SINGLE IMAGE HAZE REMOVAL BY DARK CHANNEL PRIOR FUSION WITH GUIDED FILTER AND COMPARISON WITH DARK CHANNEL PRIOR

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Abstract: In this paper, a novel and efficient Haze removal algorithm is proposed Poor visibility in bad weather such as fog, mist and haze caused by the water droplets present in the atmosphere. Haze formation is combination of attenuation and airlight. Attenuation reduces the contrast and airlight increases the whiteness in the scene. Proposed algorithm uses dark channel prior fusion with guided filter for the estimation of airlight and recovers scene contrast. Proposed algorithm is dependent of the intensity of Haze. It can handle color as well as gray images. The DCP is derived from the characteristic of natural outdoor images that the intensity value of at least one color channel within a local window is close to zero. This six step Haze removal process by DCP: input hazy image, estimate dark channel prior, atmospheric light estimation, transmission map estimation, refine transmission map by soft matting, and image recover the scene radiance. The proposed algorithm Introduces Dark Channel Prior (DCP) followed by soft matting and guided filter based Haze removal scheme. The proposed method DCP fusion with guided filter is seven steps for Haze removal process. This seven step Haze removal step: input hazy image, estimate dark channel prior, atmospheric light estimation, transmission map estimation, refine transmission map by soft matting, refine transmission by guided filter and image recover the scene radiance. The proposed method has an application in video surveillance, intelligent transportation system, remote sensing, tracking, navigation and consumer.

Keywords- Dehaze, Dark channel prior, Guided image filter, edge-preserving smoothing single image Haze removal.

1. INTRODUCTION

The image qualities of captured outdoor scenes in atmosphere are usually degraded Haze due to bad weather such as fog, haze, smog, cloud and rain. Bad weather reduces visibility and contrast of the scene. Haze, fog, and smoke are such combination due to atmospheric absorption and scattering. Visibility range is greatly affected by Haze as compared to other bad weather conditions. For road traffic, Haze can be categorized as low fog and dense fog [2, 5.6]. The atmospheric particles, mainly water droplets causes, absorption and scattering. Where there is scattering, two fundamental phenomena attenuation and airlight exist and the resulting light coming towards the camera or the observer from the scene gets attenuated due to scattering through different haze and thus degrades the image quality of an atmosphere scene. **Haze = Attenuation + Air light**

The whiteness effect in the scene towards the observer or the camera is known as airlight. These two phenomena combination produce a degraded hazy image. In this paper, we proposed techniques dark channel prior fusion with guided filter for single image haze removal. Haze removal techniques used for atmospheric Hazy image which do not cover the sky, some dark pixels (called dark pixels) very often have very low intensity in at least one color (RGB) channel.

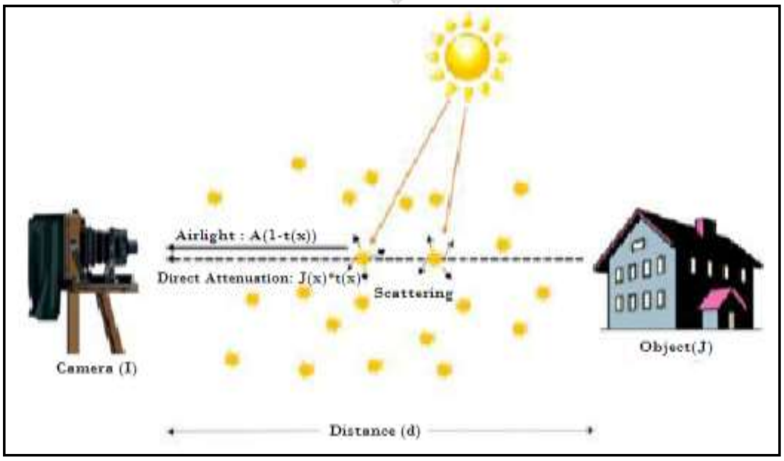

Figure 1.1 Formation of hazing model

In hazy images, the intensity of these dark pixels in that channel is mainly contributed by the airlight. Therefore, these dark channel prior can directly operated an accurate estimation dark pixels of the hazy image. We can recover a high-quality haze Removal image [1,2,3,4]. It is observed that attenuation and airlight are the functions of the distance between camera and scene. These applications are used to recognize vehicles, traffic signs, and signals clearly through vision enhancement using Haze removal. He et al. [1] proposed a very simple but effective single-image haze removal method using DCP and refined by soft matting. DCP is a kind of statistics of outdoor haze removal images that contain some pixels whose intensity is very low in at least one channel. [6]. Proposed algorithm uses DCP principle at initial stage followed by soft matting tone and Guided filter for contrast adjustment. Soft matting images represent original light values captured for the scene while Guided filter is an edge preserving and Haze removal. A Guided filter that is close to anisotropic diffusion was used previously to diminish ringing effect [9] while deblurring images in the presence of Haze.

2. BACKGROUND OF HAZE MODELING

The haze imaging equation is given by:

$$\mathbf{I}(\mathbf{x}) = \mathbf{J}(\mathbf{x})t(\mathbf{x}) + \mathbf{A}(1 - t(\mathbf{x})). \qquad (1)$$

The variables are explained in the following:

1. x = (x, y) is a 2D vector representing the coordinates (x, y) of a pixel's position in the Haze image.

2. I represent the hazy image observed. I(x) is a 3D RGB vector of the color at a pixel. The variables are explained in the following: 1. x = (x, y) is a 2D vector representing the coordinates (x, y) of a pixel's position in the Haze image. 2. "I" represents the hazy image observed. I(x) is a 3D RGB vector of the color at a pixel.

3. "J" represents the scene radiance image. J(x) is a 3D RGB vector of the color of the light reflected by the scene point at x. It would be the light seen by the observer if this light were not through the haze. So we often refer to the scene radiance J as a haze-free image.

