A Fuzzy Logic & Dark Channel Prior based Image Defogging Algorithm

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A comprehensive project report has been submitted in partial fulfillment of the requirements for the degree of

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May, 2018

CERTIFICATE OF APPROVAL

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for the partial fulfillment of the requirements for B.Tech degree in **Electronics and Communication Engineering** from **Maulana Abul Kalam Azad University of Technology, West Bengal** is absolutely based on their own work under the supervision of Mr. **Hiranmoy Roy**. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Contrast, and colour-fidelity of images degraded by heavy fog should be restored to aid the ever emerging fields of computer vision applications. The revolutionary advent of self-driven cars has made it increasingly urgent that efficient and fast enhancement techniques be developed. Accumulation of dense fog is also a major contributor to road accidents. CCTV surveillance, object tracking, and Fog Vision Enhancement System (FVES) are other areas that can be facilitated by such algorithms. Standard filtering techniques that fail to effectively restore low contrast foggy images must be replaced with time-efficient special enhancement techniques. In this paper, we have used the Dark Channel Prior (DCP), which is the most renowned prior for fog removal. This prior assumes that a fog-free, clear image has intensity value close to zero in at least one colour channel. Although DCP effectively restores most of the colour information, it fails to enhance the contrast of the image. To overcome this shortcoming, we have proposed a Fuzzy Logic based Contrast Enhancement algorithm, which converts the image into the fuzzy domain and performs spatial operations on the image to restore the contrast adequately. The performance of the proposed scheme is evaluated by various qualitative and quantitative metrics to establish the superiority of the proposed scheme.

CONTENTS

LIST OF SYMBOLS

Symbol	Description	Page No.
A_{global}	Global atmospheric light	13
β	Atmospheric scattering co-efficient	13
$\delta\ (z)$	Local Patch centered at z	16
ξ	Depth of the field normalization parameter	17
λ	Regularization parameter	18
L	Laplacian matrix	18
$\sum_n$	3×3 covariance matrix	18
$\delta_{i,j}$	Kronecker delta function	18
μ_n	Mean vector	18
W_n	Moving window	18
μ_{dark}	Linguistic variable for dark pixels	22
μ_{gray}	Linguistic variable for gray pixels	22
μ_{bright}	Linguistic variable for bright pixels	22
μ_{darker}	Linguistic variable for darker pixels	23
$\mu_{mid\text{-}gray}$	Linguistic variable for mid-gray pixels	23
$\mu_{brighter}$	Linguistic variable for brighter pixels	23
η	Percentage of saturated pixels	25

LIST OF ABBREVIATIONS

CCTV	**Closed Circuit Television**
FVES	**Fog Vision Enhancement System**
DCP	**Dark Channel Prior**
RSR	**Road Sign Recognition**
MRF	**Markov Random Field**
DOF	**Depth Of the Field**
HNS	**Human Nervous System**
MOM	**Mean Of Maxima**
FRIDA	**Foggy Road Image Database**
CG	**Contrast Gain**
CNR	**Contrast to Noise Ratio**
CI	**Colourfulness Index**
VGRM	**Visible Gradient Ratio Map**
CLAHE	**Contrast Limited Adaptive Histogram Equalization**

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Chapter 1

Introduction

1.1. Single image dehazing as an ill-posed problem

The increasing demand of intelligent machines and systems has given rise to fresh fields of study like Evolutionary Computing, Soft Computing, Machine Learning, Computer Vision, etc. which are greatly contributing to the advancement of mankind. For example, the efficiency of computer vision algorithms (e.g., shape and size detection, pattern and text recognition, etc.) are strongly dependent on the quality of the input image coming from the source imaging device. Unfortunately, due to the presence of fog, haze and dust particles often the colour and contrast fidelity of these input images are lost. Such ambiguous inputs may create hindrance in the decision making abilities of the computer vision algorithms leading to catastrophic failure [1]. Therefore it is of utmost importance to enhance and defog the image prior to them being used as inputs in any computer vision system. Removal of fog is important for the tracking and navigation applications, consumer electronics, and entertainment industries. Removal of fog from images as a preprocessing increases the accuracy of these computer vision algorithms. A feature point detector can fail if images have low visibility. If fog is removed and image is enhanced, then feature point detector can work with higher accuracy. In foggy weather, driving a vehicle is more difficult than normal weather. A real-time fog removal algorithm has a big advantage for road sign recognition (RSR) system [16]. Development of RSR in real time has two-fold advantages; on one hand, it can be used in vision-based driver assistance system that assist the driver to navigate vehicle by providing road signs information. On the other hand, RSR can be embedded in unmanned vehicles. These systems must be robust to any change of weather conditions. This robustness can be achieved by using a fog removal system as pre-processing unit.

1.2. Literature Survey

Early researchers have used some standard filtering and basic histogram stretching methods [2] that are somewhat inefficient in providing enough information to model the noise properly [3]. But recently, remarkable progress has been made in the field of single image dehazing. Fattal [4] proposed a single image defogging scheme based on surface shading and scene transmission model. In the case of dense fog, time complexity and low efficiency are the drawbacks of this scheme. Another single image defogging algorithm was proposed by Tan et al. [13], where they accomplished dehazing by optimizing a cost function in the Markov Random Field (MRF). This method does not need any geometric information of the input image but has a tendency to over-saturate the image. Tarel et al. [5] proposed a simple and fast framework where they used edge and corner preserving median filtering to achieve dehazing. This algorithm is based on the linear operation and requires several variable optimization to achieve the effect. Ancuti et al. [14] has proposed another dehazing algorithm based on Image Fusion, which is faster but less accurate in removing heterogeneous fog. Nishino et al. [15] presented a novel probabilistic method for factorizing a single image of a foggy scene into its albedo and depth values. They formulated this problem as joint estimation of scene albedo and depth with energy minimization of a factorial Markov random field, enabling full exploitation of natural image and depth statistics in the form of scene-specific priors. But, this algorithm also suffers from high computational cost. Based on statistical data from a large number of haze-free images He et al. [6] proposed a novel prior namely Dark Channel-Prior (DCP). They claimed that in the non-sky patch of the haze free images, at least one colour channel has some pixels whose intensities are nearly zero. With this assumption, they evaluated the thickness of the fog and performed defogging using atmospheric scattering model. This scheme has proven to be fruitful in most of the cases but at the cost of computational complexity of soft-matting [3]. The aim of this paper is to implement a fast yet efficient image defogging algorithm. Moreover, in this paper, the incompetence of DCP in terms of contrast enhancement is compensated by Fuzzy Contrast Enhancement. Throughout this paper, the words defogging and dehazing have been used interchangeably.

