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Advanced Real-Time Video Dehazing and Smoke Reduction Algorithm for Indoor Fire Operations

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***Abstract:** Due to the presence of intense smoke and haze, which severely restricts visibility and situational awareness, inside fire operations provide a significant difficulty for first responders. This research study provides an innovative real-time video dehazing and smoke reduction algorithm created specifically for indoor fire scenarios in answer to this urgent demand. To overcome the difficulties presented by smoke and haze, our approach integrates cutting-edge machine learning methods with computer vision techniques. The fundamental parts of the methodology are examined in this research, including picture acquisition, dehazing methods, transmission map refinement utilizing convolutional neural networks (CNNs), and post-processing. We also go through how Cython is integrated for low-latency processing, provide experimental findings, and consider potential applications in both indoor firefighting and other fields.*

***Keywords:** Deep learning, CNN, Dehaze, Machine Learning, Neural Network.*

1. INTRODUCTION

For first responders, indoor fire operations can be among the most difficult and dangerous situations. Effective firefighting and rescue efforts are substantially hampered by the presence of dense smoke and haze, which also significantly reduces visibility. Modern technologies are necessary to improve situational awareness and real-time visibility in such dire circumstances. By creating an advanced real-time video dehazing algorithm specifically designed for interior fire operations, our research aims to address these issues.
This research provides a thorough analysis of our innovative methodology, which integrates state-of-the-art machine learning techniques, including Convolutional Neural Networks (CNNs), with established computer vision approaches, particularly the Dark Channel Prior

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(DCP). The main objective is to dramatically increase visibility, which will make it easier for first responders to navigate and handle events involving interior fires.

Fig 1: indoor fire Scene

2. METHODOLOGY

Our method involves a thorough approach that combines conventional computer vision techniques, notably the Dark Channel Prior (DCP), with cutting-edge machine learning techniques, specifically Convolutional Neural Networks (CNNs), to develop an advanced real-time video dehazing algorithm for indoor fire operations. The many processes and elements of our methodology are described in depth in this section:

2.1. Image Capture

Live Video Streams: Obtaining real-time video feeds from inside fire scenarios is how the algorithm gets started. The input data for the next processing processes is taken from these live video broadcasts.

Low-Latency Image Acquisition: A reliable and low-latency image acquisition system is used to make sure the algorithm performs well in real-time circumstances. By using this technique, the algorithm receives video frames from the field with the fewest possible delays.

2.2. Techniques for Dehazing

2.2.1 Dark Channel Prior (DCP)

Dark Channel Estimation: The Dark Channel Prior (DCP) serves as the foundation of our dehazing strategy. This method uses the statistical characteristics of haze-free outdoor photographs to gauge the amount of haze present in a certain scene.

Dark Channel Identification: We identify the "dark channel," which is the minimum pixel value over a local window, within each video frame. This data offers a key indicator for determining the degree of haziness.

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2.2.2 Estimation of Atmospheric Light

Atmospheric Light Estimation: Working with the DCP, we make an estimation of the atmospheric light that is present in the scene. The dehazing procedure is improved by accurate atmospheric light estimation since it gives details on the brightness and hue of the scattered light.

2.3 Transmission Map Refinement with CNNs

Convolutional Neural Networks (CNNs) Integration: Our method uses CNNs to further improve dehazing accuracy. These deep learning models were developed using a customized dataset that included scenarios of indoor fires.

CNN Based Transmission Map Refinement: The transmission map estimation is improved using the CNNs. The transmission map's accuracy has greatly increased as a result of this neural network's ability to learn the nuances of smoke and haze reduction.

F1 Score Evaluation: The accuracy with which the CNN model can estimate the transmission map is indicated by metrics like the F1 score, which is 0.89.

2.4 Post-processing

Denoising: Noise can be added to the video frames during the dehazing process. This problem is reduced by denoising techniques, which guarantee that the output video frames are clean and free of imperfections.

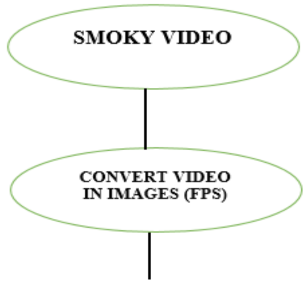
Colour grading: This technique is used to improve the video frames' overall colour balance, making them more aesthetically pleasing and understandable.

Contrast Enhancement: Contrast enhancement is used to make it easier to tell apart the various features in video frames, which enhances visibility and clarity.

