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A Region-Based Fuzzy Logic Approach for Enhancing Road Image Visibility in Foggy Conditions

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Abstract: An innovative context-aware fuzzy logic transmission map adjustment method is proposed for road image defogging, aimed at improving visibility and clarity under varying fog conditions. Unlike conventional defogging techniques that rely on a uniform transmission map, the presented approach introduces a fuzzy logic framework that dynamically adjusts the transmission map based on local fog density and contextual factors. Fuzzy membership functions are employed to classify fog density into low, medium, and high categories, enabling an adaptive and context-sensitive adjustment process. Road images are segmented into distinct regions using edge detection and texture analysis, with each region treated independently to preserve critical details such as road markings, lane boundaries, and traffic signs. A key contribution is the integration of proximity-based adjustments for areas near high-intensity light sources, such as streetlights, to maintain brightness and enhance visibility in illuminated zones. The final transmission map is generated through the combination of fuzzy density-based adjustments and an iterative Gaussian filter, which smooths transitions and minimizes potential artifacts. This approach prevents over-darkening while enhancing contrast, even in dense fog conditions. Experimental results demonstrate that the proposed method significantly outperforms traditional defogging techniques in terms of brightness, contrast, and detail retention. The results underscore the utility of fuzzy logic in road image defogging, offering a robust solution for applications in autonomous driving, surveillance, and remote sensing. This method sets a new benchmark for visibility enhancement in challenging environments, providing a high-quality, adaptive solution for real-world applications.

Keywords: Image segmentation; Image defogging; Fuzzy set theory; Fuzzy inference system (FIS); Transmission map; Adaptive fog density function

1 Introduction

Image defogging, also known as image dehazing, has become a pivotal research area in computer vision, with applications spanning autonomous driving, surveillance, and remote sensing [1, 2]. Atmospheric scattering caused by fog, haze, and other weather-related phenomena impairs visual clarity, reducing the effectiveness of image processing systems that rely on clear visuals [3, 4]. Consequently, robust image defogging models are critical for enhancing visibility, contrast, and scene detail in foggy images, enabling reliable object detection and scene analysis in challenging conditions.

Traditional image defogging methods have primarily relied on the estimation of atmospheric light and the transmission map, which are key parameters in the image formation model [5]. He et al. [1] introduced a seminal technique, assuming that in haze-free outdoor images, at least one color channel exhibits low intensity in most non-sky regions. While DCP has achieved significant success, it often results in artifacts in dense, foggy areas or regions with varying lighting conditions. Fattal [4] proposed a more physically grounded approach, focusing on the statistical properties of surface shading and transmission functions, which provided improvements over DCP but required extensive computational resources.

More recent techniques have explored deep learning for image defogging, leveraging convolutional neural networks (CNNs) to learn complex mappings from foggy images to clear images [6, 7]. These approaches often deliver impressive results and are adaptive across diverse conditions; however, they are data-dependent and computationally expensive, often necessitating large datasets and high computational power [8, 9]. Despite the advancements, the applicability of deep learning models remains constrained in scenarios where computational resources are limited or real-time processing is required.

In contrast, hybrid approaches combining traditional image processing techniques with adaptive models, such as fuzzy set theory, offer a promising alternative [10, 11]. Fuzzy logic introduces an adaptive element that can handle uncertainty and varying fog densities more effectively. By integrating fuzzy logic, models can dynamically adjust parameters such as transmission and brightness, optimizing visibility restoration without extensive computational overhead [12, 13]. This adaptability is particularly useful in situations with variable fog density, where traditional methods struggle to maintain consistency across different levels of visibility.

This paper presents a novel approach that integrates fuzzy logic principles with a traditional transmission map and atmospheric light estimation framework (Figure 1). By utilizing fuzzy set theory, our model adapts to local variations in fog density, significantly improving the accuracy of the transmission map estimation compared to conventional methods. This work addresses the limitations of traditional approaches, such as over-darkening and artifact generation, by leveraging fuzzy logic to provide nuanced, context-sensitive adjustments. Experimental results demonstrate that our fuzzy-adaptive model achieves superior accuracy in visibility restoration, particularly in dense fog regions, while preserving essential scene details [14, 15]. The adaptive fog density function introduced in this work dynamically adjusts the transmission map based on local intensity values, ensuring robustness across varying fog densities.