4. t is a map called transmission or transparency of the haze. t(x) is a scalar in [0, 1]. Intuitively, t(x) = 0 means completely hazy and opaque, t(x) = 1 means haze-free and completely clear, and 0 < t(x) < 1 means semi-transparent.[4,5,8]

5. A is the atmospheric light. It is a 3D RGB vector usually assumed to be spatially constant. It is often considered as "the color of the atmosphere, horizon, or sky".[3,4]

To find out the parameter of airlight we notice that once the transmission is zero then the equation is reduced to Equation (1).

$$I(x) = A \qquad (2)$$

As shown in Eq. (3), the transmission parameter becomes zero if the depth of a pixel *(d(x))* is infinite.

$$t(\mathbf{x}) = e^{-\infty} = \frac{1}{e^{-\infty}} = 0 \qquad (3)$$

Geometrically the fog/haze equation describes the transmission *t* as the ratio of the two line segments [4,8].

$$t(x) = \frac{\|A - I(x)\|}{\|A - J(x)\|} \qquad (4)$$

In RGB color model the vectors ***A***, ***I(x)*** and ***J(x)*** are coplanar and their corresponding end points are collinear. [4, 8]

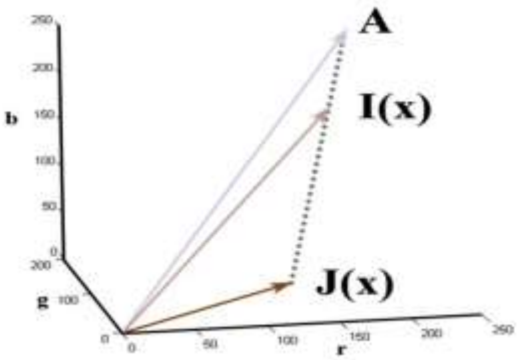

Figure (2.12) the vectors A, I(x), and J(x) are coplanar

3. METHODOLOGY:

(3.1)Haze Removal Using Dark Channel Prior:

(3.1.1) Estimate of the transmission map:

First we use the dark channel prior to estimate the transmission *t*. Recall the haze imaging equation (1)

Suppose the atmospheric light A has been estimated. We shall give an automatic method to estimate A. We normalize the haze imaging equation (1) by A:

$$\frac{I^c(x)}{A^c} = t(x)\frac{J^c(x)}{A^c} + 1 - (t) \qquad (5)$$

Note that we normalize each color channel independently. We further assume that the transmission in a local patch $\Omega(x)$ is constant. We denote this transmission as $\breve{t}\,(x)$. Then, we calculate the dark channel on both sides of (2). Equivalently, we put the minimum operators on both sides

$$\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) = \tilde{t}(x)\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) + \left(1 - \tilde{t}(x)\right) \qquad (6)$$

Since $\breve{t}\,(x)$ is a constant in the patch, it can be put on the outside of the min operators. As the scene radiance J is a haze-free image, the dark channel of J is close to zero due to the dark channel prior

$$J^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) = 0 \quad (7)$$

As A^c is always positive, this leads to

$$\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) \to 0 \quad (8)$$

Putting (5) into (3), we can eliminate the multiplicative term and estimate the transmission $\check{t}\,(x)$ simply by

$$\tilde{t}(x) = 1 - \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) \text{ Where, } 0< \tilde{t}(x) < 1 \quad (9)$$

$$\tilde{t}(x)=\begin{cases}0, & filly\ foggy\ or\ opaque\ image\\ 1, & completely\ fog\ free\ image\end{cases}$$

In fact, $\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right)$ is the dark channel of the normalized hazy image $\frac{I^c(x)}{A^c}$. It directly provides the estimation of the transmission. As we mentioned before, the dark channel prior is not a good prior for the sky regions. If we remove the haze thoroughly, the image may seem unnatural and we may lose the feeling of depth. So, we can optionally keep a very small amount of haze for the distant objects by introducing a constant parameter ω ($0 < \omega \leq 1$) into (9).

$$\tilde{t}(x) = 1 - \omega \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) \quad (10)$$

The value of ω is variable in the thesis. In the derivation of (10), the dark channel prior is essential for eliminating the multiplicative term (direct transmission) in the haze imaging model (1).

(3.1.2) Refine transmission map:

We notice that the haze imaging equation (1) has a similar form as the image matting equation:

$$I = F\alpha + B(1-\alpha) \quad (11)$$

Where F and B are foreground and background colors, respectively, and α is the foreground opacity. A transmission map in the haze imaging equation is exactly an alpha map. Therefore, we can apply a closed-form framework of matting to refine the transmission. Denote the refined transmission map by t(x). Rewriting t and $\tilde{t}$ in their vector forms as t and $\check{t}$, we minimize the following cost function:

$$E(t) = t^T L t + \lambda(t - \tilde{t})^T (t - \check{t}) \quad (12)$$

The matrix L is called Laplacian Matrix. For an image of size M*N, the size of Laplacian Matrix is MN*MN. The (i; j) element of the matrix be defined as the first term is a smoothness term and the second term is a data term with a weight λ. The matrix L is called the matting Laplacian matrix. Its (i,j) element is defined as.

$$L(i,j)=\sum_{k|(i,j)\epsilon\omega_k}\left(\delta_{ij} - \frac{1}{|\omega_k|}\left(1 + (I_i - \mu_k)^T\left(\sum_k + \frac{\varepsilon}{|\omega_k|}U_3\right)^{-1}(I_i - \mu_k)\right)\right) \quad (13)$$

where I_i and I_j are the colors of the input image I at pixels i and j, δ_{ij} is the Kronecker delta, μ_k and $\sum k$ are the mean and covariance matrix of the colors in window ω_k, U_3 is a 3×3 identity matrix,ε is a regularizing parameter, and$|\omega_k|$ is the number of pixels in the windowω_k. The optimal t can be obtained by solving the following sparse linear system:

$$(L + \lambda U)t = \lambda\check{t} \quad (14)$$

where U is an identity matrix of the same size as L. We set a small $\lambda(10^{-4}$ in the experiments) so that t is softly constrained by $\check{t}$.The matting Laplacian matrix has also been applied in to deal with the spatially variant white balance problem. The derivation of the matting Laplacian matrix in is based on a color line assumption: The foreground/background colors in a small local patch lie on a single line in the RGB color space. The color line assumption is also valid in the problem of haze removal. First, the scene radiance J is a natural image. According to the color line model holds for natural images. Second, the atmospheric light A is a constant, which of course satisfies the assumption. Therefore, it is valid to use the matting Laplacian matrix as the smoothness term in the haze removal problem.

(3.1.3) Scene Radiance Recovery

The final scene radiance **J**(**x**) is recovered by:

$$J^c = \frac{I^c(x) - A^c}{\min(t(x), t_0)} + A^c \quad (16)$$

For avoiding producing too much noise, limit the value of the transmission *t (x)* between 0.1 and 0.9. So the final function used for restoring the scene radiance **J** in the method can be expressed by:

$$J^c = \frac{I^c(x) - A^c}{\min(\max(e^{-\beta d(x)}, 0.1))0.9)} + A^c \quad (17)$$

Where J^c is the haze-free image. Note that the scattering coefficient β, which can be regarded as a constant in homogeneous regions, the ability of a unit volume of atmosphere to scatter light in all directions. In other words, β determines the intensity of haze removal indirectly. Therefore, a moderate β is essential when dealing with the images with dense-haze regions. In most cases, β = 1.0 is more than enough. For Airlight estimate assumption is required that 0.5% brightest pixels are taken.

