PRIOR BASED APPROACH FOR SINGLE IMAGE DEHAZING

A DISSERTATION

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Submitted by:

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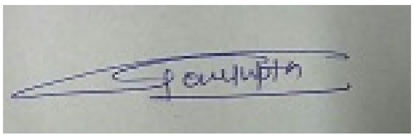
CANDIDATE'S DECLARATION

I, Gokul Gupta, Roll No. 2K18/CSE/05 student of M. Tech (Computer Science & Engineering), hereby declare that the project Dissertation titled **"Prior based approach for single image dehazing"** which is submitted by me to the Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of and Degree, Diploma Associateship, Fellowship or other similar title or recognition.



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CERTIFICATE

I hereby certify that the Project Dissertation titled **“Prior based approach for single image dehazing”** which is submitted by Gokul Gupta, 2K18/CSE/05 Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date: 27.10.2020

Dr. Anil Singh Parihar

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ABSTRACT

In the past few year, with the increase in the living standards, the understanding of security is becoming important. Video surveillance became the most crucial in terms of security, it can be used in warehouses, malls, outdoor and traffic. But in bad weather conditions, fog has a large impact on the images of the video which can degrade the quality of image and hence disturb the work of security. Hence working on removal of fog and getting a clear image became one of the most important task for the researchers. This degradation can lead to a low-quality image, which also servers input to many computer vision algorithms. Hence, dehazing is very important step for an image. The degradation can majorly be seen using the transmission map, which is one of the crucial parameters of Dehazing using a single image. The estimation of the transmission map is an underlying issue, and lots of different prior are proposed for that. Among them, one of the widely recognized prior is DCP. DCP is very efficient, effective, and easy to implement algorithm but on the same side it has some limitation. In this project we will discuss limitation of DCP and explain multiple solutions given by researchers to overcome that limitations. After that we will discuss our proposed solution and the implementation of that. We gave a simple and efficient way of dehazing a single image based on color attenuation prior and the notion of a dark channel. We first find the ambient light using decision image and dark channel then computes the transmission using the color attenuation prior (CAP). CAP uses a depth map to compute the transmission. In the later stage, we refine the transmission using the bilateral filtering and restore scene radiance using the refined transmission map and ambient light. To evaluate our approach we had used two different parameters namely discrete entropy and FADE and done comparison using two other state of the art approaches. Results shows that our model outperform the other state of the art algorithms.

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The success of this project requires the assistance and input of numerous people and the organization. I am grateful to everyone who helped in shaping the result of the project.

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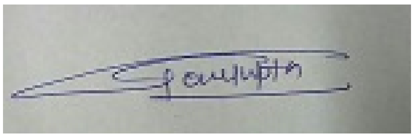
I also thank all my fellow students and my family for their continued support.



GOKUL GUPTA

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LIST OF ABBREVIATIONS

1.	HE	Histogram Equalization
2.	DCP	Dark Channel Prior
3.	CAP	Color Attenuation Prior
4.	DN	DehazeNet
5.	MSRCR	Multi Scale Retinex with Color Restoration
6.	RGB	Red, Green and Blue
7.	DI	Decision Image
8.	ADMM	Alternating Direction method of Multipliers
9.	HSV	Hue, Saturation and Value
10.	MSE	Mean Square Error
11.	BCP	Bright Channel Prior
12.	UDCP	Underwater Dark Channel Prior
13.	FADE	Fog Aware Density Evaluator

CHAPTER 1 INTRODUCTION

Images of outside locations are generally loses their quality due to the murky medium (particles of dust, water crystals) in the environment. Haze, smoke, and fog are the events due to scattering and atmospheric absorption. Brightness collected by the image shooter from the scene point diminishes down the line of vision. Further, the entering light combines with air light (atmospheric light reflects the line of vision by particles of atmospheric). The degraded outdoor images loosen the color exactness and contrast. The distance of the object or scene from the image shooter decided the quantity of the scattered light. Therefore the degradation in the image is spatial-variant. Superior quality videos and images are essential for many useful task. But not all outdoor images are in superior quality because they are taken in different light states. When a picture is taken under inappropriate light condition, the intensity values for pixels are considered to be in low dynamic range, which decreases the quality of image drastically. Moreover, the complete image looks darker, it's difficult to spot different textures or objects. Therefore, it is crucial to improve the overall characteristics of an image.

1.1 OVERVIEW

Haze is comprised of dust, aerosol, smoke etc. aerosol is the scattered system of tiny substances which are suspended in a gas. Substance disperse in ambient light beam to the line of vision and disperse out reflected light beam to a direction other than the line of vision. Due to this, blurry images are formed by scattered global ambient light and attenuation of the light reflected by scene object [1]. This type of light redistribution form the color saturation and contrast of the clicked picture degraded, that affects the visibility and is not useful to further analysis nor for processing [2]. Therefore, it is necessary for scene based applications to reduce the effect of the haze.

Dehazing is a technique that is used to remove or decrease the effect of haze from the hazy picture, which can further improve the vividness, contrast, and visibility of the given image. More Important methods to enhance the quality of image include the enhancement of contrast by using dynamic HE based on entropy [3] and gamma correction [4] [5], which give good results for low contrast image but fails for low light regions. For Low light enhancement, retinex models are discussed in [6]. In the retinex based model, the major challenge is to find illumination and reflectance. In [7], various illumination estimation methods are discussed and analyzed. Then to preserve the structural details in the estimation of illumination, a new regularization term is introduced, and then the multi-objective function is optimized by the ADMM algorithm [8].

Removal of haze has multiple advantages, which makes dehazing a common practice.

1. Haze removal can correct the color shift, which happened due to air light and also notably increases the visibility.
2. Most algorithms of computer vision depend on the scene radiance as an input parameter, which will be improved after haze removal.
3. Haze removal gives us depth information in the form of a depth map, which can further be used in many advanced image editing, vision algorithms like converting an image from 2D to 3D.

However, the problem of removal of haze is depends on the transmittance, which is associated to the depth of the scene; therefore, the solution for this problem is under constrained as a single haze image is only input available to us. Increasing the distance can also increase the effect of haze in the image, calculating the depth of the image has become a crucial thing to us. Earlier, to extract the additional information from the image, researchers try taking multiple images considering the same scene [9]. Schechner *et al.* [10] Use a method to dehaze the hazy image using the polarization concept, in which multiple images are taken with a different polarization degree. But taking images with different degrees or using different conditions and then extracting depth from them is slightly an in-efficient approach as it will be a time consuming and suffers from the heavy workload. To overcome the above problem, single image-based haze removal methods were proposed, which gives slight difficulty to dehaze image as using a single image, significantly less information is provided.