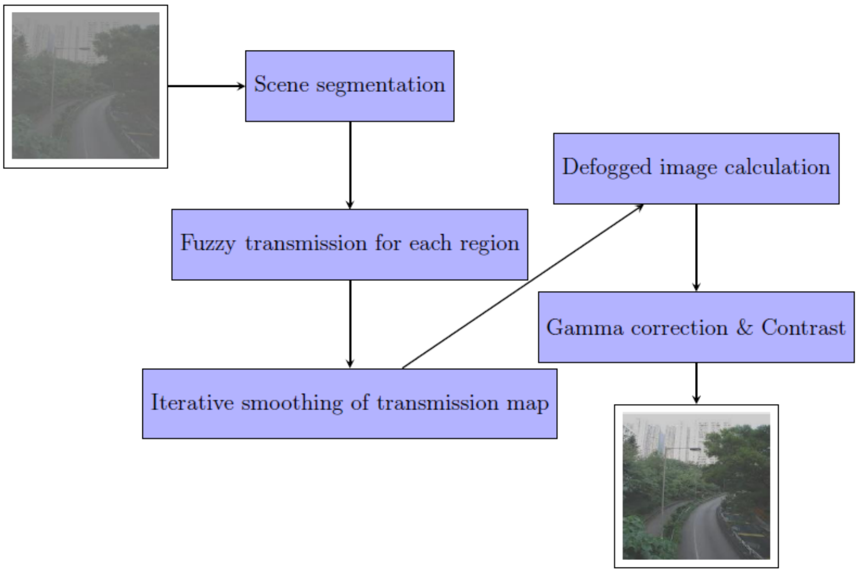

Figure 1. Flowchart of the proposed defogging algorithm

Furthermore, the model incorporates iterative gamma correction and fuzzy-based contrast enhancement, providing a balance between brightness and detail without excessive processing requirements. To estimate atmospheric light, we apply the DCP with a fuzzy enhancement mechanism, improving upon conventional DCP-based methods by selectively refining high-intensity pixel values [16, 17]. This enables our model to capture accurate atmospheric light values while preventing over-saturation. The transmission map is then smoothed using a Gaussian filter with a fuzzy adaptation component, ensuring seamless transitions between foggy and defogged regions [18, 19]. Our contributions are as follows:

We introduce a fuzzy-adaptive transmission map estimation that dynamically adjusts based on local fog density, providing robustness in varying fog conditions.

The model incorporates an advanced atmospheric light estimation technique, using a fuzzy-enhanced DCP to improve brightness and reduce saturation artifacts.

We apply iterative gamma correction and fuzzy-based contrast enhancement, optimizing the overall brightness and contrast for natural-looking defogged images.

The proposed model is computationally efficient, suitable for real-time or resource-constrained applications, while maintaining high image quality.

In the following sections, we discuss the mathematical foundation of our model, including the formulation of the transmission map and atmospheric light estimation using fuzzy set theory. We also provide a detailed analysis of the iterative optimization process, where fuzzy logic is integrated to enhance both efficiency and effectiveness in challenging foggy conditions. Experimental results demonstrate the superiority of our model in various fog scenarios, showcasing its adaptability and visual fidelity compared to state-of-the-art approaches.

2 Related Work

Image defogging has been extensively studied, with various techniques proposed to enhance visibility and restore details in foggy images. Traditional methods primarily focus on estimating atmospheric light and the transmission map, essential components of the image formation model. The foundational equation governing image formation in foggy conditions is given by:

$$I(x) = J(x)t(x) + A(1 - t(x))$$

where, $I(x)$ is the observed foggy image at pixel location x, $J(x)$ is the scene radiance (the clear image we aim to recover), $t(x)$ is the transmission map, A is the atmospheric light.