(2.1.4) flow chart of Dark channel prior

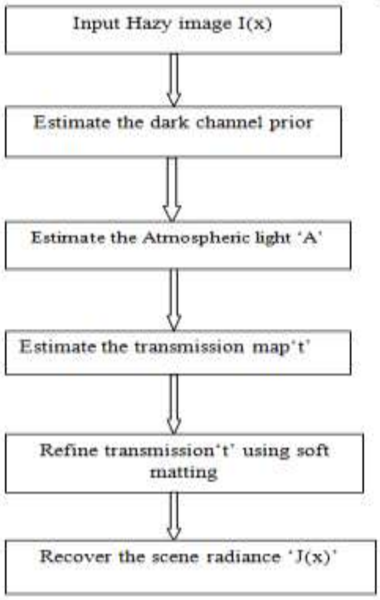

Figure 2 flow chart of Dark channel prior

(3.2)Haze removal using by DCP Fusion with Guided filter:
Main disadvantage of DCP method is that they produce halo effects and blocky effects in the output image. Guided Filter is an edge-preserving smoothing operator. In that method transmission map is refined using guided filter. Refinement of transmission map is needed to remove the halo effects. Main advantages of this method are that estimation of refine transmission map is done accurately and it could get more accurate value of the atmospheric light. So due to this the haze-free image is not looking dim. For Airlight estimate assumption is required 0.4% brightest pixels are taken.

(3.2.1) Guided Filter
We first define a general linear translation-variant filtering process, which involves a guidance image I, an filtering input image p, and an output image q. Both I and p are given beforehand according to the application, and they can be identical. The filtering output at a pixel i is expressed as a weighted average

$q_i = \sum_j W_{ij} \ (I)$ (18)

where i and j are pixel indexes. The filter kernel W_{ij} is a function of the guidance image I and independent of p. This filter is linear with respect to p.

(3.2.2) Definition
Now we define the guided filter. The key assumption of the guided filter is a local linear model between the guidance I and the filtering output q. We assume that q is a linear transform of I in a window ω_k centered at the pixel k:

$q_i = a_k \ I_I \ +b_k \ ,\forall_i \ \in \ \omega_k$ (19)

Where a_k , b_k are some linear coefficients assumed to be constant in ω_k. We use a square window of a radius r. Pixel i and windows ω_i and ω_k are shown in Figure (4.3) . Output image q has edge if and only if guidance image I has edge
To find linear coefficients, the cost function in window ω_k is defined as:

$E\ (a_{k\ ,}\ \ b_k\ ) = \sum_{i\in\omega_k}((\ a_k\ \ I_i + b_k\ \text{-}\ p_i)^2 + \omega {a_k}^2\ ))$ (20)

Where, ε is a regularization parameter penalizing largea_k.
The term εa_k 2 is used to prevent a_k from being too large. E is the blur degree to control the accuracy of edge detection. If the image I has no edges, the output will be an averaged result of input in ω_k . If the edge is present in I which represent the structure of the guidance image, the edge is transferred to the output image.
The cost function can be seen as a linear regression model & its solution can be given by,

$a_k = \frac{\frac{1}{|\omega\ |}\sum_{i\in\ \omega_k} I_i\, p_i - \mu_k \overline{p_k}}{\sigma_k\ 2 - \varepsilon}$ (21)

$b_k = \overline{p}_k \ \text{-}\ a_k\, \mu_k$ (22)

where, μ_k and $\sigma_k{}^2$ are the mean and variance of I in ω_k ,ω is the number of pixels in ω_k;

$\overline{p}_k = \frac{1}{|\omega|}\sum_{i\in\omega_k} p_i$ is the mean of p in ω_k . Using linear coefficients (a_k , b_k), the filtering output can be computed as;

$q_i = a_k \ I_I \ +b_k \ ,\forall_i \ \in \ \omega_k$ (23)

But, the values for q_i will be different when calculated for various windows. So, the solution is to find the average value of q_i . For all possible windows in the image, (a_k , b_k) values will be calculated and then the filtered output can be given as;

$q_i = \frac{1}{|\omega|}\sum_{k/i\in\omega_k}(a_k\, I_i + b_k)$ (24)

The guided filter also can be applied to colour images. In case input image is coloured, the filter should be applied to each channel separately.

Noticing that $\sum_{k|\omega_i} a_k = \sum_{k\in\omega_i} b_k$ due to the symmetry of the box window, we rewrite (24) by:

$q_i = \bar{a}_i I_i + \bar{b}_i$ (25)

Where $\bar{a}_i = \frac{1}{|\omega|}\sum_{k\in\omega_i} a_k$ and $\bar{b}_i = \frac{1}{|\omega|}\sum_{k\in\omega_i} b_i$ are the average coefficients of all windows overlapping i. With the modification in (4.29),∇q is no longer scaling of ∇I the linear coefficients $(\bar{a}_i, \bar{b}_i)$ vary spatially. But as $(\bar{a}_i, \bar{b}_i)$ are the output of a mean filter, their gradients can be expected to be much smaller than that of I near strong edges.

(3.2.4) Guided Filter Algorithm

1. Read the image say *I* (color image) which acts as the guidance image.
2. Take *p=I*, where *p* is filtering image (color image)
3. Take the values for *r* and *ε* where *r* is radius of window and *ε* is regularization parameter.
4. Compute following mean values by applying averaging filter „*fmean*":
meanI = fmean(I)
meanp = fmean(p)
corr*Ip = fmean(I .* p)*
corrII = fmean(I . I)*
5. Compute covariance of (*I,p*) using formula:
covIp = corrIp –meanI. meanp*
6. Compute variance using formula:
varI = corrII –meanI. meanI*
7. Compute linear coefficients *a* and *b* as:
a = covIp/ (varI + ε)
b = meanp – a . meanI*
8. Compute mean of *a* and *b* as:
meana = fmean(a)
meanb = fmean(b)
9. Compute filtered output as:
q = meana . I + meanb*