In the past few years, significant growth has been seen in dehazing using a single image. Majorly researchers focus is on improving the method to find transmission and ambient light. He *et al.* [2] gave a prior based model, according to which sky-free parts of the hazy image have significantly less intensity in minimum one color channel from R, G, and B in some patch of pixels. Though this prior works well for many applications but have some significant disadvantage as well, that it will not work for white objects and the sky region and also its computational time was one of the primary concern. Many methods were proposed to overcome the disadvantage of DCP, like [11] focused on reducing the overall time. In addition to this, many other prior based approaches are proposed, which studied different ways of finding the transmission more precisely, e.g., DehazeNet (DN) and Color attenuation prior (CAP). In CAP [12], the author focus on finding the transmission using the depth map. The depth map is estimated by taking the difference between saturation and brightness. DN [13]uses CNN on a synthesized hazy image to estimate the transmission. In [14], the concept of multi-scale retinex is discussed based on color restoration, which uses the luminance component out of the three component of the HSV image to find the transmission.

1.2 PROBLEM STATEMENT

Dehazing using single image is one of the challenging task as it comes with very limited information. Our major task is to find the clear image which is free from hazy effect. Among many models of haze removal, the model which is based on DCP is widely utilized and the hot topic for the researchers these days, but DCP comes with its own limitations. DCP won't work for large sky regions and white object. As a result of the use of soft matting, the model requires high computational time. So our main target is to work on the limitation of DCP and provide better results compared to other models.

1.3 ORGANIZATION OF THESIS

The project report has been divided into five chapters. Each chapter deals with one component related to this thesis. Chapter 1 being an introduction to this thesis, gives us a brief introduction about the project, thereafter chapter 2 tells about the literature survey which further includes a related work section. Following up is chapter 3 which tells about the proposed work. Chapter 4 provides us with the experiments and results followed by the final chapter, chapter 5, which is the conclusion of the thesis.

CHAPTER 2 LITERATURE SURVEY

The chapter explains, the work is done so far in this field and various background concepts.

2.1 BACKGROUND CONCEPT

In this module, we will discuss the basic image scattering model for hazy image, and priors which we are using in our proposed model.

2.1.1 Classic Haze Image Model

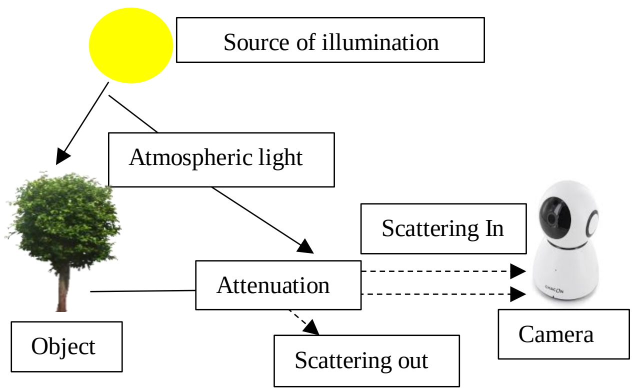


Figure 1: Classic haze imaging model diagram

As we can see in fig 1, the classic hazy image model depends on the two things. The first portion of image model is related to attenuation of reflection of the light scattered out by the scene object, and other, is related to the mechanism of scattering in due to global ambient light. Mathematically, the architecture is given as follow [1]:

$$I(y) = J(y) * t(y) + A * \left(1 - t(y)\right) \tag{2.1}$$

Where, y denotes the pixel position, I represent the foggy image, and scene reflectivity is given as J, A represents the global ambient light, t stands for transmission. First factor J(y)*t(y) represents the direct attenuation, that outline scene brightness and its degradation in the air medium, another factor A*(1-t(y)) represents the Airlight, it is the effect of previously scattered light which shifts the scene color. For a homogenous atmosphere, the transmission is given by:

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

Here, d is depth associated with the scene; β stands as a scattering factor of the atmosphere. β is kept constant, considering the atmosphere to be homogenous. Hence depth is one of the essential factor that directly affects the transmission of the image. It can be seen that as the depth of the scene decreases, scene radiance is also exponentially decreasing.

2.1.2 Dark Channel Prior

DCP was given on the observational study, that sky-free parts of the hazy image have significantly less intensity in minimum one color channel from R, G, and B in some patch of pixels. On the observation stated above, a dark channel is given as:

$$J^{dark}(x) = \min_{c\varepsilon\{r,g,b\}}\left(\min_{y\varepsilon\Omega(x)}\left(J^c(y)\right)\right) \tag{2.3}$$

Where J^c represents the pixel intensity value in a particular color channel c, Ω(y) is a neighboring local patch which have y as center. The values of dark channel are the result of 2 operators (Both minimum). For each pixel, we had to perform $min_{c\,\varepsilon\{r,g,b\}}$ In the RGB color channel space. For each patch, we will apply minimum operator $min_{z\,\varepsilon\Omega(y)}$. Keeping the path size of 15 x 15. Based on the above observation, the value of J^{dark} is very less and touches to zero (Considering only the non-sky part).

$$J^{dark} = 0 \tag{2.4}$$

The above equation/the approximation to zero and corresponding observation is called as DCP. The three factors that are responsible for the very less-intensity pixel in the dark channel calculated using equation (3) are:

1. Shadow that is reflected by any object like the shadow of leaves.
2. Sometimes, colorful objects can lack color in any 3 color channels (r, g, and b).
3. Dark object or surfaces.

2.1.3 Dehazing Using DCP

Firstly we calculate dark channel using a hazy input image. Then using that dark channel, find the ambient light and transmission map. Then after refining the transmission, calculate scene radiance. Using equation (2.1) and the DCP conjecture equation (2.4), value of transmission map t(x) is expressed as:

$$t(z) = 1 - \omega * \min_c \left(\min_{x \varepsilon \Omega(z)} \left(\frac{I(x)}{A} \right) \right) \tag{2.5}$$

The value of ω is considered as 0.95. To control over saturation ω is used. Now to calculate global ambient light (A), take the topmost 0.1% high-intensity pixel from the created DC and take the pixel with the maximum intensity from the given input hazy image. After computing the value of both A and transmission t(z), calculate scene radiance using equation. (2.1)

$$J(z) = \left(\frac{I(z) - A}{\max(t(z), t_0)} \right) + A \tag{2.6}$$

2.1.4 Color Attenuation Prior

One of the most challenging tasks in dehazing is to find an accurate transmission map. For the white object and sky region, He *et al.* [2] methodology overestimates the transmission and the other methods that are using different types of filters to refine the transmission t(x) like the median filter badly affected from color distortion or halo artifacts.