Chapter 2

Proposed Methodology

2.1. Haze Imaging Model

The proposed algorithm is shown in Fig. 2.1 in the form of a block diagram. The proposed scheme contains six steps namely, atmospheric and air-light estimation, transmission estimation, transmission map refinement, scene radiance recovery followed by fuzzy contrast enhancement and post-processing. The concept of defogging algorithms are based on atmospheric scattering model given by Koschmieder [7]. Haze or Fog is represented as,

$$I(i,j) = I_{faded}(i,j) + L_{air}(i,j) \tag{1}$$

The term I_{faded} *(i,j)* and L_{air} *(i,j)* are the attenuated image intensity and atmospheric air-light respectively. Both of them are the function of distance between the imaging device and the object of interest and can be represented as,

$$I_{faded}(i,j) = I_{actual}(i,j)e^{-\beta d(i,j)} \tag{2}$$

$$L_{air}(i,j) = A_{global}(1 - e^{-\beta d(i,j)}) \tag{3}$$

Where, I_{actual} *(i,j)* is the actual intensity of the image at point *(i,j)*. β is the atmospheric scattering coefficient, which indicates the concentration of the fog present in the image. *d(i,j)* is the distance between the scene and the camera and A_{global} is the global sky intensity. He at al. had put this model in a more simplified manner as [6],

$$I_{foggy}(i,j) = I_{radiance}(i,j)T(i,j) + A_{global}(1 - T(i,j)) \tag{4}$$

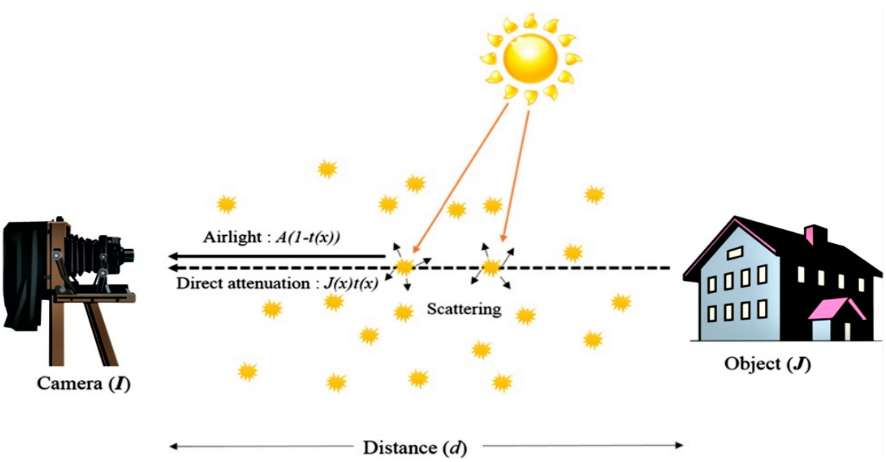


Fig. 2.1. Formation of a hazy image

Where, $I_{foggy}(i,j)$ and $I_{radiance}(i,j)$ is the input foggy image and the scene radiance (desired defogged image) respectively. $T(i,j)$ denotes transmission estimation and for homogeneous environment can be represented as,

$$T(i,j) = e^{-\beta d(i,j)} \tag{5}$$

The term $I_{radiance}(i,j)T(i,j)$ in the r.h.s of the Eq. 4 is known as Direct Attenuation and the term $A_{global}(1 - T(i,j))$ is known as the scattered air-light. Eq. 5 indicates that the scene radiance decreases exponentially with distance $d(i,j)$. With these information, the defogged image can be recovered as,

$$I_{radiance}(i,j) = \frac{I_{foggy}(i,j) - A_{global}}{T(i,j)} + A_{global} \tag{6}$$

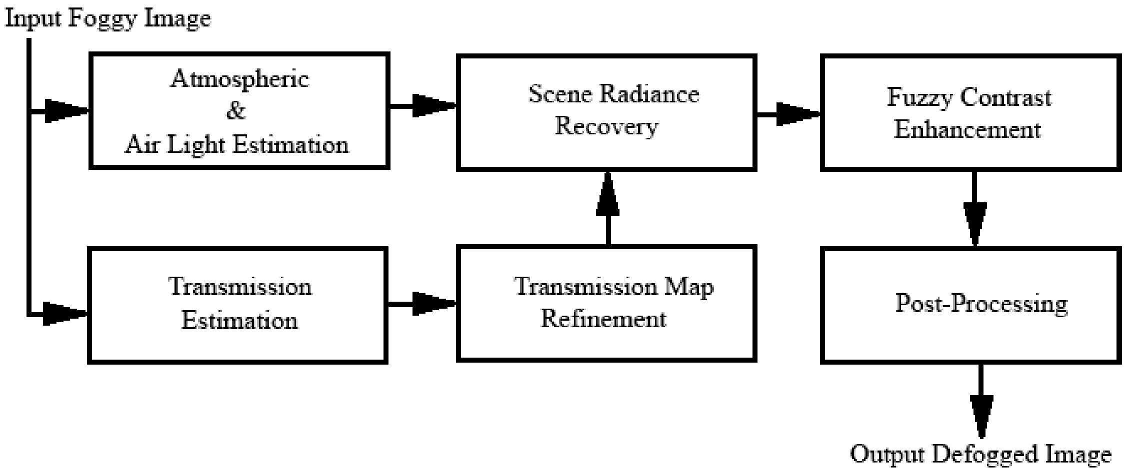


Fig. 2.2. Block diagram of the proposed algorithm

2.2. Dark Channel Prior

The Dark Channel Prior (DCP) is the statistical assumption that in an outdoor, fog-free, colour (R, G, B) image in the non-sky regions there would be at least one colour channel having pixel intensity nearly equal to zero. In other words, the minimum intensity in those pixels are quite low. From Fig. 2.3, Fig. 2.5, and Fig. 2.4, Fig. 2.6 it can be observed that the dark channel of the clear, daylight, haze free images is almost black. With this observation, we can differentiate between the fog-free and foggy image. The dark channel can be represented as,