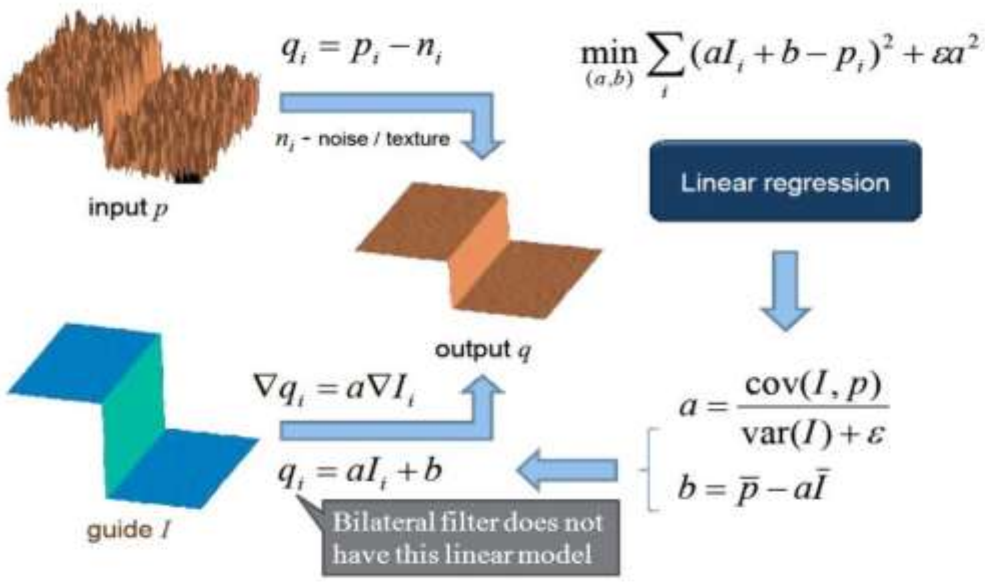

Figure 3 guided filter

(3.2.5)Estimate of Transmission Map

First we use the dark channel prior to estimate the transmission *t*. Recall the haze imaging equation.

I(x) = J(x)*t*(x) + A(1 − *t*(x)) (26)

Suppose the atmospheric light **A** has been estimated. We shall give an automatic method to estimate **A.** We normalize the haze imaging equation (4.30) by **A**:

$\frac{I^c(x)}{A^c} = \mathrm{t(x)}\,\frac{J^c(x)}{A^c} + 1 - (t)$ (27)

Note that we normalize each color channel independently. We further assume that the transmission in a local patch $\Omega(x)$ is constant. We denote this transmission as $\breve{t}\,(x)$. Then, we calculate the dark channel on both sides of (4.31). Equivalently, we put the minimum operators on both sides

$$\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) = \tilde{t}(x)\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) + (1-\tilde{t}(x))$$

Since $\breve{t}\,(x)$ is a constant in the patch, it can be put on the outside of the min operators. As the scene radiance J is a haze-free image, the dark channel of J is close to zero due to the dark channel prior

$$J^{dark\_Guided}(x) = \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) = 0 \qquad (28)$$

As A^c is always positive, this leads to

$$\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) \to 0 \qquad (29)$$

Putting (4.34) into (4.32), we can eliminate the multiplicative term and estimate the transmission $\breve{t}\,(x)$ simply by

$$\tilde{t}(x) = 1 - \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) \quad \text{Where, } 0 < \tilde{t}(x) < 1 \qquad (30)$$

If the dark channel refined by guided filtering is recorded as $J^{dark\_Guided}(x)$ and the atmospheric light refined by guided filtering is wrote for $A(x)$, the transmission map $t(x)$ can be remembered as:

$$t(x) = 1 - \omega\, J^{dark\_Guided}(x) \qquad (31)$$

(3.2.6) Scene Radiance Recovery

With the atmospheric light **A** and the transmission *t*, we can recover the scene radiance **J** by inverting haze imaging equation

$$J^c = \frac{I^c(x) - A^c}{\min(t(x), t_0)} + A^c \qquad (32)$$

For avoiding producing too much noise, limit the value of the transmission *t (x)* between 0.1 and 0.9. So the final function used for restoring the scene radiance **J** in the method can be expressed by:

$$J^c = \frac{I^c(x) - A^c}{\min(\max(e^{-\beta d(x)}, 0.1))0.9)} + A^c$$

As the dark channel image can be refined by guided filtering, we can also refine the bright channel. The halo and block effects are suppressed, and the atmospheric light is different at different pixel.

3.4 Flow Chart Proposed Methodology by Dark Channel Prior Fusion with Guided Filter

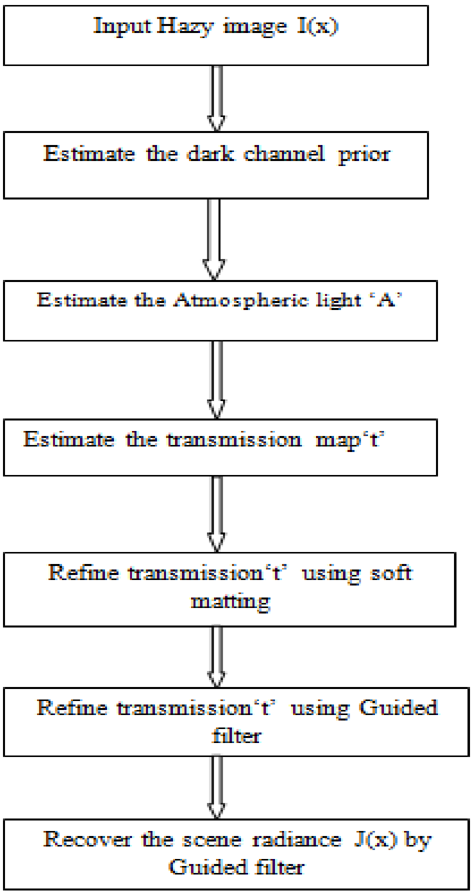

Figure 4 Flow Chart Proposed Methodology by Dark Channel Prior Fusion With Guided Filter

4. EXPERIMENTAL RESULT

4.1 Experimental Haze Removal Image

Testing of our haze removal method is performed on 3 different images. The result is show in the form of image along with different amount of haze.

