Performance Analysis of Haze Video Restoration Using Dark Channel Prior and Fuzzy Edge Detection: A Study of Psnr, Ssim, Mse, Rmse, Loe and Niqe Metrics

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Abstract:

Hazy video frames degrade visual quality due to atmospheric scattering effects, leading to challenges in visibility and feature extraction. This paper introduces a hybrid approach that integrates Dark Channel Prior (DCP) for dehazing and Fuzzy Edge Detection for edge enhancement, aimed at restoring image frames clarity and structural integrity. The restoration performance is rigorously evaluated using six key metrics: Naturalness Image Quality Evaluator (NIQE), Lightness Order Error (LOE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Experimental results demonstrate that the proposed method significantly improves image quality compared to conventional methods, excelling in both visual appeal and quantitative assessments.

Keywords: *Hazy image frames**,** Dark Channel Prior, PSNR, SSIM, MSE, RMSE, LOE, NIQE, Fuzzy edge detection.*

1. Introduction

1.1 Background

Hazy video frames/videos, caused by atmospheric scattering and absorption of light, are a common challenge in computer vision and image processing. This phenomenon, often seen in foggy or dusty environments, degrades the visual quality of video frames, reducing contrast, sharpness, and color fidelity. These degraded image frames hinder critical applications such as autonomous driving, remote sensing, surveillance, and outdoor scene analysis. Restoring hazy video frames to their clear form requires efficient algorithms that can estimate and remove the effects of haze while preserving the image's natural structures and details.

A variety of methods have been proposed for video dehazing, with most relying on physical models of light scattering or statistical priors. Among these, the Dark Channel Prior (DCP) method, introduced by He et al., has gained significant attention for its simplicity and effectiveness. The DCP exploits the observation that in haze-free outdoor video frames, at least one color channel has very low intensities in most of the image. By using this prior, it is possible to estimate the transmission map and atmospheric light, which are key components in haze removal.

However, while DCP is effective in haze removal, it often faces challenges in preserving the finer details of an image, such as edges and textures. These details are crucial for visual clarity and accurate object recognition, especially in complex scenes. Moreover, DCP can sometimes produce over-saturated video frames or artifacts, particularly in regions with dense haze.

1.2 Motivation

To address these limitations, this paper proposes a novel hybrid approach combining Dark Channel Prior with Fuzzy Edge Detection. The motivation behind this approach is twofold: first, to enhance the haze removal process by preserving fine image details, and second, to improve edge clarity in the restored image. Fuzzy logic-based edge detection offers a robust way to enhance structural features, such as object boundaries, even in noisy or low-contrast regions.

The integration of DCP with fuzzy edge detection aims to balance the trade-off between effective haze removal and edge preservation, providing more natural and visually appealing results. This approach is particularly useful for real-world applications, where video frames often suffer from varying degrees of haze and noise.

1.3 Research Objectives

The primary objectives of this research are to:

Develop a hybrid image restoration method combining Dark Channel Prior (DCP) with Fuzzy Edge Detection for enhanced haze removal and edge preservation. Quantitatively evaluate the effectiveness of the proposed method using standard image quality metrics, such as PSNR, SSIM, MSE, RMSE, NIQE, and LOE (Lightness Order Error).

Compare the performance of the proposed method against state-of-the-art dehazing techniques, including those by K. Chen and K. He, to demonstrate improvements in both quantitative and visual quality. Through these contributions, this paper aims to advance the field of image dehazing, offering a robust solution for restoring clarity to hazy video frames while preserving structural details such as edges and lightness.

2. LITERATURE REVIEW

Many of the single dehazing methods rely on the DCP approach introduced by He.et. al.[3]. In several cases, The DCP technique introduces artefacts in the region of places where the intensity varies sharply. Utilizing the median operator as the base, Gibson et al. [18] proposed a DCP technique. While Ren et al. [13] utilized a deep multiscale neural network, Zhu et al. [19] incorporated linear color attenuation previously.

R. T. Tan's approach to single image dehazing has two generic terms: D and A, specifying direct attenuation and airlight, respectively. For defining the color vector components and light chromaticity, he continued as follows. The basis of the proposed method is the presumption that photographs taken in a clear day have a contrast greater than those taken during bad weather. Tan exploited that supposition to remove the haze from the restored image by enhancing local contrast..