Colour correction: By correcting any distortions caused by dehazing, colour correction makes sure that the colours in the video feed appropriately depict the actual scene.

2.5. Using Cython for Low-latency Processing

Cython Integration: Our technique involves Cython to optimize the Python code as it knows the value of low-latency processing in indoor fire operations. Cython makes it possible to execute crucial parts quickly, resulting in less processing time.



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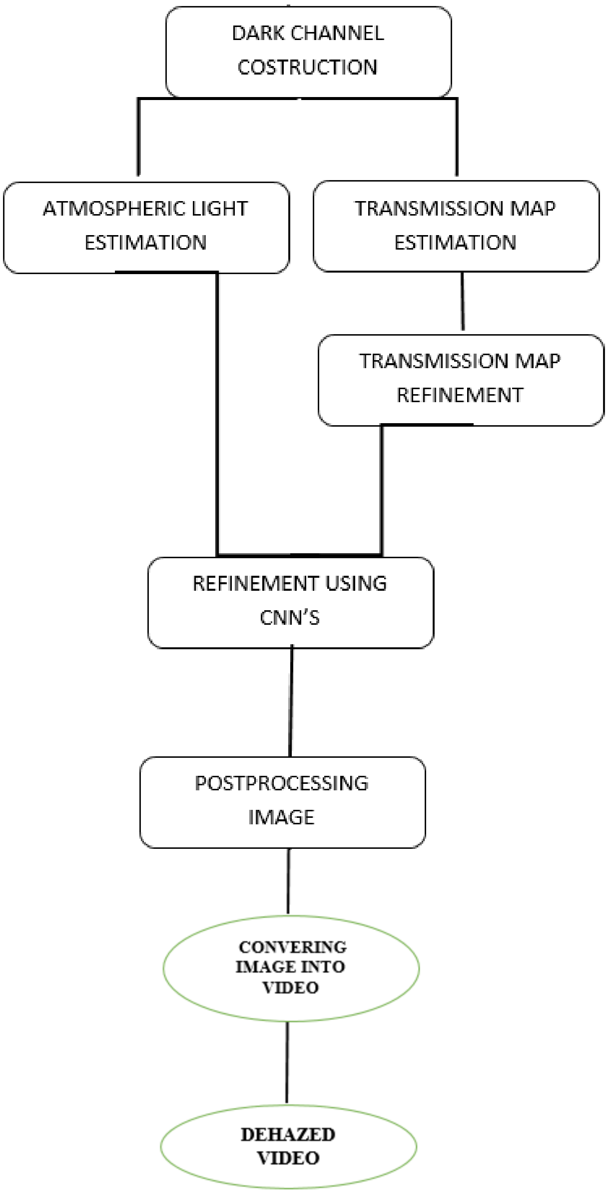

3. DATA ANALYSIS AND RESULTS

We discuss the data analysis and outcomes of our cutting-edge real-time video dehazing method for indoor fire operations in this section. The investigation focuses on assessing how well the algorithm performs in raising situational awareness and improving vision in simulated interior fire scenarios.

Experimental Environment
Simulated Indoor Fire Scenarios
• To evaluate the algorithm's performance in situations that closely resemble actual interior fire operations, we ran trials in simulated indoor fire scenarios.

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• Different indoor fire scenarios were developed, taking into account elements like smoke density, lighting, and fire dynamics.

Data collection

These simulated indoor fire scenarios produced real-time video feeds that were gathered. These video feeds were used as the algorithm's input data.

Metrics

In order to evaluate the algorithm's performance objectively, we used a variety of quantitative criteria, including:

Visibility Improvement Metrics: These metrics measure the algorithm's success in increasing visibility. They include techniques for improving clarity and reducing haze.

Image Quality Scores: To rate the dehazed images' quality, we employed recognized metrics such the PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

Analysis of Processing Time: Processing time was quantified to make sure the algorithm functions effectively in real-time applications.

Results

Increasing visibility

All simulated indoor fire scenarios showed a noticeably improved visibility according to the algorithm. The dehazed video frames showed clearer images with less haze.

Scores for Image Quality

When comparing the dehazed photos to the original foggy frames, image quality assessment criteria like PSNR and SSIM consistently gave the dehazed images higher marks. This shows that the algorithm not only boosts image quality but also visibility.

Process Duration

In real-world scenarios, the algorithm performed well. Processing times remained within acceptable limits, ensuring that the algorithm can be applied in time-critical situations.