1. Forest.jpg (this is foggy image. Size-1024*768)
2. Fruit.jpg (this is hazy image. Size-320*320)
3. Mountain.jpg (this is hazy image. Size-1366*768)
4. Station.jpg (this is foggy image. Size-600*400)
5. Village.jpg (this is foggy image. Size-600*525)

Figure (4.1) (a) Hazy Image (Forest), (b) Dark channel Image, (c) the transmission map, (d) Refine transmission by soft matting, (e) Refine transmission by Guided filter, (f) our result by DCP, (g) our result by DCP Fusion with guided filter

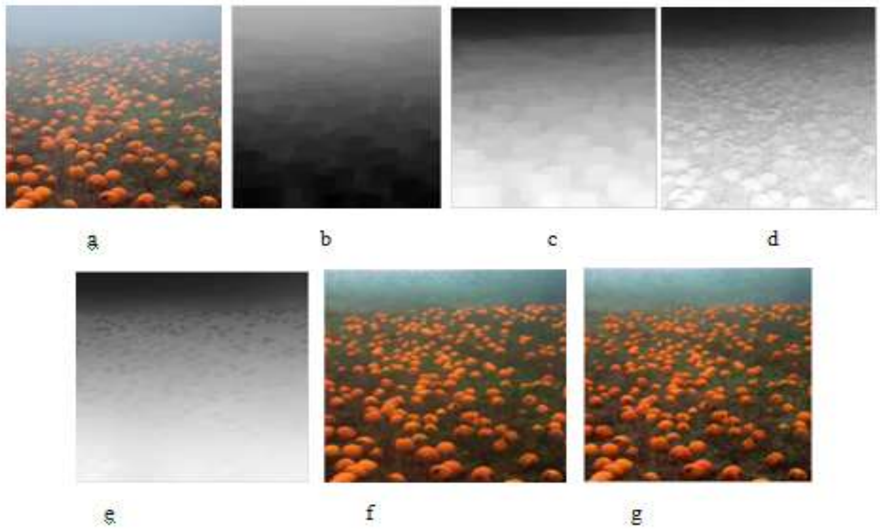

Figure (4.2) (a) Hazy Image (Fruit), (b) Dark channel Image, (c) the transmission map, (d) Refine transmission by soft matting, (e) Refine transmission by Guided filter, (f) our result by DCP, (g) our result by DCP Fusion with guided filter

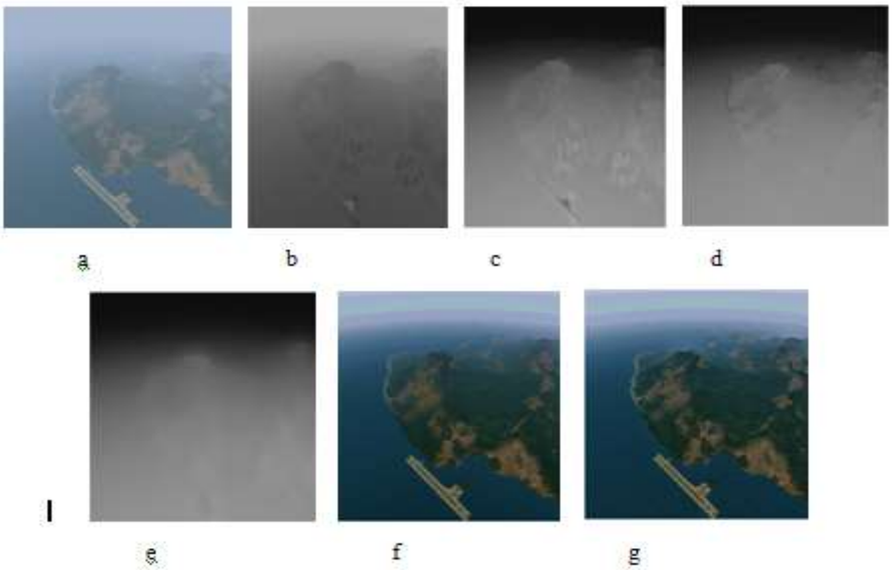

Figure (4.3) (a) Hazy Image (Mountain), (b) Dark channel Image, (c) the transmission map, (d) Refine transmission by soft matting, (e) Refine transmission by Guided filter, (f) our result by DCP, (g) our result by DCP Fusion with guided filter

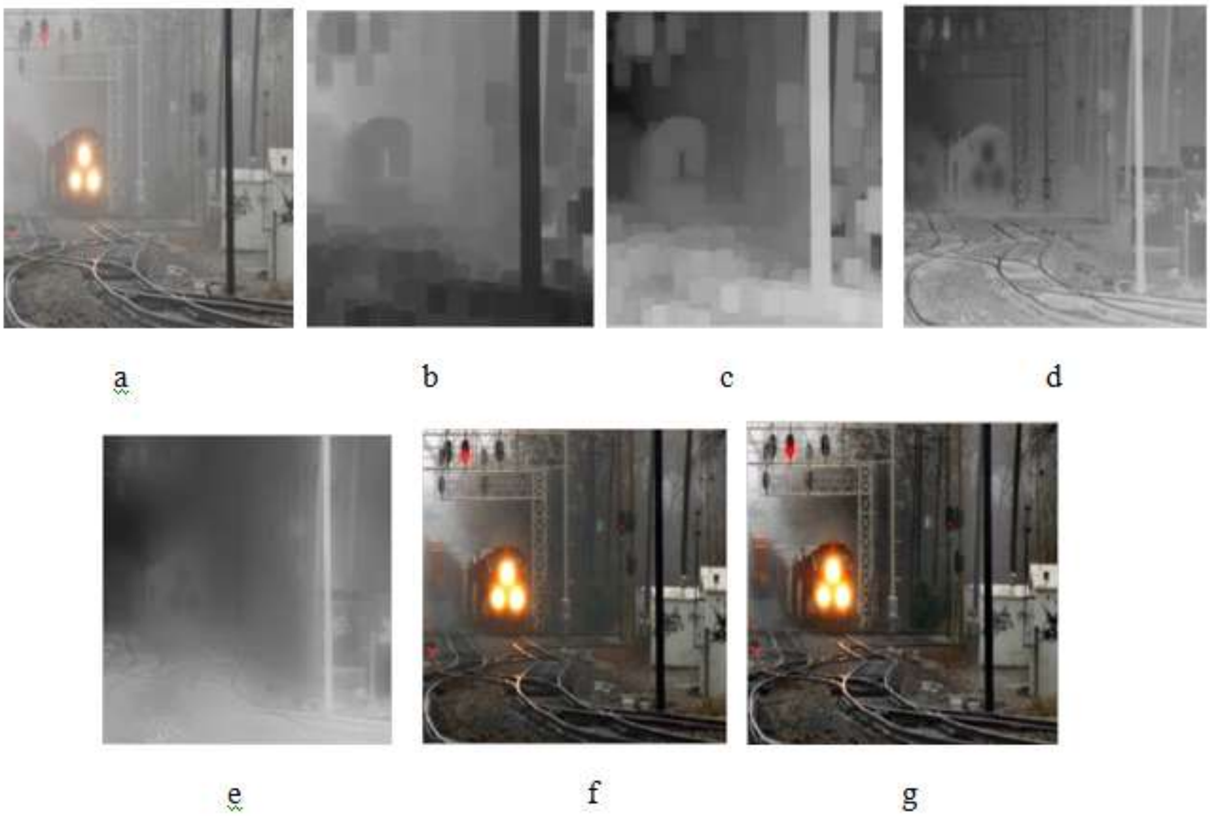

Figure (4.4) (a) Hazy Image (Station), (b) Dark channel Image, (c) the transmission map, (d) Refine transmission by soft matting, (e) Refine transmission by Guided filter, (f) our result by DCP, (g) our result by DCP Fusion with guided filter