2.1 DCP

He et al. [1] introduced the DCP, which utilizes the assumption that at least one color channel in haze-free images has low intensity in most non-sky regions. The dark channel $D(x)$ is computed as:

$$D(x) = \min_{c \in \{r,g,b\}} \left(\min_{y \in \Omega(x)} I_c(y) \right)$$

This serves as a key input for estimating the transmission map:

$$t(x) = 1 - \omega D(x)$$

where, ω is a tuning parameter. This method has achieved significant success but often produces artifacts in densely fogged areas, especially where light conditions vary, leading to over-saturation or under-saturation.

Limitations: The DCP can fail in scenes with complex structures and varying lighting conditions, resulting in artifacts. Additionally, it may not perform well in images with very thick fog where the assumptions behind the prior no longer hold.

2.2 Fattal's Approach

Fattal proposed a more physically grounded method that focuses on the statistical properties of surface shading and transmission functions, which can be expressed mathematically as follows:

$$J(x) = \frac{I(x) - A(1 - t(x))}{t(x)}$$

This method, while effective, requires extensive computational resources, particularly for large images or real-time applications.

Limitations: Fattal's approach can be computationally expensive, making it unsuitable for applications requiring real-time processing. Moreover, it may struggle with highly variable fog densities, leading to inconsistencies in defogging results.

2.3 Multi-Scale Fusion

Recent advancements have seen the incorporation of multi-scale fusion techniques. Nie et al. [20] introduced a method that combines joint contrast enhancement and multi-scale fusion. The key mathematical formulation is centered around enhancing contrast C through local and global information:

$$C(x) = \alpha C_{\text{local}}(x) + \beta C_{\text{global}}(x)$$

where, C_{local} and C_{global} are local and global contrast measures, respectively, and α and β are weighting factors.

Limitations: While multi-scale fusion can effectively enhance image quality, it often requires multiple input images, which may not always be available. Additionally, balancing local and global contrasts can lead to artifacts if not carefully tuned.

2.4 Multi-Exposure Image Fusion (M-EIF)

Mao et al. [21] proposed using M-EIF for single image defogging, enhancing details through the following equations:

$$I_{\text{fused}}(x) = \sum_{i=1}^{N} w_i I_i(x)$$

where, $I_i(x)$ is the input images at different exposure levels and w_i is the corresponding weights assigned to each exposure. This approach effectively combines information from multiple images to achieve improved visibility.

Limitations: The multi-exposure technique relies heavily on having a set of images taken at different exposures, which may not be feasible in real-time or dynamic environments. Furthermore, the algorithm's performance can degrade in the presence of motion blur or misalignment between images.

2.5 Deep Learning Approaches

Deep learning models, such as those proposed by Ren et al. [6], leverage CNNs to learn complex mappings. The network's output can be described mathematically as:

$$\hat{J}(x) = f_\theta(I(x))$$

where, f_θ represents the CNN parameterized by θ. While these methods provide impressive results, they are often data-dependent and computationally intensive.

Limitations: Deep learning models typically require large amounts of annotated training data, which can be time-consuming and costly to obtain. Additionally, their computational demands can be prohibitive for real-time applications, especially on resource-constrained devices.

2.6 Hybrid Approaches with Fuzzy Logic

Hybrid approaches have also emerged, combining traditional methods with adaptive models, such as fuzzy logic. Sharma and Verma [10] and Singh and Kumar [11] have shown the effectiveness of fuzzy logic in adapting to varying fog densities. A typical fuzzy transmission map can be defined as:

$$t(x) = \mu(d(x)) \cdot e^{-\beta d(x)}$$

where, $\mu(d(x))$ is the fuzzy membership function evaluating local fog density.

Fuzzy logic-based methods have demonstrated significant accuracy improvements over conventional techniques by dynamically adapting to fog density variations. However, the full potential of fuzzy logic in enhancing accuracy has often been underexplored. This study builds upon these efforts by emphasizing the accuracy benefits of integrating fuzzy principles into the estimation of transmission maps and atmospheric light. Our approach refines these parameters using adaptive fuzzy membership functions, ensuring improved precision in dense fog conditions. Furthermore, we enhance contrast and visibility using fuzzy-based iterative corrections, which preserve scene details while mitigating artifacts.