To address the above problem, Qingsong *et al.* [12] gave a novel prior called Color attenuation prior. To recover depth details, it makes a linear framework for the scene depth. Considering supervised based learning technique, linear model parameters are calculated, and a relation in been set up in between the hazed input image and the depth map of that input image. As this prior uses a linear model, its complexity and computational time is less compare to other priors. CAP says that the depth of the scene adheres to direct proportionality to the density of the haze. It is related to the saturation and brightness of the image. As difference increases into the saturation and brightness, the amount of haze is also increasing in the hazy input image.

$$d(y) \; \alpha \; c(y) \; \alpha \; v(y) - s(y) \tag{2.7}$$

Now, using the hypothesis stated above, a linear model is created:

$$d(y) = \theta_0 + \theta_1 v(y) + \theta_2 s(y) + \varepsilon(y) \tag{2.8}$$

Where s and v are the saturation and brightness of the hazy input image. θ_i are linear unknown coefficient, depth of the scene is denoted by d, ε(z) is a random variable that expresses the error generated in the method. To find ε, Qingsong *et al.* use the Gaussian function in which mean value is taken as zero, and variance is considered as σ^2. Taking Gaussian distribution property into consideration, we can have:

$$d(y) = N(\theta_0 + \theta_1 v(y) + \theta_2 s(y), \sigma^2) \tag{2.9}$$

To calculate the values of three linear unknown Coefficients, Qingsong *et al.* applied a supervised learning technique. He applies the joint conditional portability concept to calculate the three unknown linear coefficients.

$$l = p(d(y_1), \dots, d(y_n)|\, y_1, \dots, y_n, \theta_0, \theta_1, \theta_2, \sigma^2) \tag{2.10}$$

Where, n denotes the count of the pixels in the input hazed image, $d(x_i)$ is ith scene depth. L is known as likelihood. Now applying the property of Gaussian function on L and then doing the partial derivation w.r.t σ and putting it equal to zero, we can find the value of σ^2. Now to calculate $\theta_0, \theta_1\ and\ \theta_2$, use a gradient descent algorithm, and do partial derivative w.r.t $\theta_0, \theta_1\ and\ \theta_2$ respectively to get the values.

$$\sigma^2 = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \left(dg_i - \left(\theta_0 + \theta_1 v(y) + \theta_2 s(y)\right)\right)^2 \tag{2.11}$$

$$\theta_i := \theta_i + \frac{(\partial lnL)}{\partial \theta_i} \tag{2.12}$$

Now a relation is set up between the saturation, brightness and the depth of the scene, and all the unknown variables $\theta_0, \theta_1, \theta_2$ and σ are estimated, we can find the depth of the scene using equation (2.8).

2.2 RELATED WORK

The DCP is the widely utilized statistics for removal of haze. Though it is more straightforward and very effective, it has some limitations also. First, DCP won't work for large sky regions, and the white object as their intensity is intrinsically near to the global ambient light. Hence, DCP suffers from color distortion. Second, the standard DCP algorithm requires high computational time, as in the standard DCP, we calculate dark channel value using a patch of size 15 x 15, because of which we lose spatial information like edge. So to preserve edge, soft matting needs to done, which increases the overall computational time. Third, Due to the assumption in the classic haze imaging model that pure white and sufficient radiation is there on the object surface, DCP will not work significantly better on dense hazy images. As dense haze could exhibit the scene with color, which therefore leads to color distortion and low brightness. In this section, multiple approaches will be discussed to overcome the above limitation of DCP.

2.2.1 Dehazing using DCP & Energy Minimization Function

Standard DCP has a drawback that it won't work for large sky region and bright objects, Lei *et al.* [15] proposed a solution to resolve the above drawback and to strengthen the contrast, he uses minimizing energy function in those regions to find the value of transmittance. The energy function will be comprised of two terms, compensation and contrast term. Calculate transmission using energy minimizing function using 40 x 40 block pixels.

$$E = E_{contrast} + \lambda * E_{compensation} \tag{2.13}$$

Where λ is a weighting factor that is used to adjust compensation and contrast term. E is the energy minimization function, $E_{contrast}$ and $E_{compensation}$ are the contrast term and compensation term respectively. To calculate $E_{contrast}$ we use the MSE contrast metric. Now calculate the initial value of $t_f(x)$. Using the Otsu threshold, we can find the value by the actual transmission map. Transmission images can be divided using this value into the background and foreground. If the transmission map value is higher than the value, then that pixel belongs to the foreground and vice versa.

Then increase the value of $t_f(x)$ by 0.05 and calculate the value of E and consider the value, which gives the lowest value of energy function. If the value of $t_f(x)$ is going more than 1.0, then use 0.99 as the last value of $t_f(x)$. At last, to refine transmission author used a fast guided filter [16]. Then, finally, calculate the scene radiance using this refined transmission map.

2.2.2 Dehazing using Saliency map & DCP

Libao *et al.* [17] gave a method which works on haze removal of the image containing a large white object. He used two prior, namely saliency prior, which gives a relationship between the depth of hazy image and salience and DCP. Saliency prior states that in the salient region, instead of opaque haze, an object is always present in that region, and that region always has a similar transmission everywhere. To obtain a saliency map author used a hierarchical algorithm for saliency detection. First, find both dark channel and salience map, then using a salience map deduce the salience region. Using both saliency prior and dark channel, calculate the value of airtight. To decrease the effect of white objects while calculating A by He *et al.* method [2], we will exclude those saliency pixels whose value in a dark channel is greater than 0.7. While estimating transmission t(x), He *et al.* method [2] considers $J^{dark} = 0$, which is not correct when dealing with a large white object, and hence equation 5 will not hold. Libao *et al.* [17] gave a solution first to find the white area in the image and to estimate the white area, consider the comparison in each RGB color channel of calculated airlight and intensity.

$$W = \{x : min_{c\varepsilon\,\{r,g,b\}}(I^c - \lambda * A^C) \geq 0 \qquad (2.14)$$

Where W gives the white region in the input image. λ is a constant parameter, which is considered as 0.6. It concludes that the pixels having intensity greater than 60% of airlight A in each of the 3 RGB color channel, are considered as a white pixel. Let S be the salient region, then transmission need to be refined in the region containing white object is,

$$N = W \cap S \qquad (2.15)$$

$$t(x) = t_s\{x\varepsilon N\} \qquad (2.16)$$

Where transmission of the salient region is considered as t_s and N is a region for which we need to refine the transmission. The major drawback of this novel solution is that it considers that transmission in the same in the salient region, which is not always true.

2.2.3 Efficient Image Dehazing using Pixel based DCP & Guided Filter

Saminadan *et al.* [18] gave a novel method to enhance the computational time of standard DCP. In this paper, the author used two prior based models, namely pixel-based bright channel prior(BCP) and pixel-based DCP. Then using haze density analysis, Saminadan *et al.* [18] Estimate global atmospheric light, accompanied by calculating the transmission map and refining it with a guided filter. Haze density analysis says that shallow regions have a low density of haze compare to deeper regions that have a high density of haze. First, transform the image into HSV color space as HSV space describes color into brightness and shades, which is a better way to relate atmospheric light. Then for every pixel, estimate the HSV distance d(x). Now transform d(x) to s(x).

$$s(x) = 1 - \frac{d(x)}{\max\limits_{y\varepsilon HSV}(d(y))} \qquad (2.17)$$

For every pixel x, s(x) is proportional directly to the thickness of the haze

$$A^c(x) = \frac{A^c_{highest} - A^c_{lowest}}{\max_{y\varepsilon I}\left[1-\frac{1}{d(y)}\right] - \min_{y\varepsilon I}\left[1-\frac{1}{d(y)}\right]} * s(x) \qquad (2.18)$$

Using the J^{dark} estimate the value of $A^c_{highest}$ by considering the brightest pixel from a dark channel and selecting the same pixel from the input hazed image I and similarly estimate A^c_{lowest}. Considering the darkest pixel from the bright channel and selecting the same pixel from the input image I. considering the dark channel calculated pixel-wise and the value of global ambient light $A^c(x)$ which is calculated above, the transmission map is defined as,

$$t(y) = 1 - \omega * \min_{c\varepsilon\{r,g,b\}}\left(\frac{I^c(y)}{A^c(y)}\right) \qquad (2.19)$$

Further, this transmission is refined using the guided filter. Using guided filter doesn't suffer from artifacts like gradient reversal, unlike bilateral filter, and it also presser the spatial information like edge. And using a guided filter consumes less time compared to the soft matting.