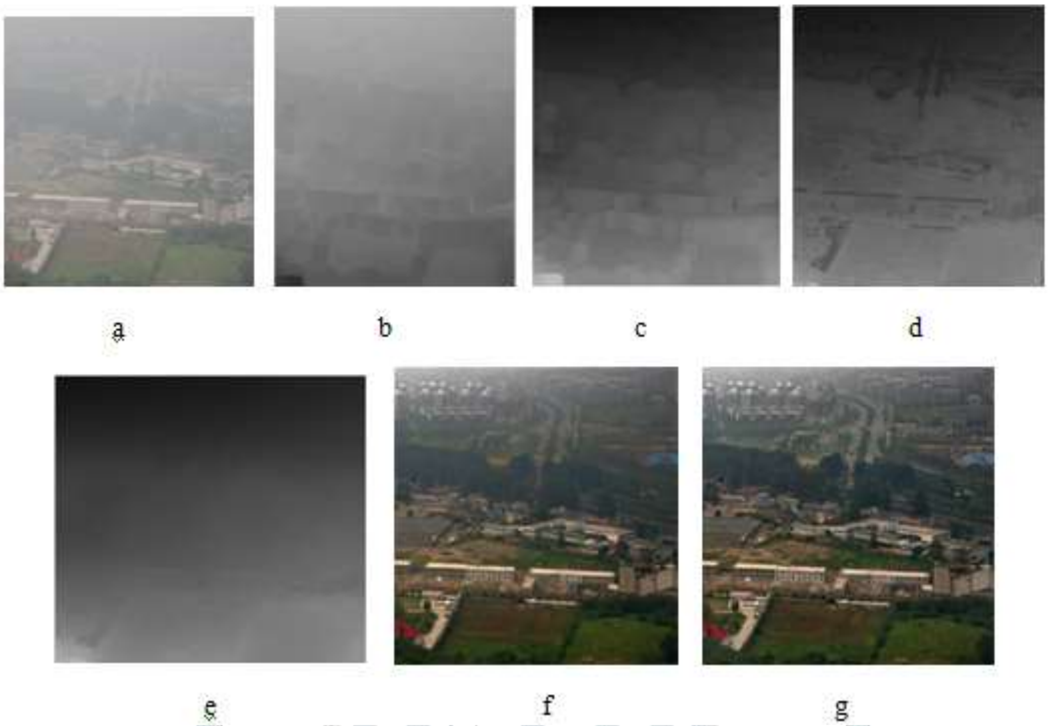

Figure (5.5) (a) Hazy Image (Village), (b) Dark channel Image, (c) the transmission map, (d) Refine transmission by soft matting, (e) Refine transmission by Guided filter, (f) our result by DCP, (g) our result by DCP Fusion with guided filter

4.2 Proposed Parameters Analysis

The quantitative analysis of performed by calculating PSNR, Contrast Gain, correlation coefficients and NPCR.

4.2.1 Peak Signal To Noise Ratio (Psnr)

PSNR indicates the visibility of noise in an image. In Multimedia application, any image with PSNR values more than 30db is acceptable. In Medical image, where the quality of the data is first priority of radiologist a PSNR around 50db is acceptable limit. Highest value of PSNR is desired.

$$\text{PSNR} = 10\log\frac{max^2}{MSE} \qquad (33)$$

Where, $\text{MSE} = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(I(x,y) - I'(x,y))^2$

4.2.2 Contrast Gain

Contrast gain denotes the mean contrast difference between the Haze removal image and original image. It is calculated by Contrast gain is described as follows. Let an image of size $M \times N$ is denoted by $X(x, y)$. Then, contrast of the pixel (x, y) is expressed as

$$C(x, y) = \frac{l_2\,(x,y)}{l_1(x,y)} \qquad (34)$$

$l_1\,(x,y) = \frac{1}{(2m+1)^2}\sum_{k=-m}^{m}\sum_{l=-m}^{m} X(x+k, y+l)$

$l_2(x, y) = \frac{1}{(2m+1)^2}\sum_{k=-m}^{m}\sum_{l=-m}^{m}(X(x+k, y+l) - l_2\,(x,y))^2$

If mean contrast is denoted as

$$\bar{C}_{\mathrm{I}} = \frac{1}{MN}\sum_{y=0}^{N-1}\sum_{x=0}^{M-1} c(x,y) \qquad (35)$$

Then Contrast gain is

$$C_{gain} = \bar{c}_{\mathrm{Idehaze}} - \bar{c}_{\mathrm{Iorg}} \qquad (36)$$

Where, $\bar{c}_{\mathrm{Idehaze}}$ is mean contrast of Haze removal image and $\bar{c}_{\mathrm{Iorg}}$ is mean contrast of original image. It is known that clear day images have more contrast than images plagued by fog. Hence contrast gain for all the existing fog removal algorithms should be positive. Moreover, stronger contrast gain indicates better Haze remove of the image.

4.2.3 Image Correlation Coefficient

Image Correlation Coefficient provides quantitative data on the fidelity of foggy image. It determines the degree to between two variables whose movements are associated.

The range of values for the correlation coefficients is -1 to1.ICC value close to 1 desired.

$$\text{ICC} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} W(i,j) * W'(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{M}(W(i,j))^2} \qquad (37)$$

4.2.4 NPCR

The number of changing pixel rate (NPCR) is the difference between the changes in pixel value of two similar images. A high NPCR value is interpreted as a high resistant to differential attacks. Suppose haze removal image before and after one pixel change in at grid (i, j) in C_1 and C_2 are denoted as C_1(i, j) and C_2(i, j).

$$\text{NPCR} = \text{N}\,(C_1, C_2) = \sum_{i,j} \frac{D(i,j)}{M \times N} \times 100\% \qquad (38)$$

The range of NPCR is (0, 1). When N (C_1, C_2) = 0, if implies that all pixels in C_2 remain the same value as in C_1. When N (C_1, C_2) = 1, if implies that all pixel value in C_2 are change compared to those in C_1 .

$$\text{D (i, j)} = \begin{Bmatrix} 0\ , if\ C_1(\text{i, j}) = C_2(\text{i, j}) \\ 1\ , \text{if}\ C_1(\text{i, j}) \neq C_2(\text{i, j}) \end{Bmatrix} \qquad (39)$$

Where, D (i, j) is change of pixels and M×N is image size.