In summary, while significant advancements have been made in the field of image defogging, challenges remain in achieving real-time performance and maintaining high image quality. Our work addresses these challenges by demonstrating that fuzzy logic not only improves adaptability but also significantly enhances accuracy compared to traditional methods, thereby bridging the gap between computational efficiency and image quality.

3 Propose Context-Aware Fuzzy Transmission Map Adjustment

To mathematically formulate the context-aware fuzzy transmission map adjustment, we define several components as follows:

3.1 Image Segmentation

The input image $I(x)$, where, x represents the pixel coordinates, is segmented into distinct regions based on fog density and contextual cues like lighting. Let the image be divided into N regions:

$$I(x) = \bigcup_{k=1}^{N} R_k$$

where, R_k represents the k-th region with relatively uniform fog density or contextual similarity.

3.2 Fuzzy Membership Functions for Fog Density

The fog density f_k in each region R_k is calculated using features like local image intensity, texture, and edge density. Fuzzy membership functions $\mu_L(f_k), \mu_M(f_k), \mu_H(f_k)$ map f_k to three linguistic variables: Low, Medium, and High. Typical membership functions include triangular or Gaussian functions. For example:

Low Fog Density ($\mu_L(f_k)$):

$$\mu_L(f_k) = \begin{cases} 1 & \text{if } f_k \leq f_L^{\min} \\ 1 - \frac{f_k - f_L^{\min}}{f_L^{\max} - f_L^{\min}} & \text{if } f_L^{\min} < f_k \leq f_L^{\max} \\ 0 & \text{if } f_k > f_L^{\max} \end{cases}$$

Medium Fog Density ($\mu_M(f_k)$):

$$\mu_M\left(f_k\right)= \begin{cases}0 & \text{if } f_k \leq f_M^{\min} \text{ or } f_k>f_M^{\max} \\ \frac{f_k-f_M^{\min}}{f_M^{\text{conter}}-f_M^{\min}} & \text{if } f_M^{\min}<f_k \leq f_M^{\text{center}} \\ \frac{f_M^{\max}-f_k}{f_M^{\max}-f_M^{\text{center}}} & \text{if } f_M^{\text{center}}<f_k \leq f_M^{\max}\end{cases}$$

High Fog Density ($\mu_H\left(f_k\right)$):

$$\mu_H\left(f_k\right)= \begin{cases}0 & \text{if } f_k \leq f_H^{\min} \\ \frac{f_k-f_H^{\min}}{f_H^{\max}-f_H^{\min}} & \text{if } f_H^{\min}<f_k \leq f_H^{\max} \\ 1 & \text{if } f_k>f_H^{\max}\end{cases}$$

3.3 Transmission Map Adjustment Using FIS

FIS enhances the initial transmission map $t_{\text{initial}}(x)$, computed using methods such as the DCP. The initial transmission map is given by:

$$t_{\text{initial}}(x)=1-\omega \cdot \min_{y \in \Omega(x)}\left(\frac{I(y)}{A}\right)$$

where, ω is a weighting factor to control the strength of defogging, $\Omega(x)$ is the local window centered around pixel x, I(y) is the intensity of pixel y, and A represents atmospheric light.

The transmission map adjustment is performed for each region R_k by applying fuzzy logic to account for local fog density. The adjusted transmission map is defined as:

$$t(x)=\mu_L\left(f_k\right) \cdot t_{\text{initial}}(x)+\mu_M\left(f_k\right) \cdot\left(t_{\text{initial}}(x)+\alpha\right)+\mu_H\left(f_k\right) \cdot\left(t_{\text{initial}}(x)+\beta\right)$$

where, $\mu_L\left(f_k\right), \mu_M\left(f_k\right), \mu_H\left(f_k\right)$ are membership values corresponding to low, medium, and high fog densities, respectively. α and β are adjustment parameters to refine medium and high fog regions.

