Haze Removal Using Color Attenuation Prior With Varying Scattering Coefficients

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***Abstract*—** *This paper deals with removal of haze using color attenuation prior. It will helps for dehazing single image. For dehazing linear model is used. It is based on atmospheric scattering model. In this technique saturation and brightness values of an image is considered. It is less time consuming algorithm and also it has greater dehazing effects. Also varying scattering coefficient is used for dehazing purpose. With the depth map of the hazy image, we can smoothly surmise the transmission and give back the scene radiance via the atmospheric scattering model, and thus effectively remove the haze from a single image. It can implement very easily.*

Keywords*— *Color attenuation prior, Scattering model, Linear model, Varying Scattering Matrix.

I. INTRODUCTION

Outdoor images taken in bad weather (e.g., foggy or hazy) usually lose contrast and color fidelity, resulting from the fact that light is absorbed and scattered by the turbid medium such as particles and water droplets in the atmosphere during the process of propagation. Moreover, most automatic systems, which strongly depend on the definition of the input images, fail to work normally caused by the degraded images. Therefore, improving the technique of image haze removal will benefit many image understanding and computer vision applications such as aerial imagery, image classification, image/video retrieval, remote sensing and video analysis and recognition. Since concentration of the haze is different from place to place and it is hard to detect in a hazy image, image dehazing is thus a challenging task.

In almost every practical scenario the light reflected from a surface is scattered in the atmosphere before it reaches the camera. This is due to the presence of aerosols such as dust, mist, and fumes which deflect light from its original course of propagation. In long distance photography or foggy scenes, this process has a substantial effect on the image in which contrasts are reduced and surface colors become faint. Such degraded photographs often lack visual vividness and appeal, and moreover, they offer a poor visibility of the scene contents. This effect may be an annoyance to amateur, commercial, and artistic photographers as well as undermine the quality of underwater and aerial photography. This may also be the case for satellite imaging which is used for many purposes including cartography and web mapping, land-use planning, archeology, and environmental studies.

Early researchers use the traditional techniques of image processing to remove the haze from a single image (for instance, histogram-based dehazing methods ([4], [5]). However, the dehazing effect is limited, because a single hazy image can hardly provide much information. Later, researchers try to improve the dehazing performance with multiple images. In [4] and [7], polarization based methods are used for dehazing with multiple images which are taken with different degrees of polarization. It is based on the fact that usually airlight scattered by atmospheric particles is partially polarized. Polarization filtering alone cannot remove the haze effects, except in restricted situations. Our method, however, works under a wide range of atmospheric and viewing conditions. We analyze the image formation process, taking into account polarization effects of atmospheric scattering.

In Chromatic Framework method [8], propose haze removal approaches with multiple images of the same scene under different weather conditions. In this develop a general chromatic framework for the analysis of images taken under poor weather conditions. The wide spectrum of atmospheric particles makes a general study of vision in bad weather hard. So, we limit ourselves to weather conditions that result from fog and haze. We begin by describing the key mechanisms of scattering. Next, we analyze the dichromatic model proposed, and experimentally verify it for fog and haze. Then, we derive several useful geometric constraints on scene color changes due to different but unknown atmospheric conditions.

In Dark Channel Prior method [9], proposes a simple but effective image prior dark channel prior to remove haze from a single input image. The dark channel prior is a kind of statistics of outdoor haze-free images. It is based on a key observation most local patches in outdoor haze-free images contain some pixels whose intensity is very low in at least one color channel.

Using this prior with the haze imaging model, we can directly estimate the thickness of the haze and recover a high-quality haze-free image. Results on a variety of hazy images demonstrate the power of the proposed prior. Moreover, a high-quality depth map can also be obtained as a byproduct of haze removal. The dark channel prior is based on the statistics of outdoor haze-free images.

In method proposed by T. Tan [10], It is automated method. This method is based on two basic observations: first, images with enhanced visibility (or clear-day images) have more contrast than images plagued by bad weather; second, airlight whose variation mainly depends on the distance of objects to the viewer tends to be smooth. Relying on these two observations, we develop a cost function in the framework of Markov random fields, which can be efficiently optimized by various techniques, such as graph-cuts or belief propagation.

In this paper, we propose a novel color attenuation prior for single image dehazing. This simple and powerful prior can help to create a linear model for the scene depth of the hazy image. By learning the parameters of the linear model with a supervised learning method, the bridge between the hazy image and its corresponding depth map is built effectively. With the recovered depth information, we can easily remove the haze from a single hazy image. The efficiency of this dehazing method is dramatically high and the dehazing effectiveness is also superior to that of prevailing dehazing algorithms

II. METHODOLOGY

a. Atmospheric Scattering Model

To describe the formation of a hazy image, the atmospheric scattering model, which is widely used in computer vision and image processing? The model can be expressed as follows:

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x)) \tag{2.1}$$

$$t(x) = e^{-\beta d(x)} \tag{2.2}$$

Where x is the position of the pixel within the image, **I** is the hazy image, **J** is the scene radiance representing the haze-free image, **A** is the atmospheric light, *t* is the medium transmission, β is the scattering coefficient of the atmosphere and d is the depth of scene. **I**, **J** and **A** are all three-dimensional vectors in RGB space. Since **I** is known, the goal of dehazing is to estimate **A** and t, then restore **J** according to Equation 2.1. It is worth noting that the depth of the scene d is the most important information. Since the scattering coefficient β can be regarded as a constant in homogeneous atmosphere condition, the medium transmission t can be estimated easily according to Equation 3.2 if the depth of the scene is given. Moreover, in the ideal case, the range of **d(x)** is $[0,+\infty)$ as the scenery objects that appear in the image can be very far from the observer, and we have:

$$\mathbf{I}(x) = \mathbf{A} \qquad d(x) \to \infty \tag{2.3}$$

b. Color Attenuation Prior

To detect or remove the haze from a single image is a challenging task in computer vision, because little information about the scene structure is available. In spite of this, the human brain can quickly identify the hazy area from the natural scenery without any additional information. This inspired us to conduct a large number of experiments on various hazy images to find the statistics and seek a new prior for single image dehazing. Interestingly, we find that the brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration.

Fig. 2.1 gives an example with a natural scene to show how the brightness and the saturation of pixels vary within a hazy image. As illustrated in Fig. 2.1(d), in a haze-free region, the saturation of the scene is pretty high, the brightness is moderate and the difference between the brightness and the saturation is close to zero. But it is observed from Fig. 2.1(c) that the saturation of the patch decreases sharply while the color of the scene fades under the influence of the haze, and the brightness increases at the same time producing the high value of the difference. Furthermore, Fig. 2.1(b) shows that in a dense-haze region, it is more difficult for us to recognize the inherent color of the scene, and the difference is even higher than that in Fig. 2.1(c). It seems that the three properties (the brightness, the saturation and the difference) are prone to vary regularly in a single hazy image according to this observation.

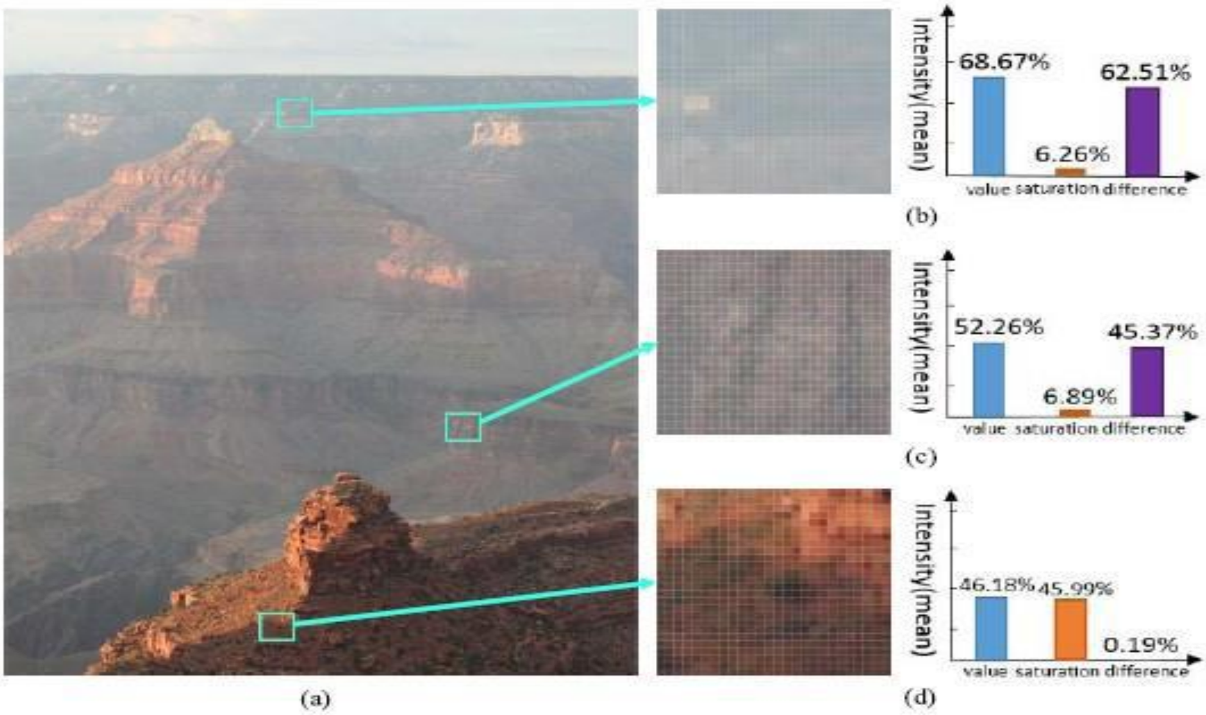

FIGURE 2.1: THE CONCENTRATION OF THE HAZE IS POSITIVELY CORRELATED WITH THE DIFFERENCE BETWEEN THE BRIGHTNESS AND THE SATURATION. (A) A HAZY IMAGE. (B) THE CLOSE-UP PATCH OF A DENSE-HAZE REGION AND ITS HISTOGRAM. (C) THE CLOSE-UP PATCH OF A MODERATELY HAZY REGION AND ITS HISTOGRAM. (D) THE CLOSE-UP PATCH OF A HAZE-FREE REGION AND ITS HISTOGRAM.