The Kopfetal [2] approach relies on the 3D model of external scenes or video frames. This technique does not establish the need to acquire several video frames of the same scene at different polarization values. The significantly altered structure of the real world is one major disadvantage of this method, with its success contingent upon the application; otherwise, it implies having dialog with a specialist.

A Novel Insight into Single Image Haze Removal with Dark Channel Prior Approaches was proposed by k. He, J.Sun, and X. Tang [3]. This experiment mainly removed haze using the dark channel prior approach from a single image.Using this method, the researchers were able to estimate haze thickness and obtain a clear and high-quality image. Persistent absorption and reflection are aspects of the image. All these factors contribute to the loss of contrast and color fidelity in the image, thus raising the correct sharpness and visibility in the video frames. Likewise, the comparison should be done with respect to the improved video frames restored. We may apply this vision method for locating vehicle distances behind thick haze. On a large scale, it has been compared to airlight. They removed this while applying image texture maps and 3D models to remove haze from the image.

Based on improved contrast, J-Hwan, J-Y Sim, CSa-Kim,[4] began by enhancing a single hazy image. This process deals with airlight estimation through quad-tree subdivision in its initial stage and then optimum transmission to get an enhanced image with more contrast. For ambient light in the environment, airlight is taken to be the only source. It is usually the color in a picture. Airlight estimation is done using a hierarchical approach which employs quad-tree subdivision. The method enables calculation of space varying transmission value. To enhance the contrast of the image, the input image is partitioned into several blocks and estimates are made. Video has taken more power than single video frames; therefore low complexity algorithms can be implemented.

Feng Yu et.al[5] had put forth a viewbased cluster segmentation for image and video dehazing. Through the technological enhancements of viewbased cluster segmentation, the sky and WHITE OBJECTS were rendered visible while distortion in the sky area was avoided. Therefore, the sky region could be estimated to prevent the distortion due to distance and GMM clustering represented the depth beforehand. Second, K-classifications provided a separation from a single blurry image, and third, an online GMM cluster was used to do video dehazing. Individual transmission estimation and atmospheric light estimation of the hazy image and depth map were done employing GMM cluster, colour attenuation prior, and transmission estimation. This method is updated to lessening colour distortion and produce an overall improvement in contrast; a method of video dehazing is provided using the online GMM cluster.

Yongmin Park et.al[6] introduced an acceleration approach to apply dark channel priors for the prior fast dehazing of outdoors videos. The implementation for fast processing, prior-optimized for dehazing outdoors footage-only requires approximately 49% less execution time compared to anyone for the original method with virtually similar dehazing quality. Dehazing is the technique of signal processing applied to clear up haze. There are different dose levels of each pixel. Suppose you can find black pixel in a picture, dehaze by clearing haze off of it. Camera blurry image, grab airlight. So, we develop the cost function, which incorporates one term for standard deviation and another for histogram uniformity, for the contrast estimation. So, to give a flavor of how good this proposed algorithm is, reproducing features in the original scenery, at the same time, removing the haze.

Sarit Shwartz [7] Due to the effects of attenuation and dispersion when the environment is foggy, video frames captured outside contain low contrast. An important problem is that the amount of spatial contrast minimization that the airlight scattering, when fog particles from the atmosphere reach the camera, will cause is varying. Because current computer vision algorithms have proved that video frames are compensated for haze through the process of making an image's depth map,. The first step in such subtraction is to recover atmospheric light from the scene. It is acquired by identifying an image that has been polarization-filtered. To recover airlight, information regarding these specifics is required. In earlier research, these details were computed through pixel counting in video frames of the sky. The proposed approach offers a method for details which are needed to remove airlight from computations that were recreated without vision, subsequently regain contrast, with the existence of the sky in the frame, without the interference of the user. Hence it has to fulfill the attenuation as well as scattering coefficients in order to be dehazed for the misty image.