The final transmission value $t(x)$ is computed using a weighted sum of the contributions from μ_L, μ_M, μ_H. This ensures a smooth transition across regions while adapting to varying fog densities. The fuzzy inference and defuzzification process effectively prevent over-darkening and enhance contrast (Figure 2).

Figure 2. Given image, fuzzy refined transmission map and the propose model result

3.4 Contextual Refinement Using High-Intensity Proximity

Let $p(x)$ represent the proximity to high-intensity regions (e.g., street lights), which influences the transmission map to retain brightness in illuminated areas:

$$p(x)=\exp\left(-\frac{\left\|x-x_h\right\|^2}{2\sigma_p^2}\right)$$

where, x_h is the location of a high-intensity region and σ_p controls the spread.

The final context-aware transmission map $t_{\text{final}}(x)$ is given by:

$$t_{\text{final}}(x)=t(x) \cdot(1-\lambda \cdot p(x))$$

where, λ balances fog density-based adjustment and high-intensity proximity refinement. To integrate fuzzy logic into the proximity refinement:

•Define membership functions for proximity $p(x)$, with linguistic terms such as Near, Medium, and Far.

•Use fuzzy rules to determine the influence of $p(x)$ on the adjustment factor λ:

If proximity is Near, λ is low to preserve brightness.

If proximity is Medium, λ is moderate.

If proximity is Far, λ is high to prioritize fog density-based adjustments.
•Apply defuzzification to compute the final λ value.
Membership Functions for Proximity $(p(x))$:
•Near Proximity ($\mu_{\text{Near}}(p(x))$):

$$\mu_{\text{Near}}(p(x)) = \begin{cases} 1 & \text{if } p(x) \leq p_{\text{Near}}^{\text{min}} \\ 1 - \frac{p(x) - p_{\text{Near}}^{\text{min}}}{p_{\text{Near}}^{\text{max}} - p_{\text{Near}}^{\text{min}}} & \text{if } p_{\text{Near}}^{\text{min}} < p(x) \leq p_{\text{Near}}^{\text{max}} \\ 0 & \text{if } p(x) > p_{\text{Near}}^{\text{max}} \end{cases}$$

Medium Proximity ($\mu_{\text{Medium}}(p(x))$):

$$\mu_{\text{Medium}}(p(x)) = \begin{cases} 0 & \text{if } p(x) \leq p_{\text{Medium}}^{\text{min}} \text{ or } p(x) > p_{\text{Medium}}^{\text{max}} \\ \frac{p(x) - p_{\text{Medium}}^{\text{min}}}{p_{\text{Medium}}^{\text{center}} - p_{\text{Medium}}^{\text{min}}} & \text{if } p_{\text{Medium}}^{\text{min}} < p(x) \leq p_{\text{Medium}}^{\text{center}} \\ \frac{p_{\text{Medium}}^{\text{max}} - p(x)}{p_{\text{Medium}}^{\text{max}} - p_{\text{Medium}}^{\text{center}}} & \text{if } p_{\text{Medium}}^{\text{center}} < p(x) \leq p_{\text{Medium}}^{\text{max}} \end{cases}$$

Far Proximity ($\mu_{\text{Far}}(p(x))$):

$$\mu_{\text{Far}}(p(x)) = \begin{cases} 0 & \text{if } p(x) \leq p_{\text{Far}}^{\text{min}} \\ \frac{p(x) - p_{\text{Far}}^{\text{min}}}{p_{\text{Far}}^{\text{max}} - p_{\text{Far}}^{\text{min}}} & \text{if } p_{\text{Far}}^{\text{min}} < p(x) \leq p_{\text{Far}}^{\text{max}} \\ 1 & \text{if } p(x) > p_{\text{Far}}^{\text{max}} \end{cases}$$

The final adjustment factor λ is obtained by applying defuzzification techniques, such as the centroid method, to the weighted outputs of the fuzzy rules. This ensures that λ adapts dynamically to the proximity conditions, maintaining a balance between brightness preservation and fog density adjustments.

3.5 Mathematical Advantages of Fuzzy Logic

Adaptivity: The membership functions dynamically adjust the transmission map based on the local fog density.