2.2.4 Fast DCP based Dehazing

To overcome the drawback of the high computational time of DCP, which is given by He *et al.* [2], an improvised version is proposed by Iwamoto *et al.* [19] on the existing version of DCP which reduces the overall computational time. In [19], author proposed a solution to find dark channel pixel-wise using a down-sampled image. In standard DCP, a dark channel is estimated using each local patch of size 15 x 15, due to which edges are not smooth and preserved, and hence we required soft matting, which increases the overall computational time. As in the method given by Iwamoto *et al.* [19] dark channel is calculated pixel-wise. Therefore soft matting is not required. Due to pixel-wise calculation, spatial information such as edge is preserved. Box averaging filter is used to down-sample an image. In this method, a dark channel is calculated using 1 x 1 instead of 15 x 15 patch, and there is a chance because of removing spatial minimization, dark channel values in dark light has very small values (not exactly zero). Therefore there is a need to improvise the transmission as well.

$$T_j = 1 - \frac{\gamma\left(min_{c\,\varepsilon\,\{r,g,b\}}\left(\frac{I(y)}{A}\right) - min_c\left(min_{y\,\varepsilon\,\Omega(x)}\left(\frac{I(y)}{A}\right)\right)\right)}{min_c\left(min_{y\,\varepsilon\,\Omega(x)}\left(\frac{I(y)}{A}\right)\right) - min_c\left(min_{y\,\varepsilon\,\Omega(x)}\left(\frac{I(y)}{A}\right)\right)} \qquad (2.20)$$

$$T(y) = 1 - \omega * \min_{c\varepsilon\{r,g,b\}}\left(\frac{I^c(y)}{A^c}\right) / T_J \qquad (2.21)$$

Where γ is the adjusting factor, and Ω is used for the whole image. To determine the value for maximum dark channel value in J, we use γ.

He *et al.* [2] method may ignore the white object while calculating the value of global atmospheric light as it calculates the value of a dark channel using a 15 x15 patch. Iwamoto *et al.* [19] gave a model to calculate the value of **A**. He first sort the 0.1% pixel, which are the pixels possessing the highest intensity in the DC of image containing haze. Then he used coarse to fine strategy to find the ambient light, take the brightest pixel from a low-resolution picture to the high-resolution picture.

2.2.5 Dense Hazy Image Enhancement using Generalized Imaging model

The standard DCP uses a classic hazy image model (as described in section II-A), which assumes that on the object surface, pure white and sufficient enough radiation is there, but this assumption won't hold for the dense, hazy images. So using classic DCP for removing dense haze results in color shift or a darker look. Yuanyuan *et al.* [20] gave a dense haze removal algorithm, which is based upon a generalized hazy image model. Haze image generalized model is given as follow:

$$I_i^c = L_\infty^c T_i^c R_i^c t_i + L_\infty^c T_i^c (1 - t_i) \tag{2.20}$$

Where c represents the 3 color channels RGB, L_∞^c is atmospheric light for the color channel c, Reflectance is denoted by R, the transmittance is expressed by t, and T, which is introduced in this model, is an attenuation coefficient of atmospheric light. Now using gradient recursive bilateral filter, first find the pseudo atmospheric illumination, then using it to remove the effect of attenuation radiation. After that, using the general regularity of the hazed image, calculate the transmission using the system of spherical coordinate.

$$L_i^c = (1 - b) * I_i^c - R_{i,i-1} * b * L_{i-1}^c \tag{2.21}$$

Where, I is the hazy input image containing haze, $R_{i,i-1} = \exp(-\frac{|I_{i-1} - I_i|^2}{2\sigma_r})$, $b = p(-\frac{\sqrt{2}}{\sigma_s})$, σ_r is range variance and σ_s is the variance of space. Now eliminate the effect of attenuation by recovering Reflectance as follow:

$$R_i^c = \frac{I_i^c}{L_i^c} \tag{2.22}$$

Now, express Reflectance in terms of spherical coordinates using radius, latitude, and longitude. In the spherical system, it is observed that transmittance t is affected by only radius r; hence we represent our equation in terms of radius and calculate the value of t as follows.

$$r_i = t_i \left| R_i - 1 \right|, \ 0 \leq t_i \leq 1 \tag{2.23}$$

$$\hat{t}_l = r_i / \hat{R}_{max} \tag{2.24}$$

2.2.6 Enhancing Underwater Image & Color Correction

Due to attenuation and scattering of light underwater images potentially suffers badly from the low contrast, distortion in the color of the image, and poor visibility. Previously standard DCP is directly applied to the underwater degraded images but it doesn't shows the major results even in the less degradation. Then Bianco et al. [21] give a solution considering that observed light in water varies according to the wavelength and red color is more attenuated than the blue or green. But due to the high absorption rate in the red channel, it becomes tougher to model the behavior of the red channel. Then a prior is made named as UDCP, which only consider green and blue channel while calculating the dark channel. UDCP lacks as the level of turbidity increases, it enhances the image to some proportion but scene characteristics are still susceptible. In [22] Min et al. proposed a method using all three color channels while calculating dark channel and color correction concept to enhance and improve the quality of underwater hazy images.

Using the combination of the saturation map and DCP Min et al. calculate the background light of the image. Then using attenuation coefficient ratio transmission t(x) of all 3 color channels is estimated. To balance the color shift in the output image lastly color correction is applied. He's method [2] to find the background light loses its effect when there is lots of sunlight, it decreases the durability while finding the atmospheric light. As the light of the sun gives a balance shade that tends to white light Min considered the saturation factor to calculate the background light. First Min finds the airlight using He's method then if the saturation of the particular pixel is less than the ρ times average saturation, that pixel is considered otherwise it will be removed.

$$saturation = \max(r, g, b) - \min(r, g, b) \tag{2.25}$$

Now to calculate the transmission map, Min uses both DCP and attenuation coefficient ratio. Mainly the shorter wavelength results in higher transmission which is expressed as

$t_r < \min(t_b, t_g)$, hence transmission is not the same in the underwater image like in the air. To deduce the transmission of the blue and green channel we use attenuation coefficient ratio and calculate transmission for red channel as follow:

$$t_r(x) = 1 - \min_{x \varepsilon \Omega(y)} \left(\min_{\lambda \varepsilon \{r,g,b\}} \left(\frac{I_\lambda(x)}{B_{x,\infty}} \right) \right) \tag{2.26}$$

$$t_g = t_r^{\eta_g/\eta_r} \tag{2.27}$$

$$t_b = t_r^{\eta_b/\eta_r} \tag{2.28}$$

To refine the generated transmission map using above equation and to preserve the edge Min used soft matting which was the major drawback of the proposed solution as soft matting increases the overall computational time to very high.