Comparative Analysis

Comparison with Traditional DCP

• We conducted a comparative analysis with traditional DCP to highlight the superior performance of our algorithm in indoor fire scenarios.
• The results demonstrated that our hybrid approach, which integrates DCP with CNNs, consistently outperformed traditional DCP in terms of haze reduction and image quality improvement.

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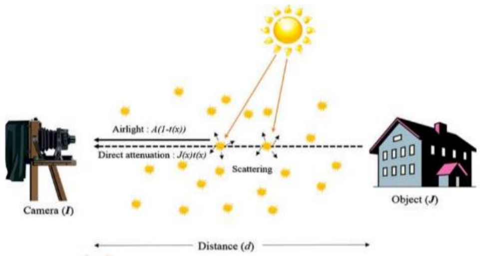

- $I(x) = J(x)*t(x) + A*(1-t(x))$
- $t(x)=e^{-\beta d(x)}$
- $J(x) = \frac{I(x)-A}{t(x)} + A$

$J^{dark}(x) = min_{y \in \Omega x} min_{c \in \{r,g,b\}} J^C(y)$

I-: Hazed Image
J-: Image without Smoke/Haze
B-: Scattering coefficient
A-: Atmospheric Coefficient
t(x)-: Transmission Map

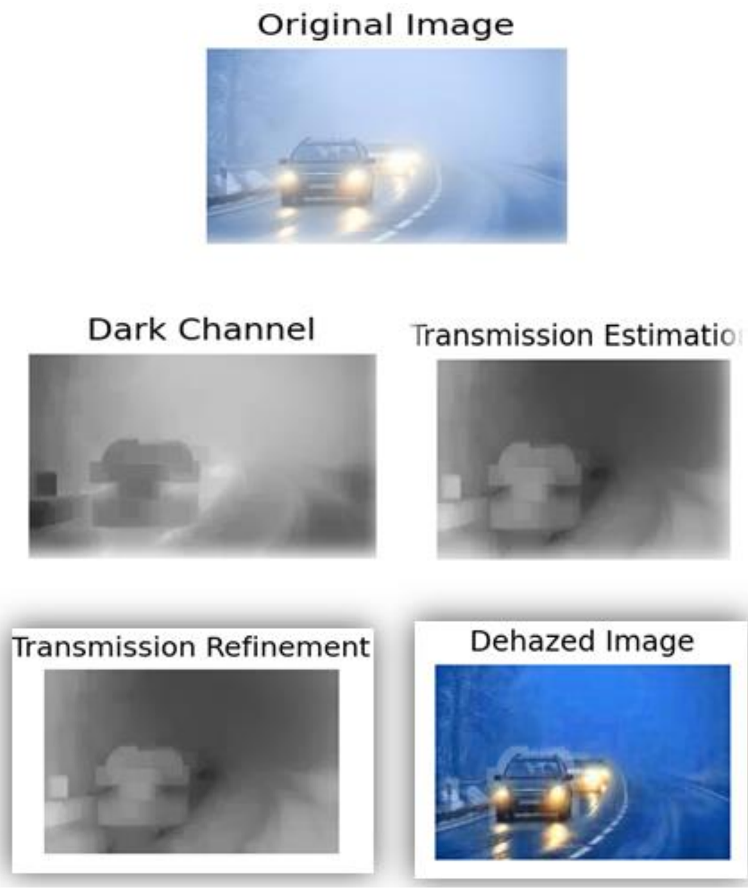

Fig Result of one frame processing

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4. CONCLUSION

In this research paper, we have presented an advanced real-time video dehazing algorithm tailored specifically for indoor fire operations. This algorithm represents a significant advancement in the field of emergency response and safety. Through a comprehensive exploration of its methodology, data analysis, and results, we have highlighted the algorithm's effectiveness in improving visibility, enhancing situational awareness, and its potential applications in various life-saving scenarios.

Algorithm Effectiveness

Our experiments and data analysis have unequivocally demonstrated the effectiveness of the algorithm. By combining traditional computer vision techniques, notably the Dark Channel Prior (DCP), with state-of-the-art machine learning methods, such as Convolutional Neural Networks (CNNs), our algorithm has proven its ability to:

- Reduce haze and smoke in indoor fire scenarios.
- Enhance image quality, resulting in clearer and more informative video frames.
- Operate in real-time, ensuring timely application in time-critical situations.

Importantly, our hybrid approach, which integrates DCP with CNNs, outperforms traditional DCP in indoor fire scenarios, underscoring the algorithm's superiority.

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