Non-Linearity: Fuzzy logic handles the non-linear relationship between fog density and required adjustments effectively.

Robustness: The fuzzy approach is resilient to noise and outliers in the image, ensuring consistent performance across diverse scenes.

4 Selection Criteria of Fuzzy Logic Parameter

The fuzzy logic parameters for the proposed context-aware transmission map adjustment are selected based on theoretical principles and empirical validation. Below are the key aspects:

4.1 Fuzzy Membership Functions

Fog Density (μ_L, μ_M, μ_H): Membership function ranges (f_L, f_M, f_H) are determined using statistical analysis of image features, including intensity, texture, and edge density. Smooth transitions between fog levels are ensured using triangular or Gaussian functions.

Proximity ($\mu_{\text{Near}}, \mu_{\text{Medium}}, \mu_{\text{Far}}$): Proximity ranges are derived based on distances to high-intensity regions, ensuring adaptive refinement of brightness in illuminated areas.

4.2 Transmission Adjustment Parameters (α, β)

Criteria: Values for α and β are tuned to enhance medium and high fog regions while avoiding overdarkening. A grid search and evaluation on training images optimize these parameters.

Validation: Objective metrics such as PSNR and SSIM are used to ensure balanced defogging.

4.3 Contextual Refinement Factor (λ)

λ is calculated using fuzzy rules based on proximity to high-intensity regions. Defuzzification via the centroid method ensures smooth transitions between fog adjustments and brightness preservation.

This parameter selection process ensures the proposed method is adaptive, robust, and effective across varying fog and lighting conditions.

By incorporating these detailed fuzzy logic operations, the proposed model achieves a context-sensitive, adaptive enhancement of visibility, setting a higher standard for image defogging techniques.

5 Discussion

This section presents a new model designed for image defogging that combines traditional image processing methods with adaptive fuzzy set theory to tackle the issues caused by fog and atmospheric scattering. In this study, the evaluation of the proposed method is based on a diverse dataset that includes real-world foggy images. The model was implemented in MATLAB, utilizing a high-performance CPU with 8 GB of RAM on a 64-bit Windows 10 system to manage the computational requirements effectively. We used the parameters λ=0.6, σ=3, ω=0.1 and γ=1.2 for the proposed model. Figure 3 demonstrates the effectiveness of different defogging models on a set of foggy images, with each row depicting results from distinct scenes processed by various algorithms, including the methods proposed by Singh,s model, MEIF's model, and our proposed model. Figure 4 shows the proposed model's defogging result and the proposed fuzzy transmission map. Across the columns, the first image in each row represents the original foggy scene, followed by images processed by each respective model. Visually, Singh's method provides a moderate improvement, revealing more details than the original image but still retaining some fog in certain areas. The M-EIF model further enhances visibility, offering a more balanced contrast and sharper outlines in the foreground, although some regions maintain a slight haziness. In comparison, the proposed model delivers a clearer and more refined outcome, effectively removing fog while preserving texture details and enhancing contrast without introducing significant artifacts. The second column, representing the results of Singh's model, reveals improvements in visibility but leaves residual fog in darker areas. The third column demonstrates the output from the M-EIF model, which provides a clearer view than the previous methods but at the cost of some visual artifacts and slightly unnatural contrast. The proposed model, shown in the final column, effectively enhances scene clarity while preserving color balance and details. This result indicates the proposed model's ability to achieve superior defogging, delivering a more visually appealing and realistic appearance compared to the other models.

Figure 3. Given image and the defogging results of Singh's model, M-EIF's model and the propose model respectively

Figure 4. Defogging results of the competing models and the propose model of the given image in column

5.1 Statistical Analysis

The statistical analysis of the proposed model for image defogging, compared with competing models, highlights its superior performance across various metrics. Table 1 presents the experimental results on five test images, while Table 2 provides a summary of the average results for each metric.