Table (1) Comparison between DCP and DCP Fusion with Guided Filter (Forest Image)

Image	Haze intensity Factor (ω)	DCP				DCP Fusion with Guided Filter			
		PSNR	Contrast Gain	ICC	NPCR	PSNR	Contrast Gain	ICC	NPCR
Forest Jpg. Image	0.50	69.8341	0.1115	0.9909	1	70.3748	0.1169	0.9870	1
	0.55	68.8291	0.1290	0.9883	1	70.3341	0.1513	0.9832	1
	0.65	67.0054	0.1861	0.9817	1	68.4280	0.2412	0.9729	1
	0.70	66.1651	0.2175	0.9774	1	67.5394	0.3032	0.9660	1
	0.79	64.7410	0.2792	0.9675	1	66.0115	0.4333	0.9498	1
	0.80	64.5886	0.2866	0.9663	1	65.8459	0.4495	0.9476	1
	0.89	63.2560	0.3583	0.9525	1	64.3751	0.6156	0.9234	1
	0.95	62.3981	0.4123	0.9407	1	63.3991	0.7521	0.9014	1
	0.99	61.8334	0.4516	0.9313	1	62.7409	0.8588	0.8830	1
	1	61.6955	0.4619	0.9288	1	62.5746	0.8879	0.8778	1

Table (2) Comparison between DCP and DCP Fusion with Guided Filter (Fruit Image)

Image	Haze intensity Factor (ω)	DCP				DCP Fusion with Guided Filter			
		PSNR	Contrast Gain	ICC	NPCR	PSNR	Contrast Gain	ICC	NPCR
Fruit. Jpg image	**0.5**	78.1674	0.0328	0.9916	1	80.2770	0.0731	0.9927	1
	0.55	77.0671	0.0410	0.9892	1	79.1876	0.0843	0.9905	1
	0.65	75.0116	0.0611	0.9823	1	77.1620	0.1081	0.9846	1
	0.7	74.0273	0.0729	0.9775	1	76.1989	0.1206	0.9805	1
	0.79	72.2708	0.0962	0.9652	1	74.4994	0.1730	0.9702	1
	0.8	72.0735	0.0990	0.9637	1	74.3106	0.1802	0.9688	1
	0.89	70.2221	0.1274	0.9407	1	72.5748	0.2556	0.9514	1
	0.95	68.8222	0.1617	0.9120	1	71.3278	0.3196	0.9323	1
	0.99	67.7282	0.1880	0.8761	1	70.4071	0.3708	0.9124	1
	1	67.4347	0.1952	0.8622	1	70.1594	0.4035	0.9059	1

Table (3) Comparison between DCP and DCP Fusion with Guided Filter (Mountain Image)

Image	Haze intensity Factor (ω)	DCP				DCP Fusion with Guided Filter			
		PSNR	Contrast Gain	ICC	NPCR	PSNR	Contrast Gain	ICC	NPCR
Moun-Tain.jpg Image	**0.50**	64.3003	0.1138	0.9965	1	66.1526	0.1157	0.9961	1
	0.55	63.1337	0.1291	0.9953	1	64.9837	0.1314	0.9947	1
	0.65	60.9505	0.1628	0.9915	1	62.7957	0.1662	0.9906	1
	0.70	59.9074	0.1817	0.9886	1	61.7502	0.1857	0.9875	1
	0.79	58.0621	0.2206	0.9803	1	59.9017	0.2257	0.9788	1
	0.80	57.8569	0.2254	0.9791	1	59.6963	0.2307	0.9775	1
	0.89	55.9640	0.2823	0.9611	1	57.8078	0.2842	0.9599	1
	0.95	54.5881	0.3262	0.9329	1	56.4500	0.3212	0.9339	1
	0.99	53.6235	0.3524	0.8984	1	55.4875	0.3446	0.9009	1
	1	53.3779	0.3592	0.8879	1	55.2418	0.3507	0.8907	1

Table (4) Comparison between DCP and DCP Fusion with Guided Filter (Station Image)

Image	Haze intensity Factor (ω)	DCP				DCP Fusion with Guided Filter			
		PSNR	Contrast Gain	ICC	NPCR	PSNR	Contrast Gain	ICC	NPCR
Stat-ion.jpg Image	0.50	71.6900	0.2520	0.9915	0.9999	73.6801	0.2132	0.9878	0.9999
	0.55	70.5284	0.2936	0.9887	0.9999	72.4991	0.2483	0.9836	0.9999
	0.65	68.3528	0.3943	0.9806	0.9999	70.2744	0.3310	0.9714	0.9999
	0.70	67.3125	0.4565	0.9747	0.9999	69.2030	0.3787	0.9624	0.9999
	0.79	65.4747	0.5982	0.9592	0.9999	67.2931	0.4787	0.9384	0.9999
	0.80	65.2711	0.6171	0.9570	0.9999	67.0798	0.4912	0.9349	0.9999
	0.89	63.4160	0.8294	0.9288	0.9999	65.1179	0.6282	0.8912	0.9999
	0.95	62.1264	1.0391	0.8977	0.9999	63.7300	0.8109	0.8436	0.9999
	0.99	61.2210	1.2281	0.8673	0.9999	62.7415	0.9892	0.7982	0.9999
	1	60.9873	1.2841	0.8582	0.9999	62.4833	1.0444	0.7844	0.9999

Table 5.5 Comparison between DCP and DCP Fusion with Guided Filter (Village Image)

Image	Haze intensity Factor (ω)	DCP				DCP Fusion with Guided Filter			
		PSNR	Contrast Gain	ICC	NPCR	PSNR	Contrast Gain	ICC	NPCR
Vill-age.jpg Image	0.50	70.1619	0.1920	0.9950	1	72.1378	0.1737	0.9932	1
	0.55	68.8857	0.2210	0.9931	1	70.8540	0.1974	0.9906	1
	0.65	66.4428	0.2893	0.9872	1	68.3911	0.2503	0.9825	1
	0.70	65.2436	0.3303	0.9823	1	67.1784	0.2801	0.9759	1
	0.79	63.0549	0.4208	0.9677	1	64.9564	0.3406	0.9560	1
	0.80	62.8052	0.4326	0.9653	1	64.7021	0.3480	0.9529	1
	0.89	60.4312	0.5628	0.9285	1	62.2725	0.4213	0.9036	1
	0.95	58.6088	0.6943	0.8669	1	60.3884	0.4804	0.8229	1
	0.99	57.1951	0.8149	0.7703	1	58.9443	0.5551	0.7101	1
	1	56.8264	0.8499	0.7361	1	58.5758	0.5921	0.6756	1

