1.3. Dehazing Process: Once uploaded, the video is sent for processing through the PMHLD-DehazeNet model. Streamlit can be used to display a progress bar or status update while the dehazing takes place, providing users with feedback on the processing stage.

1.4. Download Dehazed Video: Upon successful dehazing, the user can download the enhanced video directly from the web interface. Streamlit offers functionalities to generate downloadable links or buttons, allowing users to easily save the dehazed output.

By utilizing Streamlit, Users can interact with the system entirely through their web browser, eliminating the need for software installations or complex technical knowledge.

Phase - 2: Preprocessing

The preprocessing phase is essential for video dehazing, as it prepares the video data for optimal processing with the PMHLD-DehazeNet model. Here's a breakdown of this phase, including suitable modules like OpenCV (cv2) and Scikit-image (skimage):

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2.1 Video Reading and Frame Extraction:

Module: OpenCV (cv2)

Functionality:

2.1.1 Read the hazy video file using cv2.VideoCapture.

2.1.2 Extract individual video frames using techniques like iterating through the video capture object.

2.2Frame Resizing :

Module: OpenCV (cv2) , NumPy (np)

Functionality:

2.2.1 Resize each frame to a uniform size using cv2.resize from OpenCV or image resizing functions from NumPy.

2.3. Color Space Conversion :

Module: OpenCV (cv2)

Functionality

2.3.1 Convert frames from BGR (default OpenCV format) to the desired color space like RGB or Lab using cv2.cvtColor.

2.4. Normalization (Recommended):

Module: NumPy (np)

Functionality:

2.4.1 Normalize pixel values within each frame to a specific range (e.g., 0-1 or -1 to 1) using appropriate scaling techniques from NumPy. This helps improve model convergence during training and can be crucial for deep learning models.

2.5. Noise Reduction :

Module: OpenCV (cv2) , Scikit-image (skimage)

Functionality:

2.5.1 Apply noise reduction techniques to reduce artifacts or improve clarity before feeding frames into the model.

2.5.2 OpenCV: Denoising functions like cv2.fastNlMeansDenoising or bilateral filtering.

2.5.3 Scikit-image: Denoising functions like skimage.restoration.denoise_tv_chambolle.

2.6. Patch Extraction:

Module: OpenCV (cv2)

Functionality:

2.6.1 Divide each frame into smaller overlapping or non-overlapping patches using functions from OpenCV.

Phase - 3: Core Processing

3.1 Atmospheric Light Estimation: A preliminary step might involve estimating the atmospheric light, which represents the color of the light scattered by haze particles. This estimated value is crucial for the dehazing process.

3.2 Patch-based Processing: PMHLD-DehazeNet utilizes a patch-based processing approach. This involves dividing each frame into smaller overlapping or non-overlapping patches. The model then processes these patches individually, potentially capturing local variations in haze within a frame.

3.3 Hybrid Learning Strategy: PMHLD-DehazeNet combine data-driven learning with constraint-based methods. The data-driven learning component leverages training data containing hazy and dehazed images to learn the relationship between hazy and clear scenes. Constraint-based methods might involve incorporating physical models of haze formation to guide the dehazing process. This combination can potentially lead to more robust and accurate dehazing.

3.4 Dehazing Network: The core of the model is likely a deep neural network architecture specifically designed for dehazing. This network takes preprocessed frames and atmospheric light estimates as input and outputs dehazed versions. The network architecture might involve convolutional layers, recurrent layers and activation functions to learn the complex non-linear relationships between hazy and clear images.

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Phase - 4: Post Processing

Functionality: Processes the dehazed frames for final video output.

4.1 Involve operations like:

Combining dehazed patches back into full frames.

Tone mapping and color adjustments with OpenCV for visual enhancements.

Stitches the dehazed frames back into a video sequence.