$$I_{dark-channel}(z) = \min_{c \,\epsilon\, \{R,G,B\}} \left(\min_{(i,j) \,\epsilon\, \delta(z)} (I_c(i,j)) \right) \tag{7}$$

$$I_{dark-channel}(z) \longrightarrow 0 \tag{8}$$

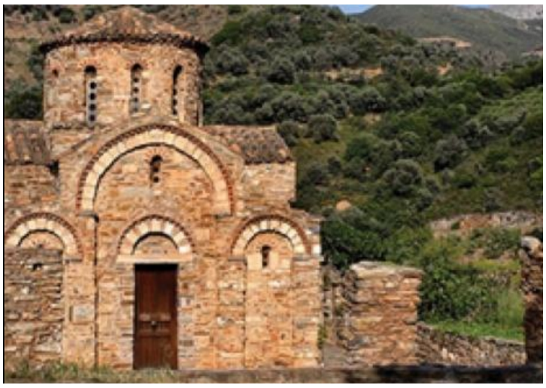


Fig. 2.3. Haze free image (Castle)

Fig. 2.4. Dark channel (Castle)

Fig. 2.5. Haze free image (Park)

Fig. 2.6. Dark channel (Park)

The term $I_c(i,j)$ is a colour channel of the fog-free image $I(i,j)$. The first 'min' operation on $I_c(i,j)$ yields any one of the three colour channels ($c \in \{R,G,B\}$) with the minimum intensity value. The second 'min' operates across the local patch $\delta(z)$, centred at z to find the minimum intensity. Unlike various other defogging algorithm (where used patch size is 15 × 15), we have used a patch size of 5 × 5 to ensure less accumulation of fog around the edges of the objects thereby preventing halo effect in the defogged image. The low intensity of dark channel in haze-free images is mainly due to three reasons: a) dark surfaces or objects; b) colourful objects or surfaces and c) shadows [6]. As a matter of fact, unlike the foggy images, clear outdoor images tend to have colourful objects, dark surfaces, and shadows and hence their dark channel intensity is always tends to be zero (Eq. 8). The foggy images and their corresponding DCP map is given in the Fig. 2.7, Fig. 2.9 and Fig. 2.8, Fig. 2.10 respectively.

Fig. 2.7. Foggy image (Forest)

Fig. 2.8. Dark channel (Forest)

Fig. 2.9. Foggy image (House)

Fig. 2.10. Dark channel (House)

2.3. Transmission Map & Atmospheric Light Estimation

The term A_{global} used in Eq. 4 denotes global atmospheric constant or sky intensity, which can be expressed as [6],

$$A_{global} = I_{foggy}(argmax_z(I_{dark}(z))) \tag{9}$$

However, this equation detects the global atmospheric constant incorrectly when the input hazy image contains some objects, which are brighter than the patches in the sky region. Therefore, pixels with top 0.1% dark-channel values are selected as the most haze-affected pixels and among them, the one with the highest intensity is used to estimate A_{global} [8]. Transmission map $T(i,j)$ is the fragment of the total reflected light from the scene that reaches the camera without scattering. To obtain the transmission map 'min' operator is used local patch $\delta(z)$, centred at z, after dividing the Eq. 4 with previously obtained A_{global}. Therefore Eq. 4 becomes,

$$\min_{(i,j)\,\in\,\delta(z)}\left(\frac{I_{foggy}(i,j)}{A_{global}}\right) = \min_{(i,j)\,\in\,\delta(z)}\left(\frac{I_{radiance}(i,j)}{A_{global}}\right)T(i,j) + (1 - T(i,j)) \tag{10}$$

Subsequently, we take the minimum out of the three colour channels on Eq. 10:

$$\min_{(i,j)\,\in\,\delta(z)}\left(\frac{I_{foggy}(i,j)}{A_{global}}\right) = \min_{c\,\in\,\{R,G,B\}}\left(\min_{(i,j)\,\in\,\delta(z)}\left(\frac{I_{radiance}(i,j)}{A_{global}}\right)\right) T(i,j) + (1 - T(i,j)) \tag{11}$$

According to DCP, the dark channel of the fog-free image $I_{radiance}(i,j)$ is tend to zero and the constant A_{global} is always positive, therefore,

$$\min_{c\,\in\,\{R,G,B\}}\left(\min_{(i,j)\,\in\,\delta(z)}\left(\frac{I_{radiance}(i,j)}{A_{global}}\right)\right) \longrightarrow 0 \tag{12}$$

Now, substituting Eq. 12 in Eq. 10 we can get the *T(i,j)* as,

$$T(i,j) = 1 - \min_{c\,\in\,\{R,G,B\}}\left(\frac{I_{foggy}(i,j)}{A_{global}}\right) \quad \forall \;\; 0 \le T(i,j) \le 1 \tag{13}$$

$$T(i,j) = \begin{Bmatrix} 0, & \forall \;\; foggy \;\; regions \\ 1, & \forall \;\; fogfree \;\; regions \end{Bmatrix}$$

Even on a clear day when visibility is excellent, small amount of fog maybe present at a greater depths of the natural image. Therefore, while rectifying a foggy image, if the fog is eliminated completely, the image will seem unnatural and the *'Depth of the Field'* may be lost. Hence to preserve the natural feel, a little amount of fog is added intentionally into the greater depths of the image by introducing a factor ξ $(0 < \xi < 1)$ in the Eq. 13. Therefore Eq. 14 denotes is the final transmission map. The value of ξ is image specific and in this scope, it has been set to be 0.9. The generated transmission map and our recovered depth map are given in Fig. 2.11 and Fig. 2.12 respectively.

$$T(i,j) = 1 - \left[\xi \, * \min_{c\,\in\,\{R,G,B\}}\left(\frac{I_{foggy}(i,j)}{A_{global}}\right)\right] \tag{14}$$

Fig. 2.11. Transmission map (Forest)

Fig. 2.12. Recovered depth map (Forest)