6. CONCLUSION

Haze removal methods have become more useful for many computer vision applications. All the Haze removal methods are useful for surveillance, intelligent vehicles, for remote sensing and under water imaging, etc. single Haze removal image is a very important challenging objective in the area of digital image processing. The dark channel prior is based on the statistics of outdoor haze-free images. Combining the prior with the haze imaging model, single image haze removal becomes simpler and more effective. Since the dark channel prior is a kind of statistics, it may not work for some particular images. The dark channel prior is invalid for shadow image. The dark channel of the scene radiance has bright values near such objects in this thesis we are used technique Dark channel prior and then Guided filter is merged in dark channel prior. There are used techniques for different Haze intensity. Guided filter is better haze removal techniques than DCP. Guide filter, which has the benefits of edge-preserving, noise removing, haze removing and a reduction in the computation time. In this research article, a novel and efficient single image Haze removal algorithm is proposed for both gray and color images. The proposed method uses dark channel prior fusion with guided filter and shows pleasant output image. We can see that the halo and block effects are suppressed by guided filter. The efficiency of the proposed method is verified using subjective and objective evaluation with fixed and variable Haze intensity factor. Results and analysis shows that the output Haze-free image contains more clear edges with details and better contrast. It also preserves color quality for RGB images and other image transformation models (YUV, HSV, CMYK etc.) seem to produce similar results. This proposed dark channel prior fusion with guided filter has PSNR, Contrast gain, correlation coefficients and NPCR better than dark channel prior techniques. Implementation of proposed work is done by using MATLAB. It is implementing both the spatial domain method. So the output image is a high quality image.

REFERENCE

[1] He, Kaiming, Jian Sun, and Xiaoou Tang, "Single image haze removal using dark channel prior", Pattern Analysis and Machine Intelligence, IEEE Transactions on pp. 2341-235, 2011 Vol. 33, No. 12, December 2011.
[2] Jiahao Pang, Oscar C. Au and Zheng Guo “Improved Single Image Dehazing Using Guided Filter” APSIPA ASC 2011 Xi’an.
[3] Divya makkar1 , Mohinder Malhotra “Single Image Haze Removal Using Dark Channel Prior” International Journal Of Engineering And Computer Science ISSN: 2319-7242 Volume 5 Issue 1 January 2016, Page No. 15467-15473.
[4] Monika Verma1, Vandana Dixit Kaushik1 Vinay Pathak1 “ Haze Removal of a Single Image by Using the Brightness Prior” International Journal of Intelligent Engineering and Systems, Vol.10, No.5, 2017.
[5] Yan Wang Bo Wu “Improved Single Image Dehazing using Dark Channel Prior” 978-1-4244-6585-9/10/$26.00 ©2010 IEEE
[6] Md. Imtiyaz Anwar, Arun Khosla “Vision enhancement through single image fog removal” Engineering Science and Technology, an International Journal 20 (2017) 1075–1083
[7] J.P. Tarel, N. Hautiere, Fast visibility restoration from a single color or gray level
image, in: Proc. 12th IEEE International Conference on Computer Vision, pp.
2201–2208 (2009).
[8] Qingsong Zhu, Jiaming Mai, and Ling Shao, “A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior” IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 24, NO. 11, NOVEMBER 2015
[9] Yue Wu, Student Member, IEEE, Joseph P. Noonan, Life Member, IEEE, and Sos Agaian, Senior Member, IEEE “NPCR and UACI Randomness Tests for Image Encryption” april 2011.
[10] N. Sangeetha and K.Anusudha “Image defogging using enhancement techniques” IEEE-2017978-1-5090-3716-2/17/$31.00 ©2017 IEEE
[11] Zhengguo Li, Senior Member, IEEE, and Jinghong Zheng, Member, IEEE “Single Image De-Hazing Using Globally Guided Image Filtering” IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 27, NO. 1, JANUARY 2018
[12]. “K. Garg and S. K. Nayar, “Detection and removal of rain from videos," in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, vol. 1. IEEE, 2004, pp. I-528.
[13]. X. Zhang, H. Li, Y. Qi, W. K. Leow, and T. K. Ng, “Rain removal in video by combining temporal and chromatic properties," in Multimedia and Expo, 2006 IEEE International Conference on. IEEE, 2006, pp. 461-464.
[14] M. Shen and P. Xue, “A fast algorithm for rain detection and removal from videos," in Multimedia and Expo (ICME), 2011 IEEE International Conference on. IEEE, 2011, pp. 1-6.
[15]. Y.-H. Fu, L.-W. Kang, C.-W. Lin, and C.-T. Hsu, “Single-frame-based rain removal via image decomposition," in Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on. IEEE, 2011, pp. 1453-1456.
[16].Ashwini Gadge1, Dr. S. S. Agrawal2 “Guided Filter for Color Image” Vol. 4, Issue 6, June 2016 IJIREEICE
[17] A. Levin, D. Lischinski, and Y. Weiss, “A Closed Form Solution to Natural Image Matting,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. 1, pp. 61-68, 2006.
[18]Kaiming He, Jian Sun, and Xiaoou Tang, “Guided ImageFiltering”IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 35,NO.6JUNE20
[19] Aparna lahane and Dr. V. B. malode “color image implementation of guided filter derived by local linear model” IETE 05 NOV, 2017 Volume No. 06, Issue No. 11
[20] Sahu, Jyoti. "Design a New Methodology for Removing Fog from the Image." International Journal 2 (2012).
[21] Xu, Haoran, et al. "Fast image dehazing using improved dark channel prior." Information Science and Technology , International Conference on. IEEE, 2012.
[22] Matlin, Erik, and Peyman Milanfar. "Removal of haze and noise from a single image." IS&T/SPIE Electronic Imaging. International Society for Optics and Photonics, 2012.
[23] Hitam, M. S., W. N. J. H. W. Yussof, E. A. Awalludin, and Z. Bachok. "Mixture contrast limited adaptive histogram equalization for underwater image enhancement." In Computer Applications Technology (ICCAT), 2013 International Conference on, pp. 1-5. IEEE, 2013.