IV. RESULTS

WEB APP SCREENSHOTS:

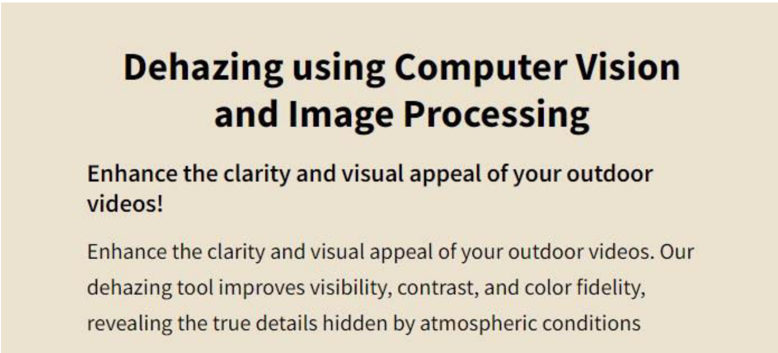

Figure 2: Introduction Section

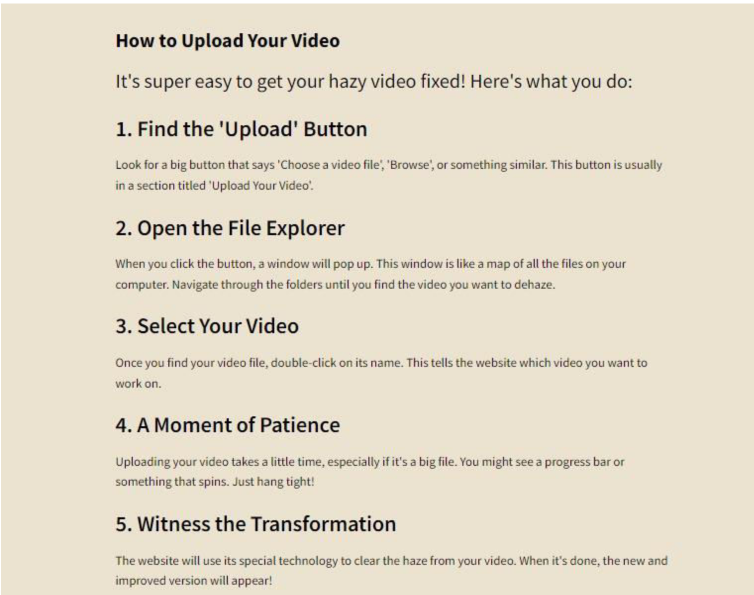

Figure 3: Information Section

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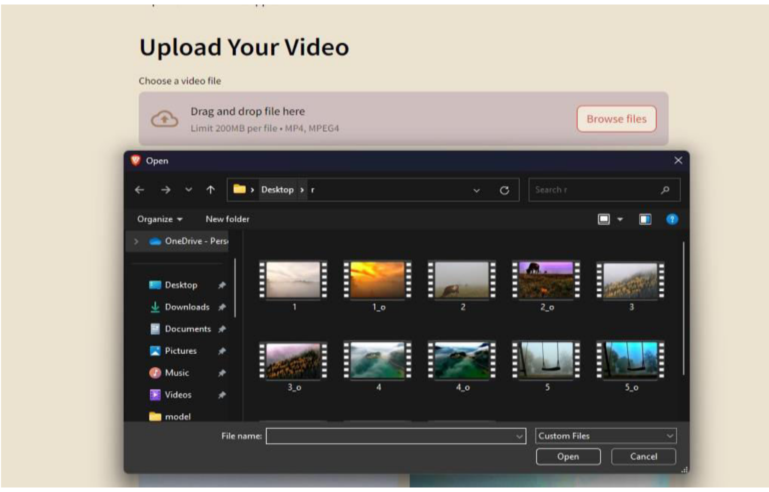