After getting the transmission and background light, scene radiance is calculated. In the recovered result slight color shift is observed, to remove this effect concept of color correction is used.

2.2.7 MSRCR & Physical Model based Dehazing

Considering the limitation of standard DCP of high computational time and adverse results in case when the intensity of scene object is similar to airtight, Jinbao *et al.* [14] give a solution using both the Retinex theory and physical model. Jinbao *et al.* [14] used the MSRCR algorithm [23] to calculate the transmission. To estimate the ambient light A, firstly, find the dark channel $J^{dark}(y)$ using input image I(y), then calculate threshold f(y) decision image from the same input image I(y). Now using $J^{dark}(y)$, I(y) and f(y) estimate global ambient light A. Decision image is used to defeat the problem of underestimation for white objects, including the sky regions also.

$$f(y) = \sqrt{(b^2 + g^2 + r^2) - \frac{(b+g+r)^2}{3}} \tag{2.29}$$

Now pick the brightest 0.1% top pixels from J^{dark}. Then choose those pixels which have $f(y) > \Delta$ (which is taken as 6). If $f(y) \leq \Delta$ that means that pixel is a bright pixel and can be discarded from a dark channel. Finally, take the average of the intensity of all the remaining pixels and considered that average value as the ambient light A. This method of calculating A overcome the problem of sky region and white object whose intensity is similar to airlight.

To estimate the transmission map author used the MSRCR algorithm. MSRCR id used as it gives us color consistency, dynamic range, and edge preservation property of an image. First, calculate the luminance and using it, find the rough transmission map, then refine it using max and blur filters. Due to computational reasonability we convert image from RGB color channel to YCrCb channel. Luminance component enhanced is defined as follow:

$$L'_{MSRCR}(x,y) = \ln\left(\frac{I_i(x,y)}{\left(\frac{1}{M}\right)\sum_{(x,y)\,\varepsilon\,\Omega} I_i(x,y)}\right) * \sum_{n=1}^{N} \omega_n * (\ln\big(I_i(x,y)\big) - \ln(G(x,y) * I_i(x,y))) \tag{2.30}$$

Where, I_i is the ith component image, total count of a pixel in an input image is denoted by M. G represents supporting function (Author used Gaussian function) with the different scales, N shows the total number of scales used, and weights are represented by ω. Now scale transformation is performed to transfer the luminance in the visible light range then rough transmission $T'(x)$ is estimated.

$$L_{MSRCR} = \delta * L'_{MSRCR} + \kappa \tag{2.31}$$

$$T'(y) = \mu * L_{MSRCR} - I(y) \tag{2.32}$$

κ is a factor of compensation to increase the image dynamic range linearity, δ is utilized to convert the image to human vision visible range, and μ is known as a gain factor. To remove low contrast and fuzzy effect, subtract image from the luminance to get the transmission. To further enhance the transmission we process $T'(y)$ with max and blur filter and obtain the final transmission t(y).

2.3 RECENT MODELS

In this part of the report, we had reviewed the recent work proposed in the area of dehazing. Haze removal for thick haze and the thin cloud using sphere model and improvised DCP is presented by Li *et al.* [24]. In this script, Li *et al.* focuses on the dense hazy image and the effect of thin cloud on the outdoor image. It also gives a solution for the unevenly distributed haze in the outdoor image. First, to improve the evenness of the Haze Li *et al.* [24] applied homomorphic filtering on the input image (basically making the illumination part even), then to find a transmission map, he used the sphere model on the DCP. Based on Rayleigh scattering and DCP, Jackson *et al.* [25] gave a fast dehazing solution for a single haze image. Jackson *et al.* [25] used the Rayleigh scattering theory to find the transmission map by making a scattering coefficient model. It finds the intensity loss of light in every direction. Then using scattering, global atmospheric light, and depth of the scene, t(x) is estimated, and after that, he prune transmission t(x) utilizing the fast guided filter. Shin et al [26] give another method to draw out the effect of haze from a hazy outdoor image, he proposed a weighted DCP based method in which no post-refinement is required, which saves our computational time. Shin *et al.* [26] considered two parameters spatial distance and the concept of color similarity to calculate the dark channel. Pei *et al.* [27] give a method to remove nighttime haze effect in which first he find the atmospheric illumination using a bilateral filter and using that illumination Pei *et al.* [27] find the value of A. Using the difference of image brightness value in the non-light time and light time, Pei calculates the transmission. In [28] Zhang *et al.* gave a fast end to end dehazing method, which learns the haze-free image using a fusion module and comprises of encoders, where each encoder is comprised of convolution and pooling layers.

CHAPTER 3 PROPOSED WORK

In this chapter, we will give detail idea of our proposed novel model for removing hazy from a hazy image using color attenuation prior, decision image, and dark channel. We had given an approach to dehaze an image using a better value of ambient light A and refinement of the transmission. We first calculate the decision image and dark channel, using which we will find the value of A (ambient light). Then using the method of CAP, we will find the transmission map and refine it with the help of a bilateral filter, unlike guided filter, which was used in CAP as it will give some artifacts. In the Figure 1, an example of hazy images and there dehazed version using our approach is given.

(a) (b)

Figure 2 Ny_city1 : (a) Hazy input image (b) Dehazed image

3.1 PROPOSED METHOD

In most models, estimation of ambient light uses the brightest pixel of an image in each RGB channel, but this can cause an issue when the image contains bright color objects. To address this issue, we will first calculate the dark channel using a 15 x 15 patch. After that, we had applied the concept of decision image, which decides which pixel to keep for the calculation of atmospheric light. For calculating transmission map, we had used the depth map which was estimated using CAP and also discussed on the refinement of the transmission map. Flowchart of the proposed model is discussed in figure 2.