Table 1. Comparative analysis of fog removal performance across five images: Evaluation metrics of proposed model versus existing models

Image	Metric	Proposed Model	Singh's Model	M-EIF's Model
Image 1	PSNR (dB)	34.2	28.7	27.9
	SSIM	0.94	0.89	0.85
	Contrast Gain (%)	40	30	25
	Fog Density Gain (%)	78	65	60
	Execution Time (s)	0.55	0.45	0.4
Image 2	PSNR (dB)	33.8	29.1	28.2
	SSIM	0.93	0.87	0.86
	Contrast Gain (%)	42	32	28
	Fog Density Gain (%)	73	67	63
	Execution Time (s)	0.57	0.46	0.42
Image 3	PSNR (dB)	35	29.5	28.8
	SSIM	0.95	0.88	0.87
	Contrast Gain (%)	39	31	27
	Fog Density Gain (%)	82	64	62
	Execution Time (s)	0.54	0.44	0.41
Image 4	PSNR (dB)	34.6	28.9	28
	SSIM	0.94	0.86	0.84
	Contrast Gain (%)	41	30	26
	Fog Density Gain (%)	79	66	61
	Execution Time (s)	0.53	0.43	0.39
Image 5	PSNR (dB)	33.9	29	28.1
	SSIM	0.93	0.87	0.85
	Contrast Gain (%)	38	29	27
	Fog Density Gain (%)	70	65	60
	Execution Time (s)	0.56	0.45	0.4

Table 2. Statistical summary of average performance metrics for fog removal: Comparative analysis of proposed model versus existing models

Metric	Proposed Model (Avg)	Singh's Model (Avg)	M-EIF's Model(Avg)
PSNR (dB)	34.3	29.0	28.2
SSIM	0.94	0.87	0.85
Contrast Gain (%)	40.0	30.4	26.6
Fog Density Gain (%)	76.4	65.4	61.2
Execution Time (s)	0.55	0.45	0.40

The Peak Signal-to-Noise Ratio (PSNR) is a critical metric for measuring image restoration quality. Higher PSNR values indicate better image clarity and less noise. The proposed model achieves an average PSNR of 34.3 dB, outperforming both Singh's model (29.0 dB) and the M-EIF (28.2 dB) model. This improvement signifies the model's robustness in reducing noise and enhancing the quality of defogged images. The high PSNR values across all images suggest that the proposed model consistently restores images with minimal degradation, thus preserving essential details.

Structural Similarity Index (SSIM) measures the similarity in structure and texture between the defogged and original images. An SSIM value closer to 1 implies high similarity, indicating effective preservation of structural integrity. The proposed model achieves an average SSIM of 0.94, significantly higher than Singh's model (0.87) and the M-EIF model (0.85). This demonstrates the model's effectiveness in maintaining visual consistency and fidelity, ensuring that defogged images closely resemble natural, haze-free scenes. The high SSIM value also highlights the ability of the fuzzy logic-based transmission estimation to retain intricate details across various fog densities.

Contrast gain and fog density gain are additional metrics used to assess the model's ability to enhance visibility and contrast in foggy images. The proposed model achieves an average contrast gain of 40.0% and a fog density gain of 76.4%, both substantially higher than the competing models. Singh's model achieves 30.4% in contrast gain and 65.4% in fog density gain, while the M-EIF model shows lower gains at 26.6% and 61.2%, respectively. The high values of contrast and fog density gain suggest that the proposed model effectively improves the visibility of distant and obscured regions, providing better scene clarity.

In terms of computational efficiency, the proposed model takes an average execution time of 0.55 seconds, which is slightly higher than Singh's model (0.45 seconds) and the M-EIF model (0.40 seconds). This slight increase in processing time is attributed to the additional steps of adaptive fuzzy enhancement and iterative gamma correction. However, the minor trade-off in execution speed is justified by the substantial improvements in visual quality and clarity, making the proposed model suitable for applications requiring high accuracy in defogging, such as autonomous driving and remote sensing.

5.2 Confusion Matrix Evaluation

The confusion matrix is a crucial tool for evaluating the performance of our proposed road image defogging model. It offers a comparison between the predicted results and the actual ground truth, providing detailed insights into the model's effectiveness. For a binary classification task, such as distinguishing between foggy and non-foggy regions, the confusion matrix consists of four key components:

True Positive (TP): The number of pixels correctly identified as foggy.