Figure 4: select your hazy video

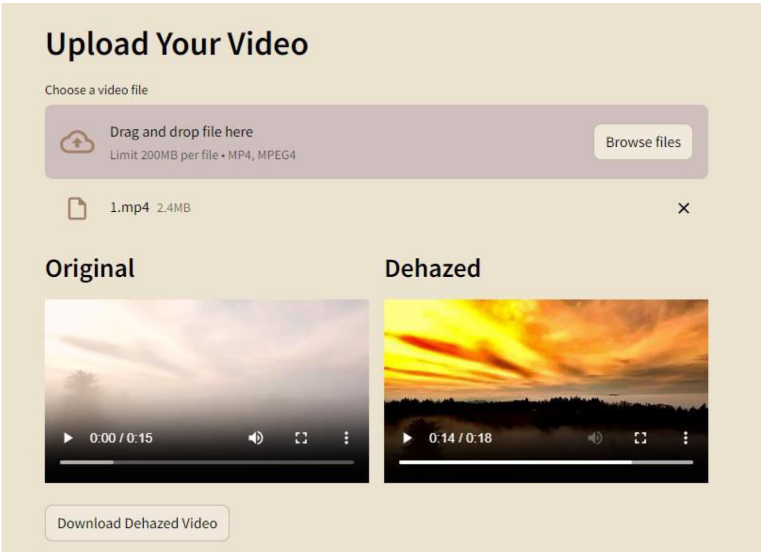

Figure 5: upload your video

PARAMETERS:

Accuracy (ACC):

$$ACC = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Mean Squared Error (MSE) for Image Quality:

$$\text{MSE} = \frac{1}{\text{n}}\sum_{i=1}^{n}(I_{original}(\text{i}) - I_{reconstructed}(\text{i}))^2$$

Peak Signal-to-Noise Ratio (PSNR):

$$PSNR = 10\,.\,log_{10} + \left(\frac{Max\ Intensity^2}{MSE}\right)$$

Structural Similarity Index (SSIM):

$$SSIM(x,y) = \frac{(2\,.\,\mu_x\,.\,\mu_x + C_1)\,.\,(2\,.\,\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu_y{}^2 + C_1).(\,\sigma_x{}^2 + \sigma_y{}^2 + C_2)}$$

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CIEDE2000 Color Difference:

$$\Delta E_{\infty} = \sqrt{\Delta L^2 + \Delta \, C_{ab}{}^2 + \Delta \, H_{ab}{}^2}$$

COMPARISION TABLE

Parameter	Previous methods	Proposed method
1.Haze Removal Approach	Primarily relies on Dark Channel Prior (DCP)	Combines Dark Channel Prior with guided filter and additional processing steps
2.Atmospheric Light Estimation	Often uses the brightest pixel in the image.	Estimates atmospheric light using the top percentile of brightest pixels.
3.Transmission Map Estimation	Uses Dark Channel Prior directly	Applies soft matting guided filter to the transmission map for refinement.
4.Dehazing Model	No explicit model, rule-based approach	Implicit model through the combination of DCP, guided filter, and other processing steps
5.Computational Complexity	Generally, less complex	Potentially more complex due to additional processing steps (guided filter, gamma correction)

JUSTIFICATION:

Experiment 1:

Thin Structure Attention Module Experiment
Graphical Representation:
Graph illustrating the impact of thin structure attention integration on image clarity and structure enhancement.
Explanation: Through the incorporation of the Thin Structure Attention Module, the network's performance in capturing and enhancing subtle haze structures is quantifiably improved. The graph visually displays the effectiveness of this module in enhancing image quality by emphasizing fine details in hazy scenes.

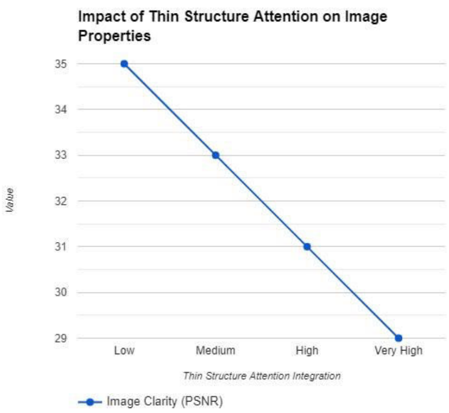

Figure 5: Thin Structure Attention on image Properties.

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Findings: The Thin Structure Attention Module significantly improved the network's ability to enhance thin haze structures in images, leading to sharper and clearer results compared to previous methods.