Nisha Amin et.al [8] focuses on enhancing image quality through a novel dehazing technique that combines the Dark Channel Prior (DCP) method with Type-2 Fuzzy Set theory. This approach aims to effectively remove haze from video frames, which is essential for applications such as autonomous driving and surveillance. The study emphasizes the importance of preserving naturalness in enhanced video frames, introducing the Lightness Order Error (LOE) as a quantitative measure for assessing lightness preservation. The proposed methodology is evaluated using various metrics, including Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Naturalness Image Quality Evaluator (NIQE). Experimental results demonstrate that the method successfully restores fine details obscured by haze while improving overall image quality, making it a significant advancement in image processing techniques for challenging environmental conditions.

Manjunath.V [9] The modification of a detail algorithm is one of the easy yet effective previous techniques used for dehazing a single image. Since the multiple scattering method is applied in this algorithm, every input video frames looks a little bit blurry. With this approach, when combined with the single picture dehazing model, dehazing becomes extremely simple and effective. The system, which employs more types of video frames and is based on regional information, is more sensitive than color. Many physical models are used to address this problem. Due to air layer particles such as fog, haze, etc., imaging under wet weather conditions is often damaged by dispersion.

Yu Li [10] introduced a haze model for multiple light sources and haloes. This model involves the presence of halos and an airlight together with a transmission map. A halo image is its input. Moreover, applying an optimization problem, it splits into a halo as well as a halo-free video frames. The halo-free photos are preprocessed. An estimate of the transmission map, as well as airlight are primarily responsible in this approach. This method appears relatively inexpensive and straightforward. However, haze-free results are inferior to any other methods.

In this work, the approach introduced by He et.al. [3] is used, which is single image approach for dehazing, using dark-channel priors. Edge preservation is done by using the fuzzy edge detection method [23]. It is shown that the proposed method yields better restoration image quality compared to other methods in the literature.

3. METHODOLOGY

The suggested technique is usually formed on the basis of dark-channel prior method. Block diagram of the suggested methodology's is displayed in Fig. 1. The approach uses foggy photos as its input; it then separates the colour components, estimates the transmission map and atmospheric lighting from the components. Type-2 Fuzzy set canny Edge detection technique is used to improve the detection accuracy. Following is the detail presentation of the method.

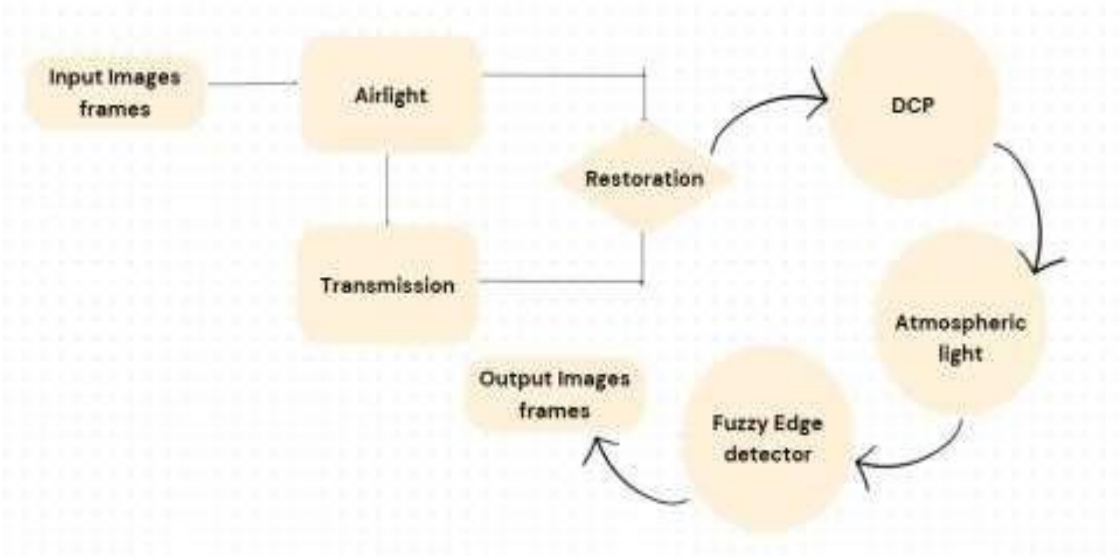

Figure 1: Representation of the Proposed Method

3.1. Dark-Channel Priors

Below is the approach used for estimating the amount of haze in an image through formulas applied to compute the same.