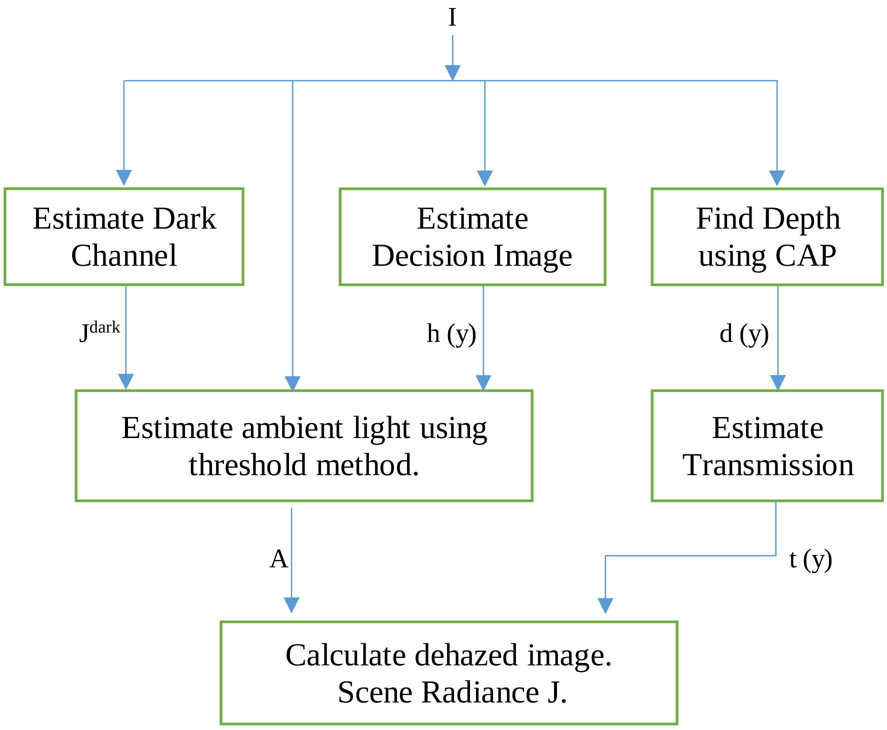


Figure 3: Flowchart of Proposed Model

3.1.1 Ambient Light Estimation

For the estimation of ambient light, we first find the dark channel, as explained in chapter 2. It has a drawback that it won't work for broader sky regions and brighter objects, Wang *et al.* [14] gave a solution to resolve the above-stated issue. He uses the concept of decision image as an intermediate step in finding the value of atmospheric light.

Wang *et al.* used the threshold method to find the ambient light, considering the white objects or area and the distribution of pixels in an immense sky region. Decision image h(y) is expressed as:

$$h(y) = \sqrt{(b^2 + g^2 + r^2) - \frac{(b+g+r)^2}{3}} \tag{3.1}$$

Where the three color channel intensity value is represented by {r, b, g}, √. is the square root symbol, y is the pixel for which we will be calculating the value of the decision image. In below Figure 4, 5 & 6, flowchart for calculation of ambient light, dark channel and decision image are shown, respectively.

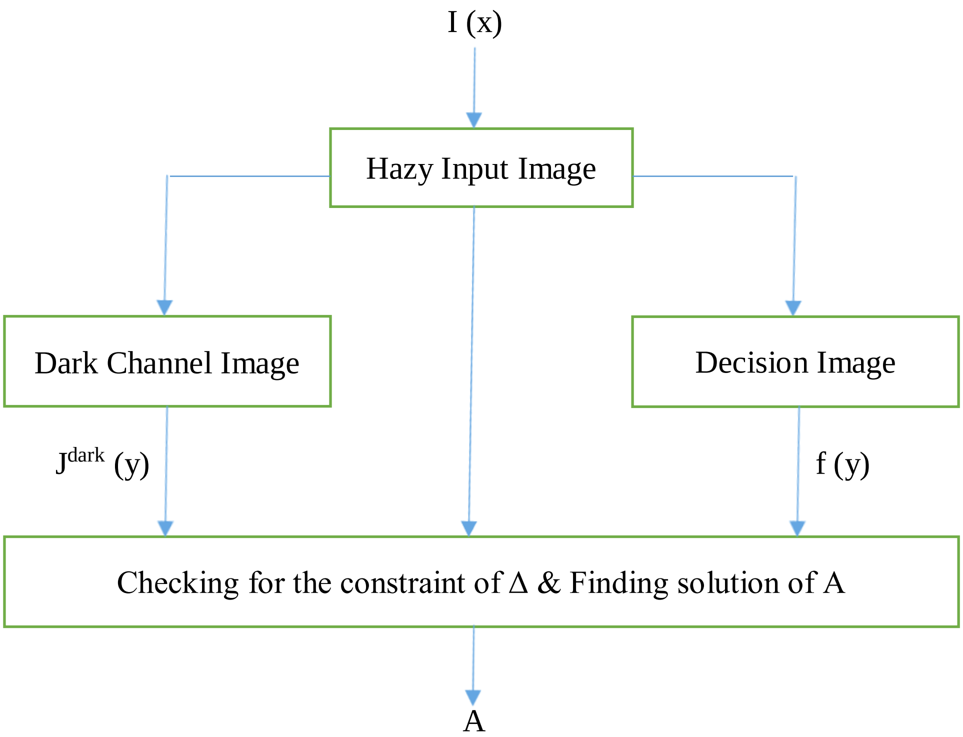


Figure 4: Flowchart for calculation of ambient light.


Figure 5: Dark channel of fig 1(a)


Figure 6: Decision Image of fig 1(a)

Now the brightest top 0.1% intensity pixels from J^{dark} are picked. Then among the selected pixels, choose which have the h(y) > Δ. If the value of $f(y)$ is less than or equal to Δ, it means that pixel is a bright pixel and can be discarded from the dark channel. At last, take the average of the intensity of all remaining pixels and considered that average value as the ambient light A. This method of calculating A (ambient light) overcome the problem of large sky region and white object whose intensity is similar to airlight.

Figure 7: Position of the atmospheric light of fig 1(a)

3.1.2 Estimation and Refinement of Transmission Map

We had given a detailed explanation of the model used to estimate depth d(y) of an input hazy image in chapter 2.1.2. In which using the prior based study, we will first estimate the value of depth. After recovering the depth of the hazy input image, the scene depth distribution will be known to us. Using the estimated depth and equation (2.2), we can find the value of transmission t(x), keeping the value of β constant. For estimating the depth, CAP uses difference of saturation and brightness. According to the observational study as the difference increase between saturation and brightness, the density of the hazy also increases.

Estimation of depth can lose the edge preservation property of the image, and artifacts will also be seen in the image. To eliminate artifacts and halo effects of the transmission image, we can use soft mating or bilateral filtering. Soft matting, which uses the Laplacian operator to refine the transmission, is a highly time-consuming process to refine the transmission. Thus in this project, we refine the transmission using bilateral filtering, which is suitable for edge-preserving and removes the halo artifacts from the map. It also removes any noise if available on our map and can do the image smoothing as well.

3.1.3 Scene Radiance

Now, as we have transmission t (z), and the ambient light, we had extracted the fog free image (Scene radiance) J using equation (2.6).

Considering the sky region, which can have transmission tending to zero as the color of the bright sky region is near to the ambient light, the value of transmission is limited by t_0, which will take care of any noise introduced because of false calculation of transmission for the sky region.

3.2 STEPS OF METHODOLOGY USED

Step 1: Using equation (2.3), estimate dark channel of input hazy image I, say J^{dark}.

1.1. Select a patch of size 15 x 15, then find minimum intensity pixel among them using minimum operator.

1.2. Then again apply minimum filter, to find the minimum intensity among all the three color channel RGB.

Step 2: Using equation (3.1), estimate decision image of input hazy image I, say f (y).

Step 3: To find the value of ambient light:

3.1. We will take brightest 0.1% pixels from dark channel and for each of those pixel we will check for the value of f (y). If value of f (y) is greater than the threshold value Δ, we will consider that y pixel for the calculation of **A** otherwise take pixel will be discarded.

3.2. At last, take the mean of all the selected pixel for the calculation of ambient light.

Step 4: Now find the transmission map t (y).