In the haze-free condition, the scene element reflects the energy that is from the illumination source (e.g., direct sunlight, diffuse skylight and light reflected by the ground), and little energy is lost when it reaches the imaging system. The imaging system collects the incoming energy reflected from the scene element and focuses it onto the image plane. Without the influence of the haze, outdoor images are usually with vivid color. In hazy weather, in contrast, the situation becomes more complex. There are two mechanisms (the direct attenuation and the airlight) in imaging under hazy weather.

On one hand, the direct attenuation caused by the reduction in reflected energy leads to low intensity of the brightness. To understand this, we review the atmospheric scattering model. The term $\mathbf{J}(x)t(x)$ in Equation 2.1 is used for describing the direct attenuation. It reveals the fact that the intensity of the pixels within the image will decrease in a multiplicative manner. So it turns out that the brightness tends to decrease under the influence of the direct attenuation. On the other hand, the white or gray airlight, which is formed by the scattering of the environmental illumination, enhances the brightness and reduces the saturation. We can also explain this by the atmospheric scatter model.

The rightmost term $\mathbf{A}(1 - t(x))$ in Equation 3.1 represents the effect of the airlight. It can be deduced from this term that the effect of the white or gray airlight on the observed values is additive. Thus, caused by the airlight, the brightness is increased while the saturation is decreased. Since the airlight plays a more important role in most cases, hazy regions in the image are characterized by high brightness and low saturation. Whats more, the denser the haze is, the stronger the influence of the airlight would be. This allows us to utilize the difference between the brightness and the saturation to estimate the concentration of the haze.

Since the concentration of the haze increases along with the change of the scene depth in general, we can make an assumption that the depth of the scene is positively correlated with the concentration of the haze and we have:

$$d(x) \alpha c(x) = v(x) - s(x) \tag{2.4}$$

Where d is the scene depth, c is the concentration of the haze, v is the brightness of the scene and s is the saturation. We regard this statistics as color attenuation prior

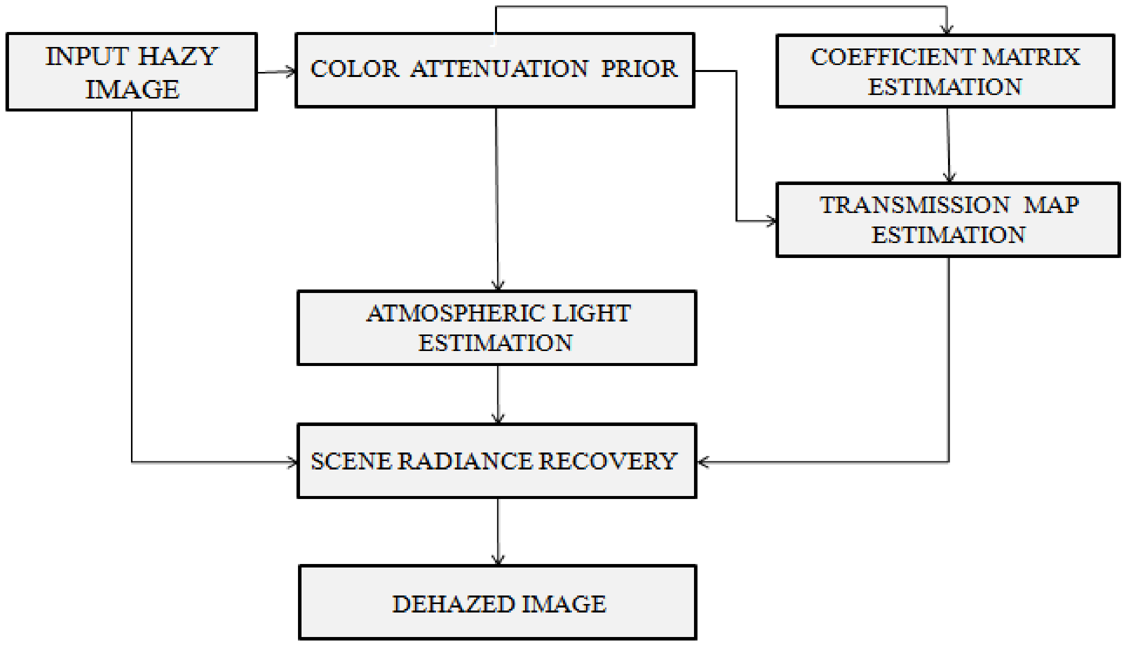

FIGURE 2.2: FLOWCHART OF PROPOSED METHOD

c. **Scene Depth Restoration**

i. The Linear Model Definition

As the difference between the brightness and the saturation can approximately represent the concentration of the haze, we can create a linear model, i.e., a more accurate expression, as follows:

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \varepsilon(x) \tag{2.5}$$

Where x is the position within the image, d is the scene depth, v is the brightness component of the hazy image, s is the saturation component, θ_0, θ_1,θ_2 are the unknown linear coefficients, $\varepsilon(x)$ is a random variable representing the random error of the model, and ε can be regarded as a random image. Gaussian density for ε with zero mean and variable σ^2.