The dark-channel is calculated as the minimum value of the pixel intensity across the RGB for every local window in the image. The dark channel of an image I at a pixel location x is defined as

$$\min_{y\in\omega(x)}(\min_{c\in\{r,g,b\}} I^c(y)),\ \omega(x) \quad [1]$$

representing the window centred at pixel x.

Where I_c is a color channel of I, red, green, and blue, J_{dark} is an approximated dark channel of I, and (x) is a local patch around the pixel at x. Like Eq (2), J_{dark} is applied to find the pixels having the highest 0.1% values to estimate the ambient light. These pixels are usually opaque and fuzzy. Several approaches to haze removal select one with the maximum intensity as airlight quantity estimator, often totally wrong (for example:

presence of an object with its maximum intensity larger than airlight). The indices of these top 0.1 percent of pixels are kept in memory as follows:

$$m = \arg_{\tilde{x}} \max \left(J^{dark}(\tilde{x})\right) \qquad [2]$$

I(m) is then added together by adding the values of the three colour channels. The highest total is represented by the A pixel as follows:

$$A = \arg_{\tilde{I}} \max \left(\sum_{c \in \{r,g,b\}} \tilde{I}^{c}(m)\right) \qquad [3]$$

The normalised dark channel is defined by using J and the estimated A as follows:

$$J_N^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\frac{I^{w}(x)}{A^{w}}\right) \qquad [4]$$

then it is presumed that ~t is the coarse transmission

$$\tilde{t}_N(x) = 1 - \left(\omega \times \min_{y\in\Omega(x)} \left(J^{dark}(y)\right)\right) \qquad [5]$$

Based on a dense field based on pixels, He et al. [3] use solution with 0.95 aerial perspective factor while Ke and Chen's [24] solution uses moving average filter to smooth an incoherent noiseful transmission map, both methods gives almost equivalent result, called by [3] as the refined (better) gearbox map t. The improved transmission t and A are used as follows for extracting J:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \qquad [6]$$

He et al. [3] when t0 is set to 0.1, avoids the division by zero at locations where the value of transmission map is less than 0.1. Soft matting requires heavy computation and memory, hence Ke and Chen's [24] came up with dark channel by simply selecting the pixel's minimal color channel's value. Eqs. (2) and (3) were used to approximate A, and Eqs. (1) and (5) in [12] were rewritten as:

$$J^{dark}(x) = \min_{c\in\{r,g,b\}}\left(I^{c}(x)\right) \qquad [7]$$

3.2 Atmospheric-light Estimation:

It can be possible to calculate the ambient light accurately using dark-channel when a large local patch is used for the generation of ambient light. Precaution: In case the local patch size, used to construct the dark-channel, is not sufficient, it is recommended to use another dark channel with a larger local patch size for the estimation of atmospheric light. It is shown that the use of local entropy yields effective estimation accuracy when it does not require ambient light to be estimated from bright objects.