2.4. Transmission Map Refinement

An apparently defogged image maybe still possess traces of fog in the sharp edges or corners of present objects [6]. These remnant parts of fog lead to halo effect and is extremely undesirable as it ruins the picture fidelity. This glitch may be easily avoided by refinement of original transmission map by using soft-matting. According to He et al. the refined transmission map $\widetilde{T(i,j)}$can be expressed as [6],

$$\widetilde{T(i,j)} = T(i,j) * (L + \lambda U) \qquad (15)$$

Where, L represents the Laplacian matrix for purpose of matting, λ is the regularization parameter (usually 0.0001), and U is an identity matrix with the same dimensions as L. Each element of L can be deduced as,

$$L(i,j) = \sum_{n \mid (i,j) \epsilon W_n} \left(\delta_{ij} - \frac{1}{|W_n|} \left(1 + (I_i - \mu_n)^T \left(\sum_n + \frac{\gamma}{|W_n|} \right)^{-1} (I_j - \mu_n) \right) \right) \qquad (16)$$

Here, $\sum_n$ represents a 3 × 3 covariance matrix, δ_{ij} is the Kronecker delta function, μ_n is the 3 × 1 mean vector of the colours I_i and I_j in a window W_n, with $|W_n|$ being the total number of pixels. γ is the normalization parameter, typically 10^{-6}. The raw and refined transmission maps are given in Fig. 2.13, and Fig. 2.14 respectively. It is clear from those figure that the refined transmission map contains much more detail than the raw one.

Fig. 2.13. Transmission map (Forest)

Fig. 2.14. Refined transmission map (Forest)

2.5. Scene Radiance Recovery

Corresponding to Eq. 4 we may say that for very small values of $\widetilde{T(i,j)}$, typically those tending to zero, the $I_{radiance}(i, j)$ computed will be erroneous [1]. Thus, to reduce noise in images, the value of $\widetilde{T(i,j)}$ is assigned a lower limit, say t_{lower}, so as to intentionally preserve a small amount of haze in regions of dense fog. Subsequently, Eq. 6 can be modified and expressed as,

$$I_{radiance}(i, j) = \frac{I_{foggy}(i,j) - A_{global}}{\max\{T(i,j), t_{lower}\}} + A_{global} \quad (17)$$

However, the resultant image suffers from poor contrast and lacks fidelity. To combat this aspect, we have devised a Fuzzy Contrast Enhancement algorithm which is the topic of discussion in our next subsection.

2.6. Contrast Enhancement using Fuzzy Logic

2.6.1. Fuzzy Sets

Crisp logic deals with information that can be either entirely true or entirely false but nothing in between. However, this bi-valued logic fails to contemplate complex structures, like the human brain. Hence, systems must be developed that can deal with multivalued logic and allow smooth transitions between 'true' and 'false', to effectively mimic the Human Nervous System (HNS). Fuzzy sets introduced by Zedah happens to be one of the very first methods to give computers the ability to deal with imprecise information [9].

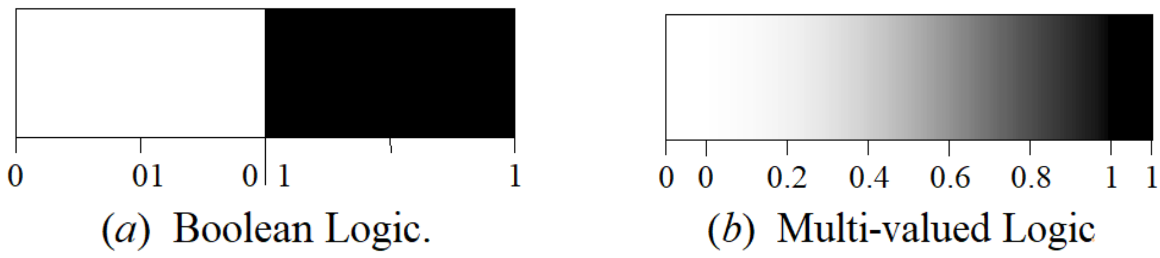


Fig. 2.15. Comparing crisp logic and fuzzy logic

Depiction of fuzziness using Fig. 2.16 -

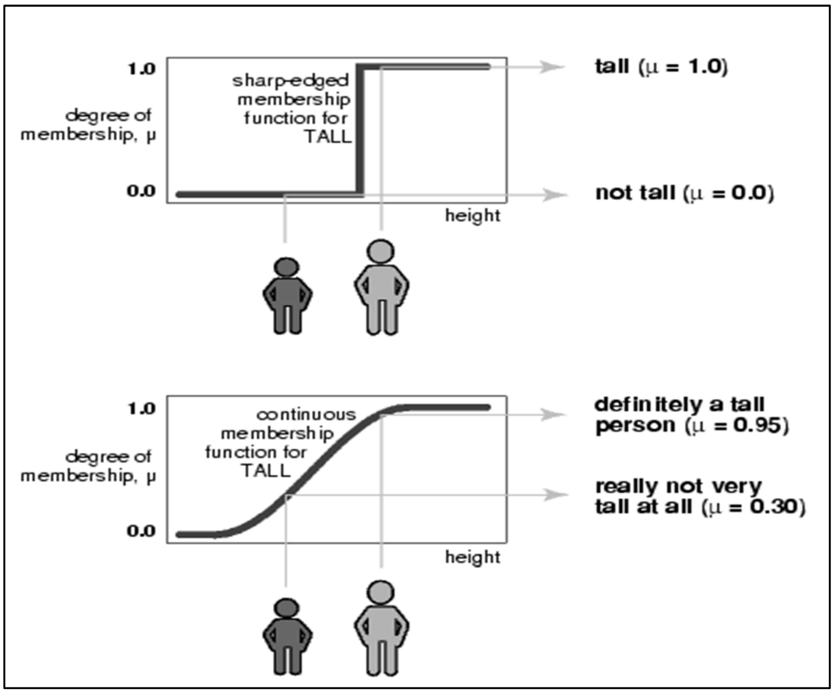


Fig. 2.16. Description of height using crisp logic and fuzzy logic

2.6.2. Probability Theory versus Possibility Theory

Among all concepts and techniques in fuzzy logic, possibility theory is one of the most often confused with probability theory. Probability and possibility measure two different kinds of uncertainty. Whereas the former attempts to explain events that are outcomes of a random experiment, the latter requires the knowledge about solution space. Possibility theory is a mathematical theory for dealing with certain types of uncertainty and is an alternative to probability theory. Professor L. Zadeh first introduced possibility theory in 1978 as an extension of his theory of fuzzy sets and fuzzy logic. For example, while tossing a coin, the possible solution space is {Head, Tail}. However, let's say we are trying to describe the quality of food of a particular restaurant. Here, it would be difficult to contemplate or predict the quality so easily because here, the solution space is not that small. In fact, it is unknown. ***However, possibility theory complements probability theory if knowledge of solution space is incomplete.***

Fuzzy sets are assigned to variables, whose values we do not know exactly, and it introduces an imprecise constraint on the variables value. We call such a constraint a possibility distribution. Hence, it can be concluded that possibility theory handles imprecise information and probability theory handles likelihood of occurrence.