As for the linear coefficients θ_0, θ_1,θ_2 we use the gradient descent algorithm to estimate their values. By taking the partial derivatives of ln L with respect to θ_0, θ_1,θ_2 respectively, The expression for updating the linear coefficients are also given below:

$$\frac{\partial \ln L}{\partial \theta_0} = \frac{1}{\sigma^2} \sum_{i=1}^{n} (dg_i - (\theta_0 + \theta_1 v(x) + \theta_2 s(x))) \tag{2.6}$$

$$\frac{\partial \ln L}{\partial \theta_1} = \frac{1}{\sigma^2} \sum_{i=1}^{n} v(x_i)(dg_i - (\theta_0 + \theta_1 v(x) + \theta_2 s(x))) \tag{2.7}$$

$$\frac{\partial \ln L}{\partial \theta_2} = \frac{1}{\sigma^2} \sum_{i=1}^{n} s(x_i)(dg_i - (\theta_0 + \theta_1 v(x) + \theta_2 s(x))) \tag{2.8}$$

$$\theta_i := \theta_i + \frac{\partial \ln L}{\partial \theta_i} \qquad i = \{0,1,2\} \tag{2.9}$$

There are many epochs are used in our case, and the best learning result is that θ_0 = 0.121779, θ_1 = 0.959710, θ_2 = 0.780245, σ = 0.041337. Once the values of the coefficients have been determined, they can be used for any single hazy image. These parameters will be used for restoring the scene depths of the hazy images in this paper.

ii. Estimation of the Depth Information

As the relationship among the scene depth *d*, the brightness *v* and the saturation *s* has been established and the coefficients have been estimated, we can restore the depth map of a given input hazy image according to Equation 2.5. However, this model may fail to work in some particular situations. For instance, the white objects in an image are usually with high values of the brightness and low values of the saturation. Therefore, the proposed model tends to consider the scene objects with white color as being distant. Unfortunately, this misclassification will result in inaccurate estimation of the depth in some cases.

To overcome this problem, we need to consider each pixel in the neighbourhood. Based on the assumption that the scene depth is locally constant, we process the raw depth map by:

$$d_r(x) = median_{y\in\Omega_r(x)} d(y) \tag{2.10}$$

Where $\Omega_r(x)$ is an r× r neighbourhood cantered at *x*, and. d_r is the depth map with scale *r* The new depth map d_{15} can well handle the geese regions.

iii. Guided Image Filtering

In some cases, the blocking artifacts appear in the image. To refine the depth map, we use the guided image filtering [2] to smooth the image. As can be seen, the blocking artifacts are suppressed effectively. haze-free images and their estimated depth maps. As can be seen, the restored depth maps have darker color in haze- free regions while having lighter color in dense-haze regions as expected. With the estimated depth map, the task of dehazing is no longer difficult. These filtering operations have good edge preserving property. The equation for the calculation of filtered output given as:

$$q_i = \bar{a}_i I_i + \bar{b}_i \tag{2.11}$$

Where q_i is filtered output, I_i is guidance image and $\bar{a}_i$ and $\bar{b}_i$ are linear coefficients. Linear coefficients values are calculated by using input image and guidance image by some sort of processing such as mean, variance, covariance values etc.

d. Transmission Map Estimation

Transmission Map (*t*) can be calculated by using the equation 3.2. In that equation β is atmospheric scattering coefficient value and *d(x)* is scene depth value after Guided Image Filtering. In the previous works constant β value is used. But in our method varying scattering coefficient matrix is used. It will create according to the haze concentration in the scene depth image. The transmission maps have effects on direct attenuation along with haze free image. The calculation of scattering coefficient matrix is given below.

i. Scattering Coefficient Matrix Generation

Scattering coefficient matrix is created according to the haze concentration in the image. For the visible light spectrum, the relationship between the scattering coefficient β, and the wavelength λ, is given by the inverse power law. β does not change appreciably with wavelength (analogous to Rayleighs law for small air particles)[5].Equation to calculate the scattering coefficient matrix is given below as:

$$\beta(\gamma) = \frac{K}{C^{\gamma}} \qquad \gamma = \{0,1,2,3,4\} \tag{2.12}$$

γ value is chosen according to the haze concentration scene depth image. If the pixel intensity value is high in the scene depth image, then the value of γ should be zero. If the intensity value is low, then the γ value is four. K and C are fixed values.

e. Estimation Of Atmospheric Light

We have explained the main idea of estimating the atmospheric light in Section 2.1. In this section, we describe the method in more detail. As the depth map o the input hazy image has been recovered, the distribution of the scene depth is known. It shows the estimated depth map of a hazy image. Bright regions in the map stand for distant places. According to Equation given below as:

$$\mathbf{A} = \mathbf{I}(x), x \in \{x \mid d(y) \leq d(x)\} \tag{2.13}$$

From it, pick the top 0.1 percent brightest pixels in the depth map, and select the pixel with highest intensity in the corresponding hazy image **I** among these brightest pixels as the atmospheric light **A**.