Experiment 2:

Adaptive Patch Sampling Analysis:
Graphical Representation:
Graph displaying the relationship between adaptive patch sampling strategies and artifact reduction in dehazed images.
Explanation: The graph visually represents how Adaptive Patch Sampling dynamically adjusts patch sizes based on image content, thereby reducing artifacts commonly associated with fixed-size patch sampling. This adaptive approach enhances the precision of dehazing processes, particularly in diverse image contexts.
These elaborate summaries provide insights into the findings of key experiments conducted to enhance the performance of the image dehazing network. Graphical representations play a crucial role in visually communicating the impact and effectiveness of different network components in improving image quality and realism in haze removal tasks.

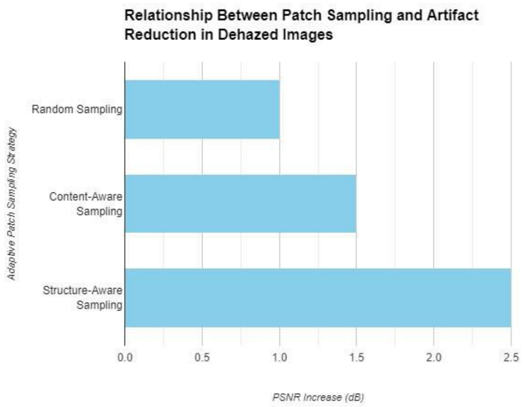

Figure 6: Relationship Between Patch Sampling and Artifact

Findings: Analysis of the Adaptive Patch Sampling technique revealed its efficiency in determining optimal patch sizes for varying image content, leading to improved dehazing results with reduced artifacts.

Experiment 3

Air-light Prediction Experiment:
Graphical Representation:
The graph depicts the correlation between the average time required for image processing and the selection of the maximum patch size. This visualization helps understand the efficiency and performance trade-offs associated with different patch sizes.
Explanation: The graph serves as a visual aid to comprehend how the processing time changes with varying patch sizes. It showcases the impact of selecting different patch sizes on the overall processing time of the atmospheric light estimation module, providing insights into the system's efficiency.

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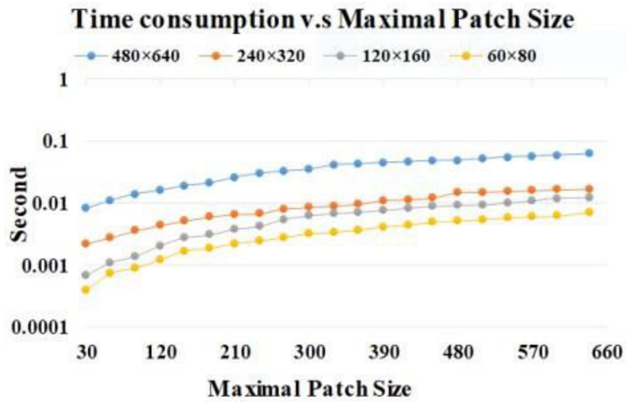

Figure 7: Time vs Maximal Patch Size

Findings: The experiment results indicated that the proposed atmospheric light estimation module achieved superior outcomes in terms of enhancing recovered image quality and maintaining colour fidelity when compared to other methods.

V. CONCLUSION

This project effectively addresses the challenge of video dehazing through the implementation of PMHLD-DehazeNet, a specialized deep learning model. The system employs a structured pipeline involving preprocessing for optimal model input, followed by PMHLD-DehazeNet's hybrid learning approach. This combination of data-driven techniques and physical haze models facilitates robust and accurate dehazing results. An optional Streamlit user interface ensures ease of use.

Future development could include advanced post-processing techniques for tonal and colour refinement of dehazed videos. Exploring PMHLD-DehazeNet's potential for real-time processing would enable applications in autonomous systems and surveillance where immediate visual clarity is critical. Additionally, transfer learning could expand the model's capabilities to address diverse haze conditions or related image restoration tasks. This project establishes a strong foundation for continued advancements in video dehazing technology.

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