A New Approach for Removing Haze from Images

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Abstract-The presence of suspended particles like haze, fog, mist, smoke and dust in the atmosphere deteriorates quality of captured image. It is of paramount importance to reduce these deteriorating effects from the image for various image based applications; viz. ADAS, CCTV surveillance, etc. In this paper, this interesting problem of enhancing the perceptual visibility of an image that is degraded by atmospheric haze is addressed. An efficient way of estimating the transmission map and the atmospheric light is proposed, which is further used in reducing effects of haze from the image. The underlying idea is to restore the true color of each pixel by using our proposed method that minimizes the lowest of RGB values per pixel. This is accomplished using the HSV color space and the haze image model. In comparison with the other state of the art methods that are available in literature, the proposed method is shown to be capable of recovering better haze-free images both in terms of visual perception and quantitative evaluation.

Keywords: HSV color space, Atmospheric light, Transmission map, De-hazing

1. INTRODUCTION

There has been tremendous research in the areas related to Advanced Driver Assistance Systems (ADAS), video surveillance systems etc., in the last few years. As the need for such systems increase, the associated challenges also increase. These challenges can arise due to technology (footprint on embedded platform, cost etc.), or because of nature (weather, ambient light etc.). In the field of image processing and computer vision, image degradation due to the natural factors manifests as a very challenging problem. There are many aspects that affect the quality of an image in terms of visual perception and interpretation. Some aspects caused due to natural factors include loss of contrast, poor rendering of color and loss of depth information. When such an image is to be processed, it manifests into the reduced image understanding and difficulty in feature detection and identification of the object of interest. To overcome these disadvantages, many researchers have worked in areas related to the removal of atmospheric effects like haze, fog, smoke etc. It is a well-known phenomenon that every particle of significant size in the atmosphere scatters and absorbs light from the scene; thereby causing degradation in the scene visibility. This degradation in acquired images caused due to homogeneous atmospheric haze is modelled as:

\[ I(x) = D(x)T(x) + A(I - T(x)) \]  

(1)

The first term \( D(x)T(x) \) represents decayed scene radiation and hence is called as the direct attenuation term. Here, \( D(x) \) denotes haze free image intensity value at pixel \( x \) and \( T(x) \) denotes the transmission map describing the amount of the light that is not scattered. It is to be noted that transmission map has direct relation to the depth of the scene point from the camera. The second term \( A(I - T(x)) \) represents the scattered light from the atmospheric particles. It is called the air light attenuation term in which \( A \) describes the global atmospheric light and is independent of the position of object point. To restore visibility of images from given hazy image \( I(x) \), one needs to infer global atmospheric light \( A \) and transmission map \( T(x) \) from the given image information.

Currently, many image de-hazing algorithms are available in the literature. These image restoration and enhancement algorithms are either multiple images [2, 3] based, or single image [5-13] based techniques. Although the multiple images based de-hazing algorithms are efficient in image restoration, they rely heavily on clear scene information which makes them unsuitable for real time systems. Thus, single image based de-hazing algorithms are preferred. Of late, single image de-hazing algorithms have progressed significantly. These approaches can be broadly classified into image enhancement [4] based methods and physical model [5-13] based methods.

It is to be noted here that the model based de-hazing algorithms restore images with very minimal loss of information. However, the only challenge of these algorithms is that they require real world information viz. Depth and global atmospheric light of the scene. Literature available on de-weathering is significant in terms of model based de-hazing techniques. Narasimhan et al. [5] proposed a user interactive algorithm to remove haze effect from the single image. In their algorithm, the depth map is computed by calculating the pixel distance from the user approximated vanishing point. The drawback of this method is the need for human intervention. Tan [6] proposed a method to automate the single image de-hazing by rewriting the haze removal model and by developing a cost function using the Markov random field framework. Using the white balanced hazy image, he increased the contrast of an input image without considering the atmospheric light. In Fattal’s work [7], statistically uncorrelated shading and transmission field are separated and utilized to de-haze the thin hazy images. While using the implicit graphical model, he extrapolated the solutions to pixels with unreliable transmission for de-hazing. Guo et al. [8], in their work,
transformed the hazy image into YCbCr space and used retinex theory on the computed luminance component to de-
haze single images using physical model. He et al. [9] proposed a dark channel prior which assumes that color
channel of each pixel having very low intensity gets more
contribution from the atmospheric light. In their method, the
soft matted transmission map are estimated directly from the
dark channel prior and utilized for de-hazing images at higher
computational cost. Zhang et al. [10] proposed an improved
optical model by classifying the transmission into objective
and distance transmission. They used color clustering
technique to segment different objects and thereby estimating
the depth and atmospheric light depending on the position of
object point. A fast method of enhancing the visibility of hazy
image has been proposed by Tarel et al [11] for both color and
gray value images. The proposed method computes
atmospheric veil instead of inferring depth map for de-hazing
and uses median of median filter for preserving edges with
large depth jumps. Gibson et al. [12] presented a two-step
single image de-hazing method using adaptive Wiener filter.
In the first step, they computed naive statistical estimates using
foggy image and then updated the estimates in the second step
using naive defogged image to efficiently smooth the
transmission map. Lan et al. [13] showed that efficiency of de-
hazing algorithm improves when the hazy images are
preprocessed prior by removing sensor blur and noise.