f. Scene Radiance Recovery

Now that the depth of the scene *d* and the atmospheric light **A** are known, we can estimate the medium transmission *t* easily according to Equation 2.2 and recover the scene radiance **J** in Equation 2.1. For convenience, we rewrite Equation 2.1 as follows:

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{t(x)} + \mathbf{A} = \frac{\mathbf{I}(x) - \mathbf{A}}{e^{-\beta d(x)}} + \mathbf{A} \tag{2.14}$$

Where **J** is the haze-free image we want. For avoiding producing too much noise, we restrict 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 proposed method can be expressed by:

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{\min(\max(e^{-\beta d(x)}, 0.1), 0.9)} + \mathbf{A} \tag{2.15}$$

III. EXPERIMENTAL RESULTS

This algorithm is mainly based on the concept of color attenuation prior; in this technique difference between saturation and brightness values of a given image is considered. According to the equation 3.1 haze removal is possible only when if we know the values **I**, **A** and *t*. Value of **I** is already given, it is hazy input image. Other parameters are calculated by using color attenuation prior technique.

First of all we have to calculate the value of *t* according to the equation 3.2. In that equation scene depth *d(x)* is calculated by using color attenuation prior. β is scattering coefficient value which is constant for homogeneous condition. In order to calculate the value of *d(x)*.

Here considered a linear model given in the equation 3.5. Linear model calculates the scene depth image using the linear coefficients and random error. In linear model saturation and brightness values are considered. To obtain saturation and brightness values convert RGB hazy image into HSV color space. Then saturation and brightness values are obtained. Using this values scene depth is calculated using linear model. This model has some parameters, these values learned by using supervised learning method. For the calculation of linear model more than hundred images are considered.

Depth obtained using linear model should be modified for further processing. Firstly, modify the raw depth image using median filtering operation to avoid misclassification results due to white objects. This resulted image further used for the calculation atmospheric light calculation. This same raw depth image then smoothened using Guided Image Filtering (GIM) [2]. This guided image filtering not only smoothens the raw depth image but also avoids blocking artifacts in image. Filtering output is linear transform of guidance image. For the calculation of guided image filtering two images are used one is input image and guidance image. Here input image is scene depth image and guidance image is another version of input image. That is input hazy image in this case is taken as guidance image.

Next aim is to calculate the value of atmospheric light. For that considers modified raw depth image. In that, finds the location in modified raw depth image that have 0.1 percent brightest pixel values. Then finds corresponding locations in the input hazy RGB image. From these locations finds the brightest pixel values in each color channel. For doing this inbuilt function sort is used. Three values corresponding to each color channels. These three values is consider as the atmospheric light values.

Now we have to calculate transmission map *t* by using the smoothened depth value*d(x)* and β value. Calculation of smoothened depth value is already discussed. scattering coefficient matrix is generated according to the concentration of haze in the scene depth image. Calculation of the scattering coefficient matrix is based on the equation 3.11. In that equation C =1.44 is the fixed value and the constant value is 1.2. Finally, scene radiance is recovered by using the values of **I**, **A** and *t*. These values are given to equation 3.13 to get haze free images. We can also use the equation 3.14. This equation more effectively remove noise from the image.