4.1. First find the depth map using CAP.

4.2. For finding depth map use equation (2.8), taking the difference of saturation and brightness. Values for constants can be taken from [12].

4.3. After calculating depth map, using equation (2.2) we can find the value of t(y).

Step 5: To preserve the edges and remove artifacts, refine the transmission t (y) using bilateral filter.

Step 6: Finally, find the value of J (dehazed image) using the value of ambient light calculated in step 3, the value of refined transmission from step 5 and putting them in equation (2.6).

CHAPTER 4 EXPERIMENTAL RESULTS

In the present section, we will do the comparison with two more state-of-the-art methods. We had implemented the above-discussed algorithm on windows 10 64 bit machine with an i3 processor and 4GB RAM using Matlab.

The parameters used in the implementation for ambient light are as follow: $\Delta = 6$, experimental analysis for the value of Δ, says that if we decrease the value of Δ or increase it from 6, the image will start losing its information due to the introduction of color cast in the image, making ambient light erroneous. Parameters for transmission are taken from the experimental results of [12] and are as follows: $\theta_0 = 0.1211779$, $\theta_1 = 0.959710$, $\theta_2 = -0.780245$ and $\sigma = 0.041337$. For the dark channel, the radius for considering neighbors is kept as 15. Keeping the radius less (say 3) will increase the halo artifacts and also give false results for large white objects and sky region, and taking a larger value (say 15 or more than 15) can lost the essential information of the actual image.

4.1 QUALITATIVE RESULTS

We had performed the qualitative analysis on 9 different images, which comprise of white object, large sky area, and dense hazy area in the image. To compare our proposed model we had use two other state of art methods, color attenuation prior and DehazeNet. Fig 6 to 14 shows the result. In each figure there are four images, (a) hazy input image, result of, (b) CAP, (c) DehazeNet, and (d) Our proposed model.

(a)

(b)

(c) (d)

Figure 8: Results for Ny_2 image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c) (d)

Figure 9: Results for Cones image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c) (d)

Figure 10: Results for Mountain image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c) (d)

Figure 11: Results for Toys image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c) (d)

Figure 12: Results for Trees image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c) (d)

Figure 13: Results for Canon image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a) (b)

(c)

(d)

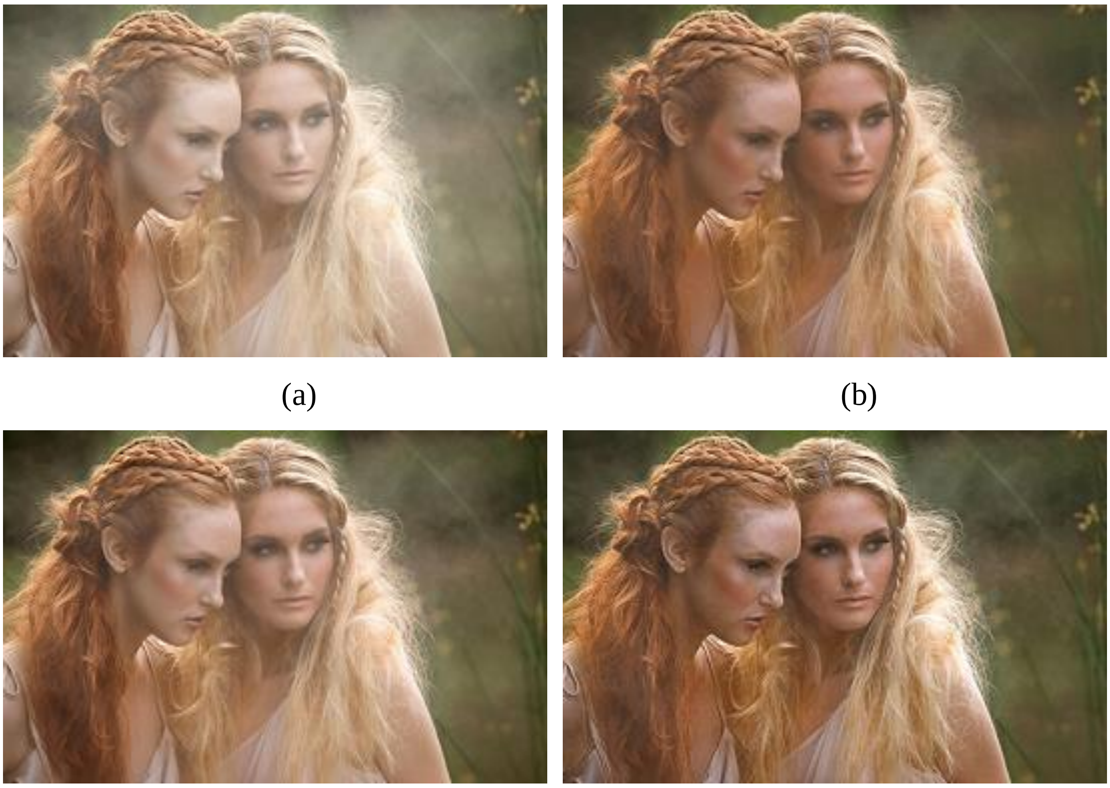
Figure 14: Results for Man image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

(a)

(b)

(c) (d)

Figure 15: Results for Gugong image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method



(a) (b)

(c) (d)

Figure 16: Results for Girls image. (a) Hazy input Image, (b) CAP, (c) DehazeNet, and (d) Proposed Method

Fig 8 to 12 are normal hazy images, Fig 13 is a dense hazy image and Fig 14 to 16 are the images having large white regions. As you can see results of the CAP looks brighter compare to other methods but actually those results are erroneous as it loses more information compare to other algorithms. Our model suffer from one drawback which we can clearly see using fig 12, proposed model suffers from reversal artifacts due to use of bilateral filter.

4.2 QUANTITATIVE RESULTS

Human visual system have some limitations due to which we are required to do quantitative analysis. We need to focus on two things mainly, one is the information that is present in the image, and the other is the dehazed level. In order to perform the quantitative analysis, we are using two parameters, discrete entropy and FADE. We had used 2 other algorithms to compare our methodology.

Evaluation parameter entropy gives us the information about the statistical measure of randomness of a picture, and its output value represents the amount of the exact information that the image contains. The higher the value of entropy more the information in the image. In the case of an image taken in the foggy environment, the image loses its information, and the value of entropy is minimal. We define entropy as:

$$Entropy = -\sum_{k=1}^{m}\left(p(k)\log p(k)\right) \tag{4.1}$$

Where $p(k)$ denotes the probability for the k^{th} grey level pixel, and the Intensity level count in the image is represented by m. The dynamic scale of the output image can be quickly evaluated using the entropy parameter.

Evaluation parameter FADE (fog aware density evaluator) [29] is used for the hazy density analysis. It can be used to analyze the density of hazy on the entire image or for any local patch. It does not require any other image apart from the image, which is to be evaluated. The lower value of FADE represents better visibility and quality and low density of haze.