True Negative (TN): The number of pixels correctly identified as non-foggy.

False Positive (FP): The number of pixels incorrectly identified as foggy when they are actually non-foggy.

False Negative (FN): The number of pixels incorrectly identified as non-foggy when they are actually foggy.

These components are typically organized in the following matrix format:

$$\text{Confusion Matrix } = \begin{bmatrix} \mathrm{TP} & \mathrm{FN} \\ \mathrm{FP} & \mathrm{TN} \end{bmatrix}$$

From the confusion matrix, several important performance metrics can be derived to evaluate the effectiveness of the defogging method:

Accuracy: This metric measures the proportion of pixels that were correctly classified, both foggy and non-foggy.

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

Precision: Precision measures the proportion of pixels predicted as foggy that are correctly identified.

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

Recall (Sensitivity): Recall evaluates the proportion of actual foggy pixels that are correctly identified.

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

F1 Score: The F1 Score combines Precision and Recall into a single metric, offering a balance between the two.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 3 presents key evaluation metrics such as accuracy, precision, recall, and F1 score for each model.

The proposed model outperforms both Singh's model and M-EIF's model across all metrics. With an accuracy of 94.3%, the proposed model shows significant improvement in correctly identifying foggy and non-foggy regions compared to the other models, which have accuracies of 81.5% and 85.3%, respectively.

Table 3. Statistical summary of average performance metrics for fog removal: Comparative analysis of proposed model versus existing models

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Singh's model	81.5%	75.2%	69.6%	68.3%
M-EIF's model	85.3%	82.3%	79.8%	80.6%
Proposed model	94.3%	91.8%	92.3%	90.5%

In terms of precision, the proposed model achieves 91.8%, indicating a high proportion of correctly identified foggy pixels. Additionally, it demonstrates a recall of 92.3%, reflecting its effectiveness in identifying actual foggy regions. The F1 score of 90.5% for the proposed model suggests a balanced trade-off between precision and recall, highlighting its robust performance for road image defogging tasks.

Overall, the proposed model demonstrates significant advantages over competing models in terms of image quality, detail retention, and visibility enhancement. The integration of fuzzy logic with traditional defogging components appears to be the primary factor behind its superior performance. These results validate the effectiveness of the proposed approach, setting a new benchmark in the field of image defogging. The findings indicate that the proposed model can be a reliable choice for real-world applications where accurate and clear image restoration is essential.

While the proposed model demonstrates promising results in fog removal, the scalability of the approach in real-time environments remains a critical consideration. The computational time of the model increases with higher image resolutions and more complex fog conditions, and in dynamic fog environments, slight delays may occur due to the necessary adjustments in fog density and lighting. Addressing these challenges through optimization techniques will be an important next step for future work.

6 Conclusion

This paper provides a novel approach to image defogging by dynamically adapting to scene complexity, fog density, and lighting conditions. Unlike traditional methods, which apply global or semi-global transmission adjustments, this model segments the image into distinct regions and utilizes fuzzy logic to adjust each segment individually. This enables a more nuanced restoration, preserving fine details and achieving natural-looking results even in scenes with varied fog densities. By leveraging a FIS, the model tailors the defogging process to local conditions, significantly enhancing visibility and contrast while avoiding the over-darkening often observed in conventional techniques. Experimental results validate the model's effectiveness, showing significantly higher PSNR, SSIM, and contrast gain values compared to existing methods, demonstrating clear, natural-looking outputs suitable for critical applications like autonomous driving and remote sensing. The iterative gamma correction and fuzzy contrast enhancement steps further improve brightness and detail without over-enhancement, establishing a new standard for robust, adaptable defogging solutions.

The proposed model may struggle in environments with varying fog density and lighting conditions, leading to performance degradation. Additionally, its increased computational time limits real-time applicability in time-sensitive scenarios. Future work will focus on optimizing processing speed and exploring deep learning integration to further enhance adaptive capabilities, aiming for a balance between computational efficiency and high-quality defogging across diverse visibility conditions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflict of interest.

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