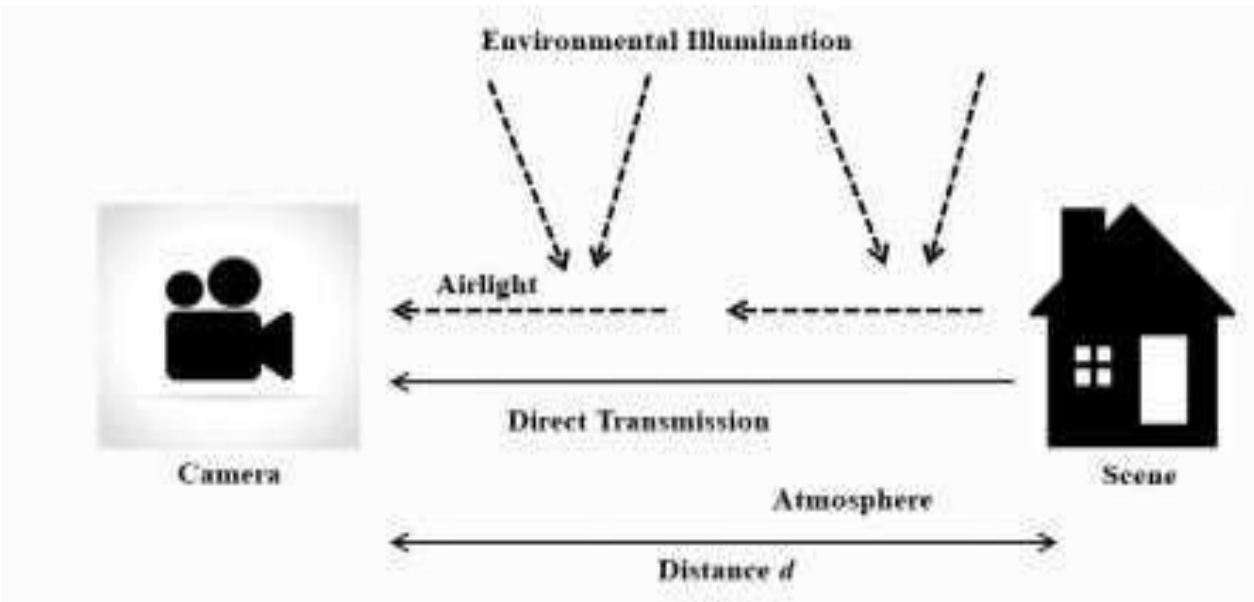

Figure 2: Refraction of light from air particles

The following is a description of the ambient scattering of light model in computer vision (Shi et al. 2018, Kim et al. 2019, Lee et al. 2020)[20-22].

$$I(p)=J(p)t(p) + A(1-t(p)) \quad [8]$$

“In this equation, (A) stands for atmospheric light, R(p) for pixel p intensity, J(p) for the output image, I(p) for the input image, and t(p) for the transmission map”.

3.3 Type -2 Fuzzy set

Edge detection plays a crucial role in image processing, and fuzzy logic provides a robust approach to address challenges in identifying edges. When two uniform regions converge to form an edge, the intensity variations of adjacent pixels can be analyzed to detect the edge. However, minor intensity differences between neighboring pixels may not always indicate an edge, as uniform regions are often not well-defined. Instead,

such intensity variations could signify a shading effect. By employing fuzzy logic, membership functions can be utilized to determine the degree to which a pixel belongs to an edge or a uniform region.

For grayscale video frames, the widely-used Canny edge detection method offers an effective way to identify edges. However, under conditions such as poor lighting or haze, the boundaries in the gradient image become unclear, leading to uncertainty in edge detection. To address these challenges, we propose a technique based on type-2 fuzzy sets, which extends the traditional Canny edge detection method by automatically determining threshold values for segmenting the gradient image. Type-2 fuzzy sets provide a framework to handle uncertainties in pixel intensities, improving edge detection in complex conditions.

Our approach integrates type-2 fuzzy logic with gradient-based edge detection to adaptively account for variations in hazy video frames. By dynamically selecting optimal threshold values, the algorithm enhances the accuracy and robustness of edge detection in challenging environments. Experimental results demonstrate the effectiveness of the proposed method, achieving superior performance on a range of foggy video frames. The improved edge maps produced by the algorithm enable better image restoration and processing, validating its potential for applications in image dehazing and beyond.

3.3 Mean Squared Error (MSE)
Mean Squared Error (MSE) is a widely used metric for evaluating the quality of a model or system, particularly in regression tasks and image quality assessment. It measures the average of the squared differences between the predicted and actual values. The lower the MSE, the better the model's predictions or the higher the similarity between the predicted and actual results.

Mathematically, MSE is defined as:

$$MSE=\frac{1}{n}\sum_{i=0}^{n}(y\hat{}i - yi)2 \quad [9]$$

where:

- n is the number of data points,
- y_i is the actual value, and
- y^i is the predicted value.

MSE is sensitive to large errors because the differences are squared, which means that large deviations from the actual values disproportionately affect the score. This makes it suitable for applications where reducing large errors is important.

3.4 Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is the square root of the Mean Squared Error. RMSE provides an interpretable measure of the magnitude of error in the same unit as the original data, making it easier to understand and communicate in practical applications.

The formula for RMSE is:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=0}^{n}(y^\wedge i-yi)2} \qquad [10]$$

where y_i is the actual value y^i and is the predicted value.