Images	Different Models		
	CAP	DehazeNet	Proposed
Ny_2	7.4567	7.4588	**7.5036**
Cones	6.8855	**7.0146**	6.9044
Mountain	6.854	6.9495	**6.9736**
Toys	7.4317	7.3257	**7.5345**
Trees	6.6932	**6.7613**	6.7287

Canon	6.7417	6.7859	**6.8626**
Man	7.5222	**7.6977**	7.5761
Gugong	7.2125	7.2513	**7.3532**
Girls	7.03	**7.2092**	7.1363

Table 1: Quantitative results for discrete entropy parameter.

Images	Different Models		
	CAP	DehazeNet	Proposed
Ny_2	1.5622	1.5148	**1.4619**
Cones	2.1661	2.1984	**2.0203**
Mountain	3.074	2.9031	**2.8869**
Toys	2.2267	2.4773	**2.1367**
Trees	1.8497	1.9249	**1.715**
Canon	3.0845	3.0651	**2.9765**
Man	2.1009	2.2687	**1.7958**
Gugong	1.9137	2.0602	**1.5863**
Girls	1.9038	2.1373	**1.8719**

Table 2: Quantitative results for fade parameter.

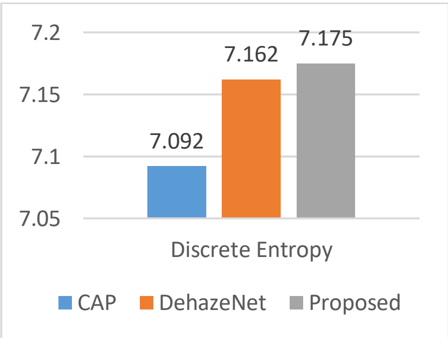


Figure 17: Mean value of all images For Discrete Entropy

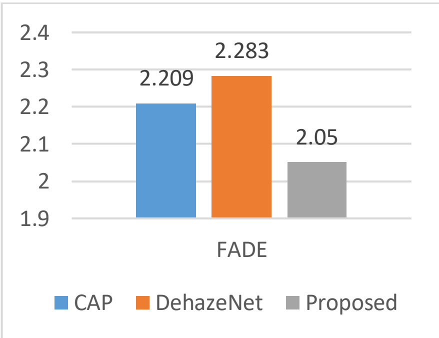


Figure 18: Mean value of all images for FADE

As we can see in tables 1 and 2, our approach gives more information about the image, and hazy density is less, comparable to other state of the art methods. In the case of trees, man and girls image, due to reversal artifacts, we lose some information, and hence the highest value of entropy is not of our proposed model. We can clearly see in the fig. 15 that our approach give the maximum exact information in the dehazed image compare to other state of art algorithm. DehazeNet method also gave the sufficient amount of information, but as fig. 16 says that it does not remove haze efficiently compare to our proposed dehazing method.

CHAPTER 5 CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

In this report, we had discussed an model based on color attenuation prior and decision image. Using the concept of CAP, we have calculated the depth of the image and using the decision image and dark channel, we had estimated the ambient light. Transmission is estimated using the depth of input image and then refined using the bilateral filter. We had also given a detail survey in this report related to the limitation of DCP and the solutions proposed by different authors for every limitation.

Experimental output show that the proposed approach gives better results than the previous state of the art models. Our model has a limitations that on some particular images, it suffers from reversal artifacts due to the use of a bilateral filter and it does not work well in night scene based images.

5.2 SUMMARIZATION

In this part of the report, I will discuss each and every chapter of this thesis in the brief manner. Main aim of the thesis is to give a state of art solution for dehazing a single hazy image.

In chapter 1, we had discussed basic introduction of the dehazing. We had explained the reasons behind dehazing and then the advantages of the dehazed image. As image is used as an input to many computer vision algorithm it's become important to dehaze the image so that results of CV doesn't have degraded effect of haze. We had also discussed some approaches to dehaze the image like polarization method, dark channel prior etc. DCP plays a vital role in the study of dehazing but it comes with some limitations as well.

In chapter 2, we had first explained all the important methods used in our approach like DCP, CAP, dark channel etc. Then for each limitation discussed in chapter 1, we had given a brief survey with the solution of each limitation. We had discussed methods which uses pixel wise calculation of dark channel and for transmission authors had used different approaches like using depth estimation (CAP), MSRCR theory, spherical coordinate etc.

Chapter 3 illustrate our proposed method. We had used dark channel and threshold based method to estimate ambient light and for estimation of transmission we had used depth of the image, which can be extracted using the brightness and saturation of the input hazy image. Further we had refined our transmission map with bilateral filter and at last extracted the scene radiance using the classic image hazy model.

Chapter 4 gives us the idea of betterment of our proposed method. In chapter 4 we had given the experimental analysis of our approach with other two state of art algorithms (Color Attenuation Prior and DehazeNet). To analyses our result we have used FADE and discrete entropy to compare results with other two models. Results shows that our method gives significantly good results compare to other approaches.

5.3 FUTURE SCOPE

Our proposed work have some limitations that it will not work very efficiently in case of night scene hazy image and due to the use of bilateral filtering our method suffers from the reversal artifacts. These limitations we are leaving for the future research and additions to the above future scope, we can further make our proposed method work for video dehazing as well. Addition to that there is further scope of improvement in the methodology to estimate the depth of the input image.

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APPENDIX

LIST OF PUBLICATIONS

[1] Anil Singh Parihar, Gokul Gupta, "A Study on Dark Channel Prior based Image Enhancement Techniques". Accepted, Presented and Published at **10th International Conference on Computing, Communication and Networking Technologies (ICCCNT 2020).**

Abstract - The existence of haze and cloud degrades the quality of the image taken by camera sensors and decreases their clarity. The degradation can majorly be seen using the transmission map, which is one of the crucial parameters of Dehazing using a single image. The estimation of the transmission map is an underlying issue, and lots of different prior are proposed for that. Among them, one of the widely recognized prior is a dark channel prior (DCP). DCP is based on the statistics that a local patch in the sky-free region often has some pixel which has less-intensity value in at least one of the R.G, and B color channel. In this paper, we first discuss the limitations of the DCP and then give a detailed review on how to overcome the limitations of DCP by improving the calculation of global ambient light and transmission map compared to the standard DCP.

[2] Anil Singh Parihar, Gokul Gupta, "Prior based Single Image Dehazing Using Decision Image". Accepted at **4th International Conference on Electronics, Communication and Aerospace Technology (ICECA 2020).**

Abstract- Visibility of outside images is mainly degraded due to dust, fog, and other tiny particles available in the air when captured using a camera. This degradation can lead to a low-quality image, which servers input to many computer vision algorithms. Hence, dehazing is very important step for an image. In this letter, we gave a simple and efficient way of dehazing a single image based on color attenuation prior and the notion of a dark channel. We first find the ambient light using decision image and dark channel then computes the transmission using the color attenuation prior (CAP). CAP uses a depth map to compute the

transmission. In the later stage, we refine the transmission using the bilateral filtering and restore scene radiance using the refined transmission map and ambient light. Experimental analysis shows that our methodology enhances the quality of the image, which got degraded due to hazy weather.