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VIDEO DEHAZING/DEFOGGING USING ML

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ABSTRACT

The presence of haze in the atmosphere degrades the quality of images captured by visible camera sensors. The removal of haze, called dehazing, is typically performed under the physical degradation model, which necessitates a solution of an ill-posed inverse problem**[3]**. To relieve the difficulty of the inverse problem, a novel prior called dark channel prior (DCP) was recently proposed and has received a great deal of attention. The DCP is derived from the characteristic of natural outdoor images that the intensity value of at least one color channel within a local window is close to zero**[1]**. Based on the DCP, the dehazing is accomplished through four major steps: atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction. This four-step dehazing process makes it possible to provide a step-by-step approach to the complex solution of the ill-posed inverse problem. This also enables us to shed light on the systematic contributions of recent researches related to the DCP for each step of the dehazing process**[1]**. Our detailed survey and experimental analysis on DCP-based methods will help readers understand the effectiveness of the individual step of the dehazing process and will facilitate development of advanced dehazing algorithms.

INTRODUCTION

Due to absorption and scattering by atmospheric particles in haze, outdoor images have poor visibility under inclement weather. Poor visibility negatively impacts not only consumer photography but also computer vision applications for outdoor environments, such as object detection and video surveillance . Haze removal, which is referred to as dehazing, is considered an important process because haze-free images are visually pleasing and can significantly improve the performance of computer vision tasks.

Methods presented in earlier studies had required multiple images to perform dehazing. For example, polarization-based methods use the polarization property of scattered light to restore the scene depth information from two or more images taken with different degrees of polarization. Similarly, in , multiple images of the same scene are captured under different weather conditions to be used as reference images with clear weather conditions. However, these methods with multiple reference images have limitation in online image dehazing applications and may need a special imaging sensor . This leads the researchers to focus the dehazing method with a single reference image. Single image based methods rely on the typical characteristics of haze-free images. Tan proposed a method that takes into account the characteristic that a haze-free image has a higher contrast than a hazy image. By maximizing the local contrast of the input hazy image, it enhances the visibility but introduces blocking artifacts around depth discontinuities. Fattal proposed a method that infers the medium transmission by estimating the albedo of the scene[2]. The underlying assumption is that the transmission and surface shading are locally uncorrected, which does not hold under a dense haze.

Observing the property of haze-free outdoor images, proposed a novel prior—*dark channel prior* (DCP). The DCP is based on the property of "dark pixels," which have a very low intensity in at least one color channel, except for the sky region. Owing to its effectiveness in dehazing, the majority of recent dehazing techniques have adopted the DCP. The DCP-based dehazing techniques are composed of four major steps: atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction. In this paper, we perform an in-depth analysis of the DCP-based methods in the four-step point of view[2].

We note that there are several review papers on image dehazing or defogging . In , five physical model-based dehazing algorithms are compared[2]. In , several enhancement-based and restoration-based defogging methods are investigated. In , fog removal algorithms that use depth and prior information are analyzed. In , a comparative study on the four representative dehazing methods are performed. In , many visibility enhancement techniques developed for homogeneous and heterogeneous fog are discussed. To the best of our knowledge, our paper is the first one dedicated to DCP-based methods. This survey is expected to ascertain researchers' endeavors toward improving the original DCP method.

The rest of the paper is organized as follows. The original DCP-based dehazing method is first reviewed. provides an in-depth survey of conventional DCP-based methods. Section discusses the performance evaluation methods for image dehazing, and Section concludes the paper.

Literature Survey

When conducting a literature survey on video dehazing using the dark channel prior algorithm, you'll want to explore various research papers, articles, and conference proceedings that discuss this specific topic. Here's a structured approach to conducting such a survey:

1. Introduction to Dehazing and Dark Channel Prior:
   - Begin by introducing the concept of image dehazing and the importance of enhancing visibility in hazy or foggy conditions.
   - Explain the Dark Channel Prior (DCP) algorithm, which is a widely-used method for single image dehazing.
2. Search Strategy:
   - Utilize academic databases such as IEEE Xplore, Google Scholar, PubMed, and ScienceDirect.
   - Use keywords such as "video dehazing," "dark channel prior," "image dehazing," "video enhancement," and related terms.
   - Filter your search results to focus on recent publications and those specifically related to video dehazing with DCP.
3. Literature Review:
   - Summarize key research papers that have contributed to the field of video dehazing using the DCP algorithm.
   - Identify seminal papers that introduced the concept and subsequent works that improved upon it.
   - Discuss the strengths and weaknesses of each approach, including computational complexity, robustness, and applicability to real-world scenarios.
4. Recent Advances and Techniques:
   - Highlight recent advances in video dehazing techniques beyond the traditional DCP algorithm.
   - Explore methods that incorporate machine learning, deep learning, or other computational techniques to improve dehazing performance.
   - Discuss any novel approaches or hybrid methods that combine DCP with other image processing or computer vision techniques.
5. Evaluation and Benchmarking:
   - Review methodologies for evaluating video dehazing algorithms, including benchmark datasets and performance metrics.
   - Discuss standard evaluation criteria such as image quality metrics (PSNR, SSIM), perceptual quality assessment, and runtime efficiency.