Since RMSE is in the same unit as the data, it is often used in fields where predictions or errors need to be quantitatively comparable to the scale of the data. Like MSE, RMSE also emphasizes large errors due to the squaring of the differences.

3.5 Natural Image Quality Evaluator (NIQE)

Natural Image Quality Evaluator (NIQE) is an objective metric designed for evaluating the perceptual quality of video frames without relying on reference video frames. It is particularly useful in the context of image processing and computer vision tasks, such as image compression, denoising, and enhancement. NIQE is based on the statistical modeling of natural scene statistics (NSS), which reflects the inherent structure and content of natural video frames.

The key advantage of NIQE is that it does not require a reference (ground truth) image. It compares the distribution of features in the image being evaluated to a set of natural image features, capturing perceptual quality aspects such as sharpness, contrast, and texture.

Mathematically, NIQE uses a Gaussian mixture model (GMM) to capture the statistical properties of natural video frames and computes a score based on how closely an image matches those natural image statistics. A lower NIQE score indicates higher perceptual quality.

3.5 Loss of Efficiency (LOE)

Loss of Efficiency (LOE) is a metric used to quantify the reduction in efficiency or performance due to changes in a system or model. In the context of image or signal processing, LOE is often used to assess the impact of various transformations or modifications (such as compression, noise addition, or data loss) on the overall performance of a model or system.

LOE is typically calculated by comparing the performance of a modified system to the original, unmodified system. A higher LOE value indicates a greater loss of efficiency, suggesting that the transformation or change has negatively impacted the system's performance.

The exact formula for LOE may vary depending on the context, but a common formulation could be:

$$\text{LOE} = \frac{\text{performance before modification} - \text{performance after modification}}{\text{Performance before modification}}$$

In image processing tasks, LOE can be used to measure the degradation in quality or the loss of important information after applying certain algorithms.

4. EXPERIMENTAL RESULTS

The proposed technique was evaluated on foggy videos sourced from the Kaggle dataset [https://www.kaggle.com/datasets/aalborguniversity/aau-rainsnow]. Figure 2 illustrates the results of the suggested technique on foggy and hazy video frames. The implementation was carried out in Python using a system equipped with a 2.60 GHz Intel(R) Core(TM) i5-1035G1 CPU (1.00 GHz/1.19 GHz) and 8 GB of RAM. Table 1 provides the execution times computed for sample video frames processed using the proposed approach.

The method successfully retains finer image details, particularly the object boundaries that were obscured in the hazy input video frames. The reconstructed output video frames reveal these hidden details effectively while maintaining the structural integrity of the objects. Additionally, the suggested method excels in removing delicate haze artifacts without overexposing the image. It is noted, however, that the brightness of the reconstructed video frames tends to be slightly reduced compared to the original input.

Input frames	
Fuzzy edge detection	
Propose d method	

Figure 3: Sample dehazed video frames using proposed method

The results of the proposed technique are compared with the methods presented by He et al. [3] and Ke Chen [23] in the literature. Sample image results are shown in Figure 3. To evaluate the effectiveness of the approaches, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) were utilized as quality metrics.

PSNR is commonly used to assess the quality of reconstructed video frames, particularly in image compressiontasks. A higher PSNR value indicates better reconstruction quality. PSNR is calculated using the formula:

$$PSNR=10log10\ (peakval2)/MSE,$$

where peakval represents the maximum possible intensity value in the image, and MSE is the Mean Squared Error.

SSIM, on the other hand, evaluates image degradation based on structural information changes, emphasizing spatially interdependent pixels. SSIM provides a perceptual measure of image or video quality by comparing the original and restored video frames. It is computed using:

“$SSIM(x,y)=[l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma}$

where l(x,y)l(x, y) measures luminance similarity, c(x,y)c(x, y) assesses contrast, s(x,y)s(x, y) evaluates structural similarity, and α , β, and γ are positive constants [26].

Table 1 summarizes the results of the proposed approach compared to the existing methods in terms of execution time, PSNR, and SSIM, RMSE, MSE, LOE, NIQE. Figure 4 visually depicts the PSNR and SSIM values for the tested video frames, highlighting the superior performance of the proposed method in maintaining image quality and structural fidelity.