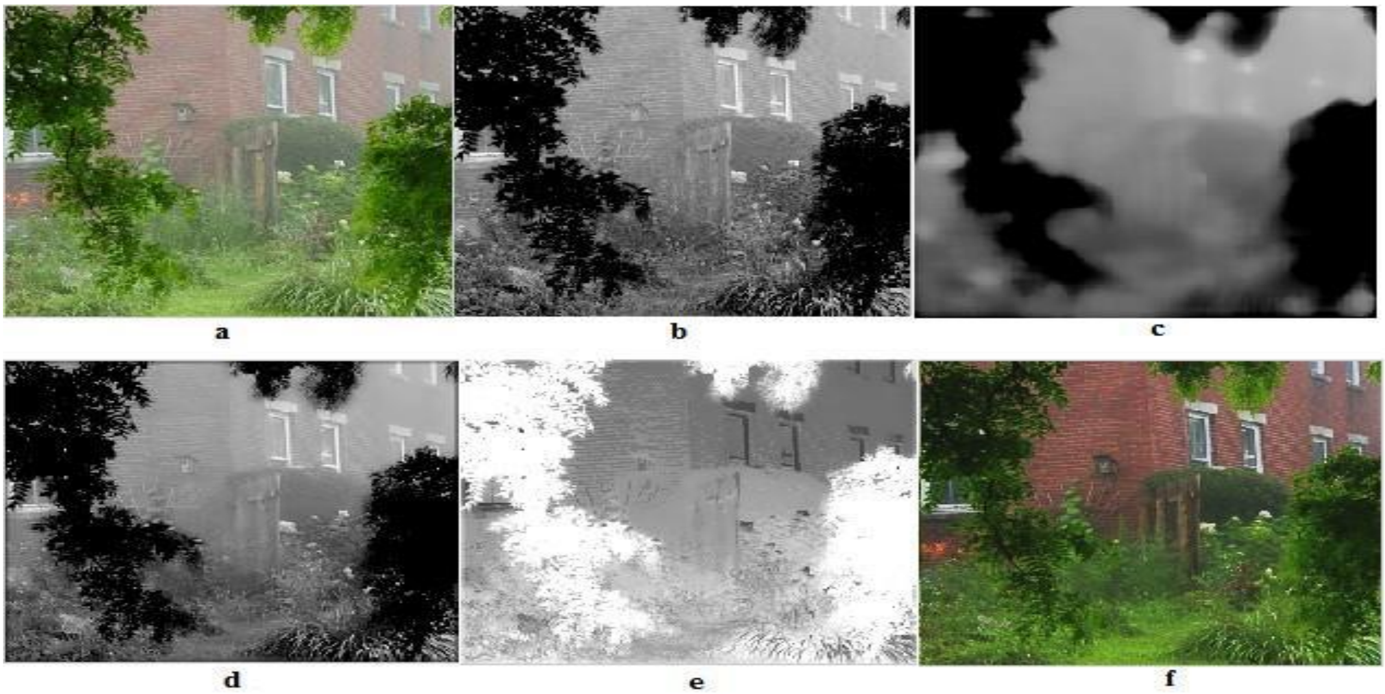

FIGURE 3.1: RESULTS OF WORK:(A)INPUT HAZY IMAGE (B)RAW DEPTH IMAGE (C)MODIFIED RAW DEPTH IMAGE (D)SMOOTHENED DEPTH IMAGE (E) TRANSMISSION MAP (F) HAZE-FREE IMAGE

IV. PERFORMANCE EVALUATION

In order to verify the effectiveness of the proposed dehazing method, we test it on various hazy images and compare with He et al.s [9], Tarel et al.s [19], Nishino et al.s [21] and quingsong [1] methods. All the algorithms are implemented in the MatlabR2013a environment on a I3 -3.30GHz PC with 4GB RAM. The parameters used in the proposed method are initialized as follows: r = 15, θ_0 = 0.121779, θ_1 = 0.959710, θ_2 = -0.780245 and σ = 0.041337.

In order to quantitatively assess and rate the algorithms, we calculate the mean squares error (MSE)[1], the structural similarity (SSIM) [20] and peak signal to noise ratio (PSNR) are considered. Let as consider each performance evaluation in detail. The MSE of each result can be calculated by the following equation:

$$e = \sqrt{\frac{1}{3N} \sum_{c\{r,b,g\}} \left\| \mathbf{J}^c - \mathbf{G}^c \right\|^2} \tag{4.1}$$

Where **J** is the dehazed image, **G** is the ground truth image, **J***c* represents a color channel of **J**, **G***c* represents a color channel of **G**, N is the number of pixels within the image **G**, and e is the MSE measuring the difference between the dehazed image **J** and the ground truth image **G**. Note that **J** and **G** have the same size since they are corresponding with the hazy image **I**. Given **J** and **G**, a low MSE represents that the dehazed result is satisfying while a high MSE means that the dehazing effect is not acceptable.

The structural similarity (SSIM) image quality assessment index [] is introduced to evaluate the ability to preserve the structural information of the algorithms. A high SSIM represents high similarity between the dehazed image and the ground truth image, while a low SSIM conveys the opposite meaning. The luminance of the surface of an object being observed is the product of the illumination and the reflectance, but the structures of the objects in the scene are independent of the illumination. Consequently, to explore the structural information in an image, we wish to separate the influence of the illumination. We define the structural information in an image as those attributes that represent the structure of objects in the scene, independent of the average luminance and contrast. Since luminance and contrast can vary across a scene, we use the local luminance and contrast for our definition.