Fuzzy set theory can define set membership as a possibility distribution and can measure the degree to which an outcome belongs to an event, whereas probability measures likelihood of an event to occur.

This is precisely why we have implemented fuzzy set theory for the purpose of contrast enhancement, rather than conventional histogram stretching methods, to boost overall accuracy by fuzzifying individual pixel intensities into linguistic variables and thereby modifying them as required. In the process, the histogram automatically gets equalized.

The steps involved are summarized in Fig. 2.17

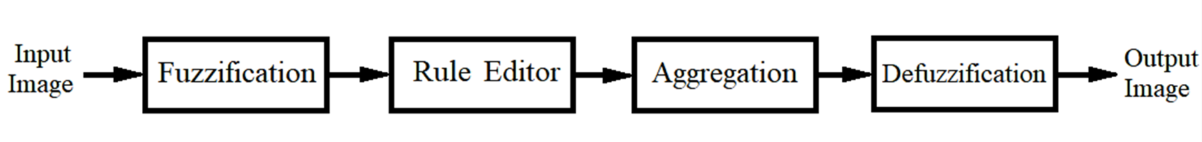


Fig. 2.17. Block diagram for fuzzy contrast enhancement

However, prior to fuzzification, we propose one step of pre-processing for synthetic images taken from FRIDA [1] image database, for better retention of colours where dense fog has left behind very little colour information to retrieve from. For this purpose, we have devised the algorithm such that it will modify pixels with values very near or equal to one in all the R, G, and B channels simultaneously.

2.6.3. Fuzzification of Inputs

Fuzzification of inputs is the process of mapping of *'Crisp Set'* values to *'Fuzzy Set'* values by assignment of appropriate Membership Functions. In this paper, we have fuzzified the pixel values, by fitting Gaussian curves (thereby obtaining Convex Fuzzy Sets) as illustrated in Fig. 2.18. In Fig. 2.18 μ_{dark} represents the membership degree of dark pixels, μ_{gray} represents the membership degree of gray pixels which are neither too dark, nor too light and μ_{bright} represents the membership degree of bright pixels. Here, *'dark'*, *'gray'* and *'bright'* are simply the *'linguistic variables'* of the fuzzy system that will be modified using implication methods as per requirement.

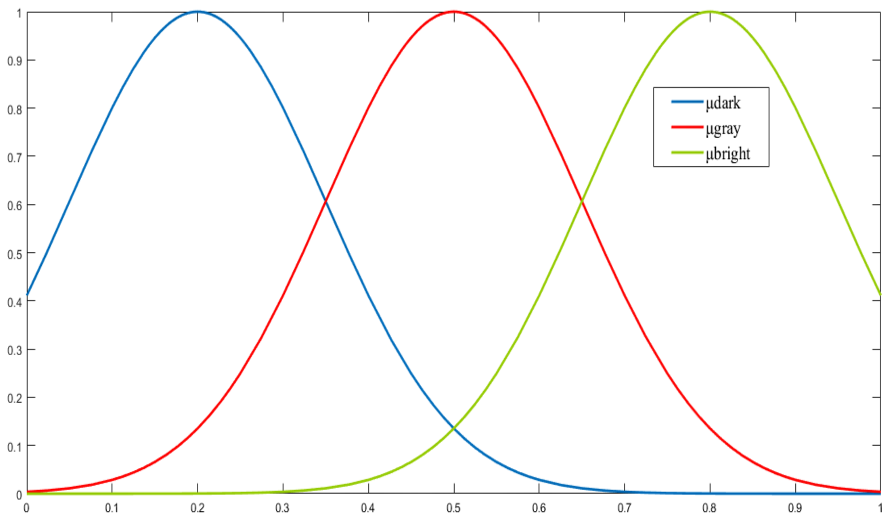


Fig. 2.18. Input membership functions

2.6.4. Fuzzy Propositions

A fuzzy proposition is a sentence that depicts the truth value in the interval [0, 1] unlike crisp logic where it has a value of either 0 or 1. The truth of a fuzzy proposition is a matter of degree. This truth value is used in correlation and inferring the output fuzzy solution space. The final output is created by combining the collection of fuzzy propositions based on the truth of each fuzzy proposition. We will use such propositions for contrast improvement.

2.6.5. Fuzzy Implication Relations

Fuzzy implication attempts to correlate the semantic meaning of the antecedent with the semantics of the consequents, and generates a solution. *The functional tie between the degrees of truth in related fuzzy regions is called the method of implication.* Most of the conditional statements describe the dependence of one or more linguistic variables on one another. *'If-Then'* statements, which we will use to improve contrast by modifying pixel intensities, work in a similar way. Contrast enhancement relies on the principle of intensity modification which can be manifested using the fuzzy If-Then rules as follows,

If the pixel value is ***'dark'***, then modify it as ***'darker'***

If the pixel value is ***'gray'***, then modify it as ***'mid-gray'***

If the pixel value is ***'bright'***, then modify it as ***'brighter'***.

Images that have high contrast are characterized by the large difference between the maximum and minimum pixels values of that image. Hence, to greatly improve the contrast we are required to escalate the existing difference to higher values. Furthermore, reduction of the number of gray pixels enhances the image fidelity thereby boosting the overall contrast even more.