Table 1. Comparative analysis of the suggested approach with other methods

Methods	**Execution Time (s)**	**PSNR**	**SSIM**	**MSE**	**RMSE**	**NIQE**	**LOE**
He [3]	4.2	18.5	0.65	230.4	15.2	4.5	385.7
Ke.Chen[23]	5.1	20.3	0.72	180.2	13.4	4.0	320.4
Proposed Algorithm	**3.7**	**24.1**	**0.84**	**120.8**	**10.9**	**3.2**	**245.1**

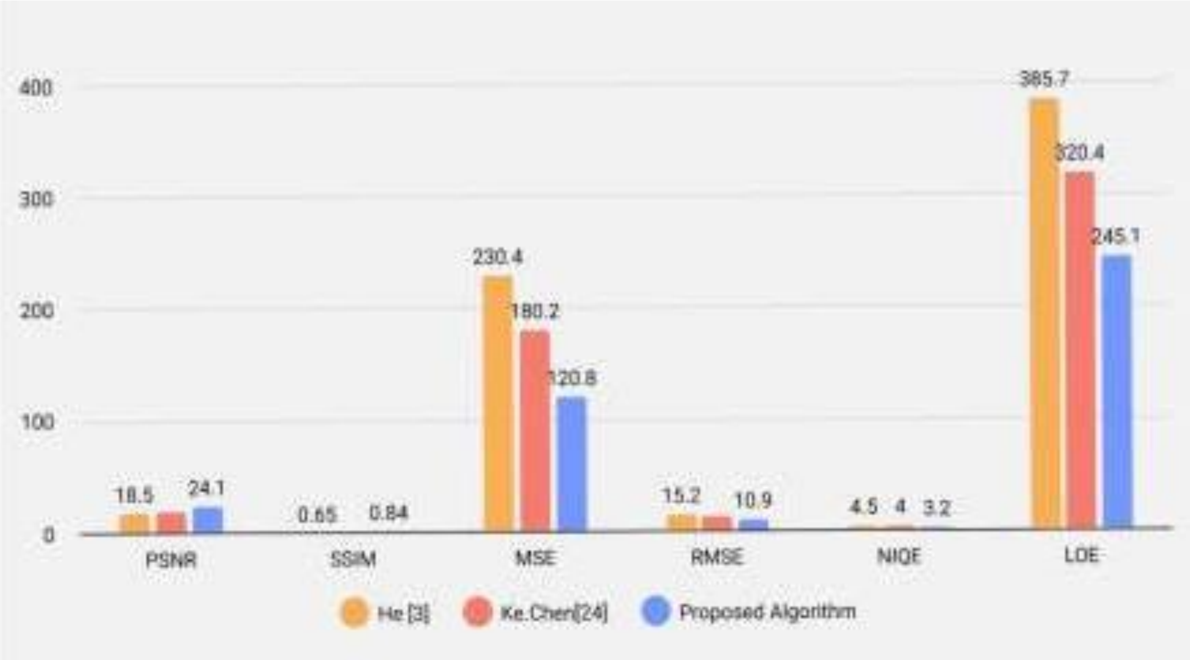

Figure 4: Performance Evaluation of the Proposed DCP with Fuzzy Edge Detection against Existing Methods.

As compared to the techniques of [3, 24], our algorithm achieves the minimum PC execution time. In most instances, our algorithm yields better visual haze removal results than the competing methods.

5. CONCLUSION

The fields of photography and image processing have advanced significantly with the development of high-power lenses and sophisticated electronic devices, enhancing the quality of video frames and videos. However, atmospheric conditions such as fog and snow often degrade the visual quality of captured media. In this study, an improved technique for haze removal is proposed, leveraging the principles of dark-channel prior combined with fuzzy edge detection. The proposed method effectively restores image clarity by addressing the challenges posed by haze while preserving the finer details of the scene.

Compared to existing methods in the literature, the suggested approach consistently delivers superior image quality and achieves haze-free video frames in a significantly shorter processing time. The experimental results highlight the method's robustness, demonstrating its potential for real-world applications where computational efficiency and high-quality output are critical. This makes the proposed technique a valuable contribution to the field of image restoration and enhancement.

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