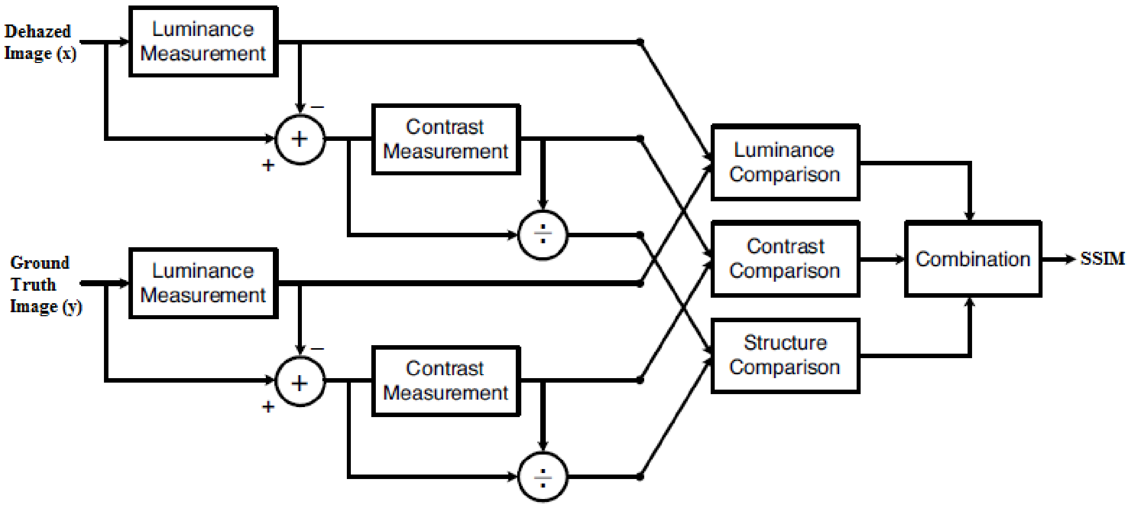

FIGURE 4.1: DIAGRAM OF THE STRUCTURAL SIMILARITY (SSIM) MEASUREMENT SYSTEM.

The system diagram of the proposed quality assessment system is shown in Fig.4.1. Suppose and are two nonnegative image signals, which have been aligned with each other (e.g., spatial patches extracted from each image). The system separates the task of similarity measurement into three comparisons: luminance, contrast and structure. Here we calculate structural similarity between dehazed image and ground truth image. The equation for the calculation of SSIM is given here as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (4.2)$$

If we consider one of the signals to have perfect quality, then the similarity measure can serve as a quantitative measurement of the quality of the second signal. In the above equation $C1$ and $C2$ are the constants. Its values are C^1=(0.01* $L)^2$ and C_2=(0.03 * $L)^2$ (default values), L is dynamic range and its value is 255 (for 8-bit grayscale image).

The third quality assessment method is based on peak signal to noise ratio (PSNR). This value is calculated by using the results of MSE. If the PSNR value is high, then the dehazed image has close similarity with ground truth image. If its value is low, opposite effect is obtained. The equation for the calculation of PSNR value is given here as:

$$p = 10 * \log_{10}\left(\frac{256^2}{e}\right) \quad (4.3)$$

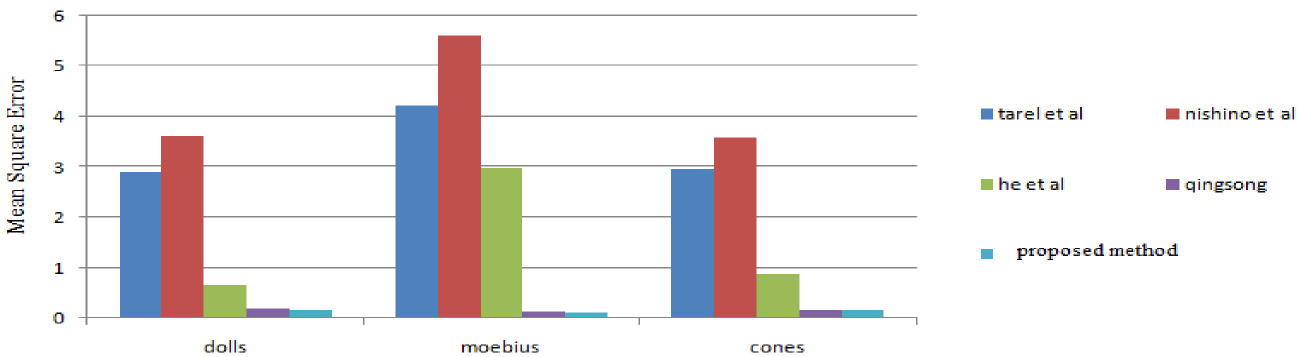

FIGURE 4.2: MEAN SQUARED ERROR (MSE) OF DIFFERENT ALGORITHMS

In the Fig. 4.2, we can see that a slight performance improvement in the cases of our method and previous method quingsong method. Both these method have MSE values less than one. Nishino et.al method have large MSE value, so it have less performance. He et.al method also have MSE value less one. It also shows better dehazing effects but its effect is less than our method according to MSE.

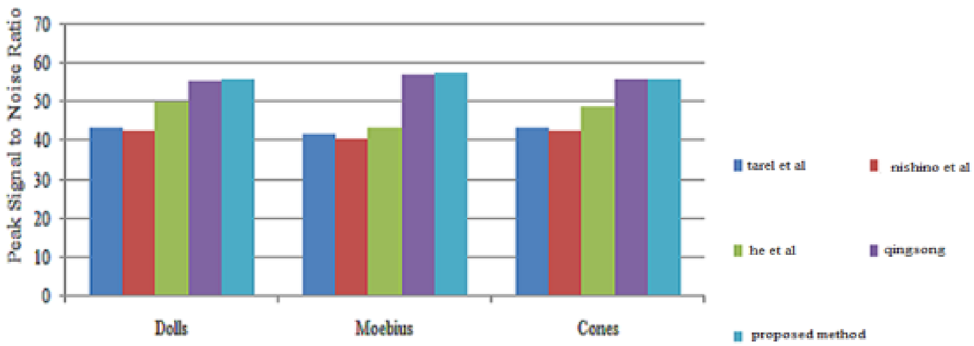

FIGURE 4.3: PEAK SIGNAL TO NOISE RATIO (PSNR) OF DIFFERENT ALGORITHMS

The Fig. 4.3 shows the comparison of different algorithm with our method based on PSNR values. From the figure, we can analyze that the PSNR values of our method and quingsong method are greater than fifty. But by close analysis we can find that our method is slightly better than quingsong method. Remaining methods have PSNR value less than our method.