2.6.6. Aggregation

The goal is to make sure that each rule yields a single output fuzzy set. It can be done in a number of ways. Here, we have used the union of the individual outputs, therefore 'max' operator is employed.

$$h : [0, 1]\, k \longrightarrow [0, 1] \tag{18}$$

2.6.7. Defuzzification

In this final step, we obtained the *'Crisp Set'* from the *'Fuzzy Set'* by assigning the appropriate output membership function as depicted in Fig. 2.19. Generally, the membership functions are sampled to find the membership grade used in the fuzzy logic equations to define an outcome region, thereby obtaining the crisp output. The crisp output is the result of the implication and aggregation steps of the fuzzy output, which is the union of all the outputs of individual rule. The crisp output can be sent as a control signal for any decision-making purposes. Several de-fuzzification techniques can be implemented. In this scope we have used, the *Mean-of-Maxima (MOM) technique.* We have fitted the Gaussian Bell as our membership function (for purely analytical reasons), where μ_{darker} represents the membership degree of darker pixels, $\mu_{midgray}$ represents the membership degree of mid-gray pixels and $\mu_{brighter}$ represents the membership degree of brighter pixels. It is desirable that the output membership function corresponding to mid-gray values be narrow so as to increase the image fidelity and richness.

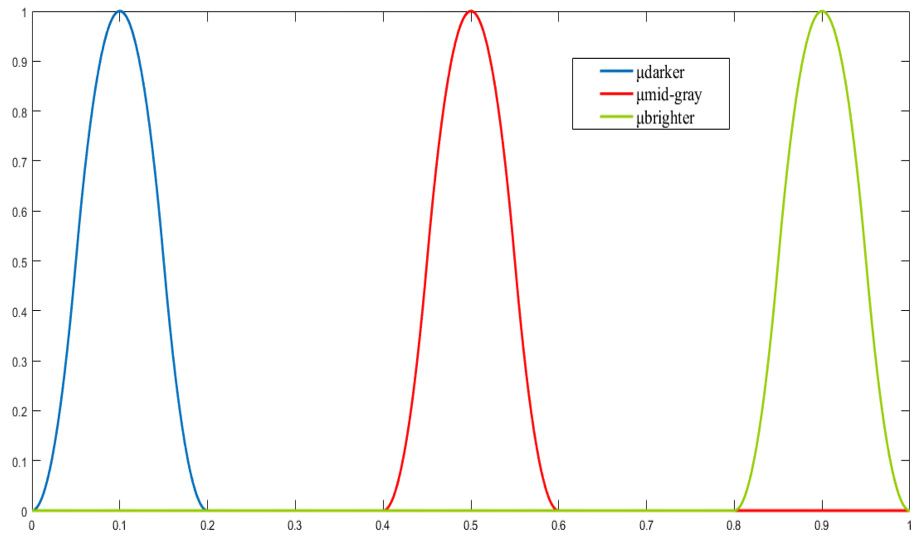


Fig. 2.19. Output membership functions

In addition, we have carried out some image specific brightness intensification, which is optional.

Chapter 3

Result Analysis & Discussion

Simulation of the proposed algorithm has been carried out over a large number of foggy images, including natural as well as synthetic images from FRIDA image database. All simulations have been done in MATLAB 9.2.0 environment.

3.1. Performance Test against Qualitative & Quantitative Metrics

The qualitative performance of the dehazing algorithm has been measured against various well-established metrics like ***Contrast Gain (CG), Contrast to Noise Ratio (CNR), Colourfulness Index (CI), and percentage of the number of saturated pixels (η)*** [10]-[11].

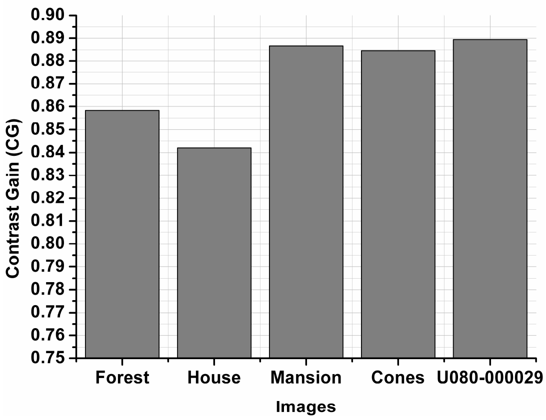


Fig. 3.1. Value of CG for various images

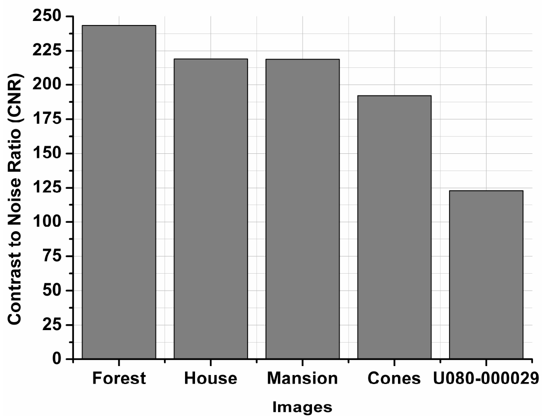


Fig. 3.2. Value of CNR for various images

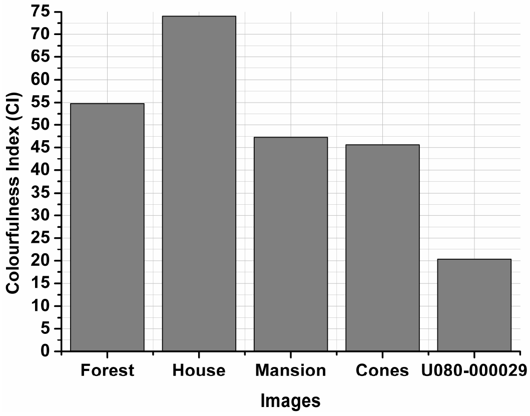


Fig. 3.3. Value of CI for various images

Values of different metrics has been depicted in Fig. 3.1, Fig. 3.2, and Fig. 3.3 for some renowned foggy images like *'Forest', 'House', 'Mansion', 'Cones'* and *'U080-000029'*. Contrast gain (CG) is described as mean contrast difference between de-foggy and foggy image. If, $C_{I_{def}}$ and $C_{I_{fog}}$ are mean contrast of defogged and foggy image, respectively, then contrast gain is defined as,

$$CE_{gain} = C_{I_{def}} - C_{I_{fog}} \tag{19}$$

Higher value of contrast gain means better performance. Moreover, contrast gain should not be so high that pixels of the enhanced image become saturated (i.e., either completely black or white). Percentage of the number of saturated pixels (η) is denoted as,

$$\eta = \frac{n}{M \times N} \times 100 \tag{20}$$

Where, n is the number of pixels which are saturated after fog removal but were not before. Low value of number of saturated pixels (η) indicates better performance of fog removal algorithm.