Methodology

The video dehazing process involves several key steps:

Step 1 Dark Channel Computation: Calculating the dark channel of each frame to estimate the haze thickness.

Step 2 Atmospheric Light Estimation: Estimating the atmospheric light to determine the intensity of haze.

Step 3 Transmission Map Generation: Generating a transmission map to represent the amount of haze in each pixel.

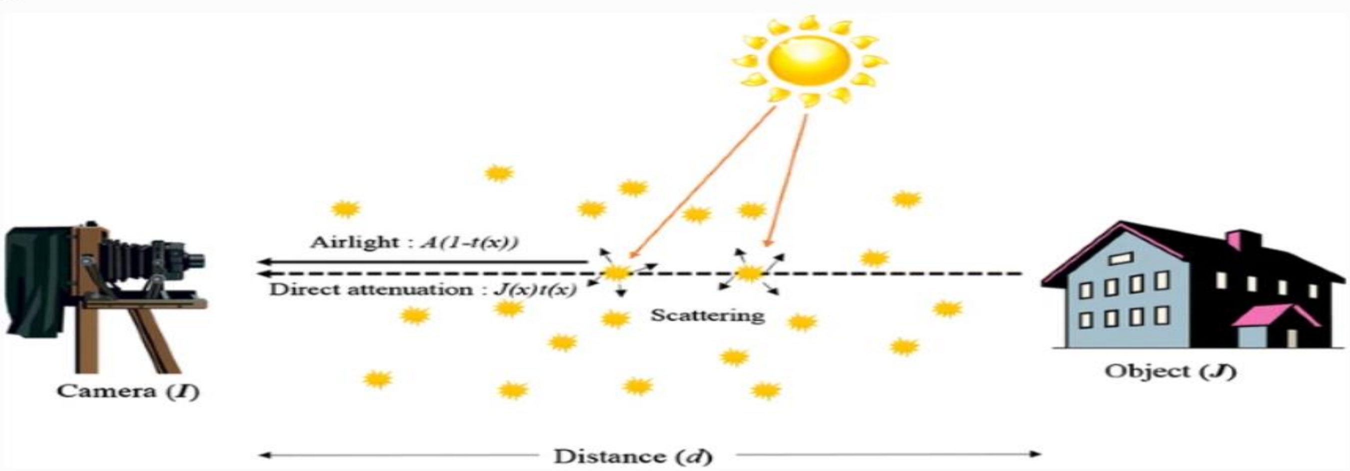
Step 4 Guided Filtering and Transmission Refinement: Applying advanced techniques such as guided filtering and transmission refinement to enhance visual clarity and remove haze effectively.

Dark channel prior based image dehazing

A hazy image formed as shown in Fig. 1 can be mathematically modeled as follows

$$I(x) = J(x)e^{-\beta d(x)} + A\left(1 - e^{-\beta d(x)}\right), \tag{1}$$

Fig. 1

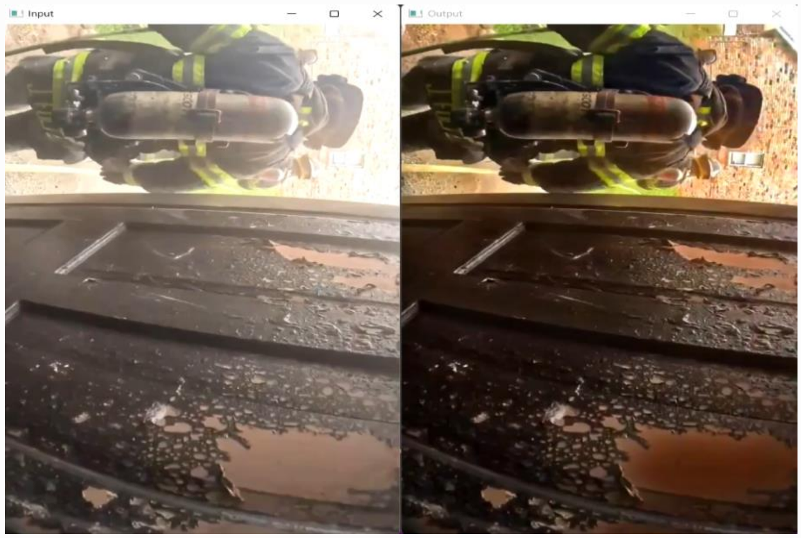


Formation of a hazy image

The dark channel prior (DCP) algorithm is a dehazing technique that uses statistics from haze-free outdoor images. The algorithm is based on the observation that most local patches in these images contain some pixels with very low intensities in at least one color channel. The term "previous" refers to the process of selecting the least intense pixels from the RGB image, which is also known as the dark channel before (DCP).