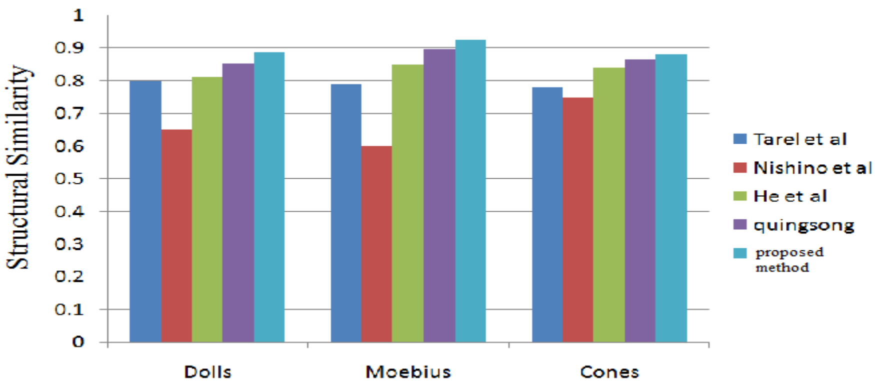

FIGURE 4.4: STRUCTURAL SIMILARITY (SSIM) OF DIFFERENT ALGORITHMS

The structural similarity also calculated for different algorithm with our algorithm in Fig. 4.4. By comparing the values three algorithms have SSIM values greater than 0.8. But our algorithm shows Structural Similarity values greater than 0.9. Nishino etal shows lower values for structural similarity. By comparing the values MSE, PSNR and SSIM values our algorithm shows better performance. In future, we can use this algorithm for removing haze from live video inputs. We can implement this algorithm in vehicles while travelling through the hazy hill stations.

Now we are going to qualitative comparison of different algorithm with our algorithm. This qualitative comparison also done on the basis of ground truth image. Fig. 4.5 shows the qualitative comparison different algorithms. From this figure we can say that 4.5 (d), 4.5 (e) and 4.5 (f) shows better performance which is very close to ground truth values.

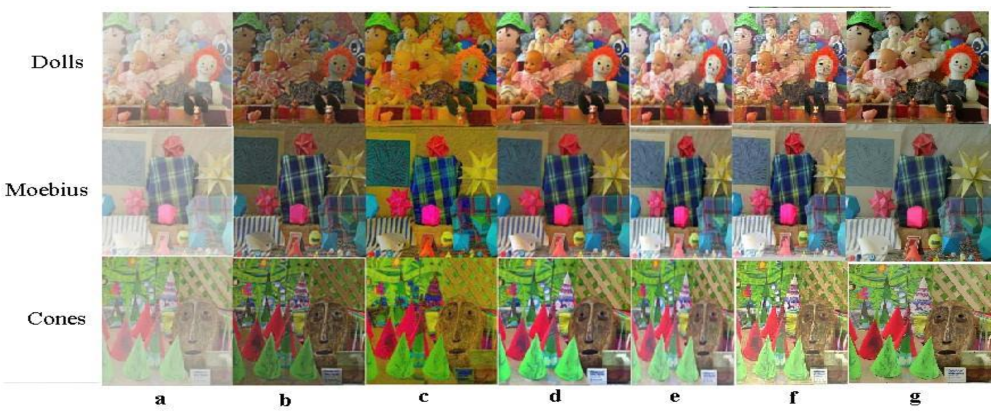

FIGURE 4.5: QUALITATIVE COMPARISON: (a) Hazy images (b) Tarel et. al. s method. (c) Nishino et. al. s method. (d) He et al.s method. (e) qingsong method. (f) Proposed method. (g) Ground truth image.

V. CONCLUSION

In this paper, we have proposed a novel linear color attenuation prior, based on the difference between the brightness and the saturation of the pixels within the hazy image. By creating a linear model for the scene depth of the hazy image with this simple but powerful prior and learning the parameters of the model using a supervised learning method, the depth information can be well recovered. The scene radiance of the hazy image can be recovered easily. Very simple smoothing operations are required for getting modified scene depth image. Simple linear model equations are used for scene depth calculation and the required terms are recovered from the linear model and the scene recovery became easier. Equations for scene depth recovery are derived from the atmospheric scattering model. Instead of using fixed value scattering coefficient, a scattering coefficient matrix is generated. It can be used only for color images. Dense haze and fog cannot be removed by this method. This simple algorithm can implemented effectively for outdoor images. images used effectively. As a future work this algorithm can be extended to videos also and can also be used for vehicles travelling in foggy conditions.

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