Contrast-to-noise ratio (CNR) is a measure used to determine image quality. CNR is similar to the metric, signal-to-noise ratio (SNR), but subtracts off a term before taking the ratio. This is important when there is a significant bias in an image, such as from haze. One way to define contrast-to-noise ratio is,

$$CNR = \frac{|S_A - S_B|}{\sigma_0} \tag{21}$$

Where, S_A and S_B are signal intensities for signal producing structures *A* and *B* in the region of interest and σ_0 is the standard deviation of the pure image noise.

The above 3 metrics judge the contrast enhancing efficiency of the proposed algorithm. However to judge the colour restoration capability of the proposed scheme we used Colourfulness Index (CI). CI can be defined as the measure of how much colour an image has. It ranges from 0 to 109, where 0 represent 'Not colourful' and 109 represents 'Extremely Colourful'.

It is evident from those figures that, the proposed algorithm has excelled in all the aforementioned cases, as for all the three metrics higher values indicate greater dehazing efficiency. The percentage of the number of saturated pixels (η) is equal to zero for all the images, which indicates superiority of the proposed algorithm. Our algorithm takes approximately 14 Secs to perform defogging on a 450×440 image in a 2 GHz computer. All the simulations have been carried out with fixed patch size of 5×5 and $\xi = 0.9$. The values of patch size and ξ also affects the qualitative indexes like CG, CI, and CNR etc. It is also noteworthy, that patch size and ξ values are image specific and best performance has been achieved with the values mentioned above. Another metric for defogging algorithm quality judgment is ***Visible Gradient Ratio Map (VGRM)*** [8]. This map gives the visible gradients present in an image. Foggy image due to air-light scattering lacks details and hence visible gradient present in a foggy image will be far less than defogged image. Fig. 3.4 and Fig. 3.5 portrays visible gradient ratio before and after defogging respectively and it is clear from those images that the proposed algorithm has succeeded to recover even minute details which were blemished by the fog.

Fig. 3.4. Foggy image VGRM

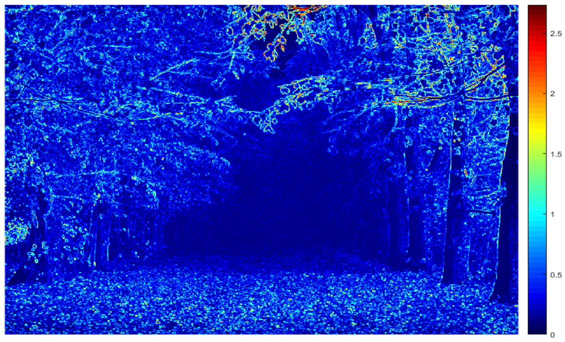


Fig. 3.5. Defogged image VGRM

It is evident from Fig. 3.6 and Fig. 3.7 that our algorithm not only recovers the colour and contrast information but also equalizes the histogram greatly.