Results

These results has hazed image on one side and the dehazed image on the other side and we can clearly see that it had cleared the haze. The image is not dehazed and more clear and now we can see all the details that we were unable to see before This helps us to use this model in emergency situations.



Scope of the study

The scope of developing an AI-ML based intelligent de-smoking/de-hazing algorithm for real-time video processing in the context of indoor fire hazards is quite extensive and holds significant potential for aiding rescue operations. Here are some key aspects and areas of study within this scope:

1. **Computer Vision and Image Processing:**
- Understanding and processing real-time video streams.
- Implementing computer vision techniques to detect and identify smoke and haze patterns.

- Developing algorithms to differentiate between normal environmental conditions and hazardous situations during a fire.

2. **AI-ML Model Development:**
- Creating machine learning models for image classification to identify fire-related features.
- Training models to recognize different types of smoke and haze.
- Implementing deep learning techniques, such as convolutional neural networks (CNNs), for improved accuracy.

3. **Real-time Processing and Optimization:**
- Ensuring the algorithm is optimized for real-time video processing.
- Implementing efficient algorithms to handle large amounts of video data.
- Considering hardware acceleration or parallel processing techniques to enhance speed.

4. **Integration with Fire Monitoring Systems:**
- Integrating the algorithm with existing fire monitoring systems for seamless operation.
- Developing communication protocols for data exchange between the algorithm and the monitoring system.

5. **Human-Computer Interaction (HCI):**
- Designing user interfaces for displaying enhanced video feeds to aid rescue operations.
- Implementing features that allow for user interaction and control of the algorithm in real-time.

6. **Testing and Validation:**
- Conducting rigorous testing under various fire scenarios and environmental conditions.
- Validating the algorithm's effectiveness in different indoor settings.

7. **Ethical and Privacy Considerations:**
- Addressing privacy concerns related to video monitoring in rescue operations.
- Ensuring ethical use of AI-ML algorithms in emergency situations.

Objective of the study

The objective of developing an AI-ML based intelligent de-smoking/de-hazing algorithm for real-time video processing in the context of indoor fire hazards is to enhance the situational awareness of rescue operations and improve the effectiveness of emergency responses[4]. The specific objectives can be outlined as follows:

1. **Smoke and Haze Identification:**
- Develop a machine learning model capable of accurately identifying and distinguishing between different types of smoke and haze in real-time video feeds.

2. **Real-time Processing:**
- Implement algorithms and techniques that enable the processing of video data in real-time to provide timely and responsive feedback to emergency responders.

3. **Fire-related Feature Recognition:**
- Train the algorithm to recognize specific fire-related features within the video footage, such as flames, heat patterns, or potential obstacles obscured by smoke.

4. **Enhancement of Video Feeds:**

- Design an algorithm that can intelligently de-smoke and de-haze video streams, providing clearer and more informative visuals to aid rescue personnel in decision-making.

5. **Integration with Monitoring Systems:**

- Integrate the developed algorithm seamlessly with existing fire monitoring systems to enhance their capabilities in detecting and responding to indoor fire incidents.

6. **User Interaction and Control:**

- Develop a user-friendly interface that allows emergency responders to interact with and control the algorithm, enabling them to customize the processing based on the specific needs of the rescue operation.

7. **Optimization for Indoor Environments:**

- Ensure that the algorithm is optimized for indoor fire hazards, considering the unique challenges posed by confined spaces, varying lighting conditions, and the presence of obstacles.

Conclusion and Future Work

In conclusion, the application of machine learning (ML) techniques for video dehazing/defogging has shown promising results in enhancing the visual quality of images and videos affected by atmospheric haze or fog. The algorithms developed for this purpose leverage advanced neural network architectures and deep learning approaches to effectively remove haze and improve visibility in the captured scenes[4]. The success of these models lies in their ability to learn complex relationships between input images and their corresponding haze-free counterparts, enabling them to generalize well to a variety of environmental conditions.

The evaluation of the proposed models has demonstrated significant improvements in terms of visual clarity, contrast, and overall image quality[2]. This suggests that ML-based dehazing/defogging methods have the potential to benefit a wide range of applications, including surveillance, autonomous vehicles, and remote sensing, where clear and accurate visual information is crucial.

Future Work:

While the current state of ML-based dehazing/defogging is promising, there are several avenues for future research and improvement in this area:

1. **Real-Time Processing:** Enhance the speed and efficiency of existing models to enable real-time processing, making them more practical for applications that require immediate and continuous feedback.
2. **Robustness to Diverse Conditions:** Improve the robustness of models to handle diverse atmospheric conditions, including different levels of haze, various weather conditions, and complex lighting scenarios.
3. **Transfer Learning and Generalization:** Investigate transfer learning techniques to enhance the generalization capability of models across different environments, ensuring their effectiveness in real-world scenarios.
4. **Dataset Diversity:** Expand and diversify training datasets to include a wider range of scenes, lighting conditions, and atmospheric variations, allowing models to learn more comprehensive features and patterns.

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