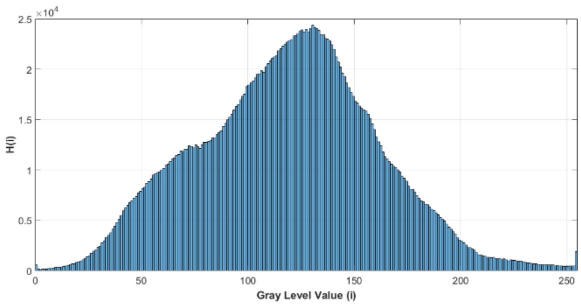


Fig. 3.6. Foggy image histogram

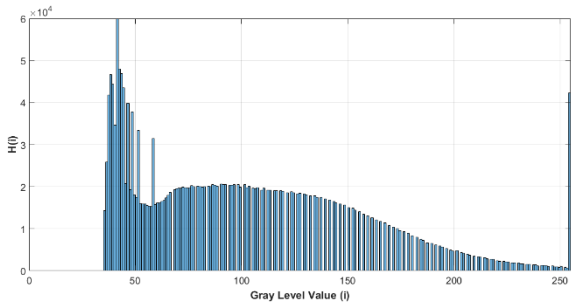
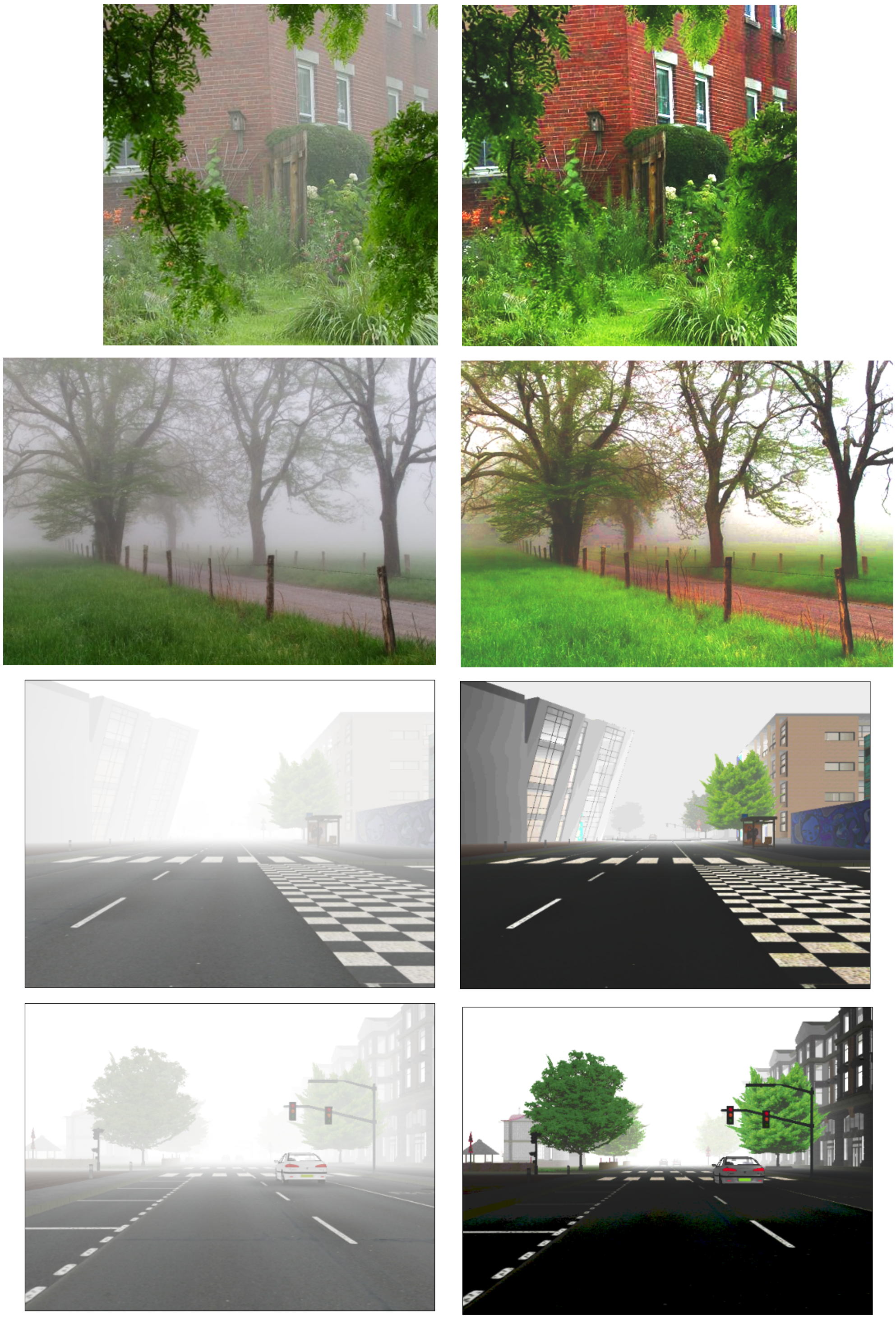


Fig. 3.7. Defogged image histogram



a.) Input foggy images b.) Output Defogged images

Fig. 3.8. Output of our algorithm for natural as well as synthetic images

3.2. Performance against other State-of-the Art Methods

We have compared our projected algorithm with various other well established State-of-the Art methods in terms of both time complexity and defogging efficiency. Fig. 3.9 compares the output of various other well established defogging methods like He et al. [6], Tarel et al. [5], Wang et al. [12] and Fattal [4] with the proposed method. It is clearly visible that the image defogged by the proposed method stands out from others and offers highest visibility.

Fig. 3.9. Comparison with State-of-the-Art Image defogging algorithms

Table 3.1 compares our proposed method with other state-of-the-art methods in terms of required approximate processing time represented in terms of second. Fig. 3.10 shows the comparison result of different methods with respect to CG. Since we have used fuzzy contrast enhancement technique for fast and improved contrast, CG comparison result in Fig. 3.10 and Table 3.1 prove the same.

Table 3.1. Comparison of the proposed method against state-of-the-art methods in terms of processing time

Methods	Approx. processing time (in seconds)
He et al. [6]	22
Tarel et al. [5]	18
Wang et al. [12]	36
Fattal [4]	26
Proposed	**14**

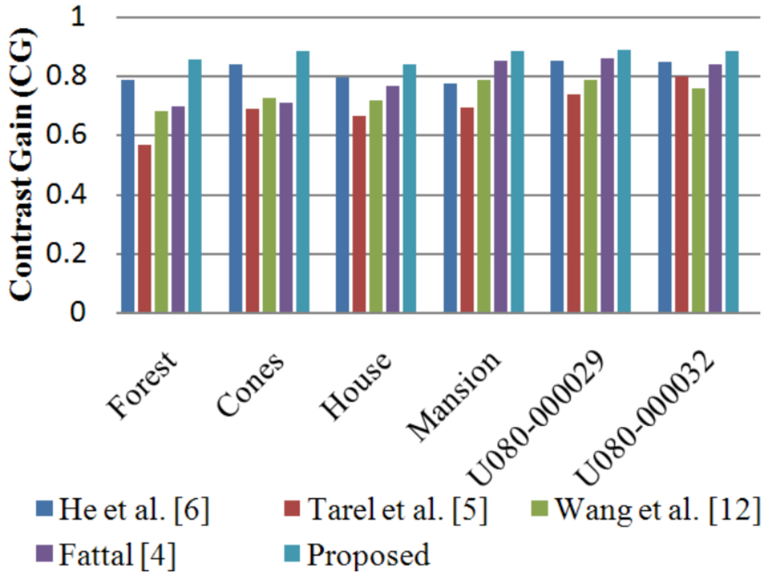


Fig. 3.10. Comparison of Contrast Gain (CG) of different methods

a.) Foggy image b) Histogram Eq. c.) CLAHE d.) Fuzzy (proposed)

Fig. 3.11. Comparison with other well established contrast enhancement technique

From the Fig. 3.11 is can be perceived that our proposed Fuzzy contrast enhancement outperforms all other well established contrast enhancement techniques (e.g, Histogram Equalization, Contrast Limited Adaptive Histogram Equalization, etc.) in terms of contrast upliftment.

Chapter 4

Conclusion

Single image fog removal is one of the most important task in the field of computer vision to be able to aid visibility restoration, surveillance and object tracking. In this paper a novel algorithm is proposed which is time efficient and competent in both homogeneous and heterogeneous fog removal. The proposed method uses DCP along with fuzzy contrast enhancement to reinforce the minute details of the fog-degraded image and to restore visibility. Different parameter values are exploited and optimized to make the algorithm more efficient. The performance of the proposed scheme is also verified with some well-established qualitative metrics. Simulation results show that the enhanced output image is rich in colour, contrast, sharp details, and fidelity. Although fog removal algorithms are difficult to implement for a foggy video clips but in near future we aim to make the algorithm faster for effective real-time hardware implementation.

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