In the present work, a simple yet effective de-hazing algorithm
using HSV color space has been proposed. Fundamentally, the
algorithm minimizes the RGB channel of each pixel by using
the HSV values and the global atmospheric light to bring back
the true color. The process of restoring color begins with
normalizing the RGB values of hazy image with optimized
global atmospheric light. This is followed by transformation
of the normalized RGB space into HSV color space. The
computed saturation (S) and intensity values (V) of each pixel
are utilized for estimating the transmission map. The
computed transmission map is further processed and smoothed
using the Guided Image filter [14] and is used with our
modified de-hazing model for restoration of hazy image. The
restoration results using our proposed approach has enhanced
perceptual visibility and are subjectively better when
compared with results from He et al. [9], Tarel [11] and Gibson
[12]. We have also conducted a quantitative comparative study
of our results with respect to [9], [11] and [12], by using the
visible edges segmentation method proposed by Hautiere et al.
[15].

The rest of this paper is organized as follows: In section I, an
effective way of computing the global atmospheric light and
normalizing the RGB channels of input hazy image is detailed.
In Section II, we describe the estimation of transmission map
from the image using the HSV color space. In Section III, the
process of smoothing of transmission map using guided filter
is described. The de-hazing of hazy images using the modified
physical model is demonstrated in the Section IV. In Section
V, the results of the proposed algorithm and its comparison
with other well-known algorithms are shown. Section VI
concludes the paper with discussion and summary.

2. IMAGE NORMALIZATION

We intend to normalize the RGB channels of input hazy
image using the computed global atmospheric light. Global
atmospheric light (A) is a position independent scalar value
that represents the atmospheric light of the scene. It plays an
important role in changing the vivacity of the image. It is,
therefore, vital to compute A precisely to restore better
visibility in a hazy image. In [9], it is seen that the global
atmospheric light is calculated from the brightest pixels in
hazy image. However, we have found out that the presence of
sky or saturated region would exaggerate the value of A. Applying
this over-estimated A in any de-hazing model tends to
increase contrast. In some cases, it also creates false color
in the de-hazed output. In order to avoid any saturated or sky
region during the calculation of A, our method initially
segments out the sky and other saturated regions in the image.
This is achieved by exploiting the obvious condition that
pixels having saturated or sky regions will have maximum
intensity values in all three RGB channels. In line with this,
we present a simple thresholding technique to segment out the
sky or saturated region in the image. The method initially
normalizes each channel (in RGB color space) of the hazy
image with their global maximum intensity value and
thereafter converts them (J_c(x)) into binary image (B_c(x)) with
95% threshold (See Equation 2 and 3). The intersection of the
three binarized channels determines the exact sky or saturated
regions. The working of this technique is as shown in Figure
1.

\[
J_c(x) = \frac{I_c(x)}{\max(I_c(x))} \quad (2)
\]

\[
B_c(x) = \text{graytobinary}(J_c(x)0.95) \quad c \in \{R,G,B\} \quad (3)
\]

\[
Saturated\_region = B_R(x) \cap B_G(x) \cap B_B(x) \quad (4)
\]

![Figure 1. Input hazy images (a & c) and binary images highlighting the segmented sky region (b & d)](image)
The proposed segmentation method helps masking the detected sky or saturated region prior to the calculation of atmospheric light. By using this masked image, the atmospheric light for each channel are calculated by averaging 0.1% of the remaining brightest pixels’ intensity values. Thus the computed atmospheric light values pertaining to R, G and B channels is averaged to obtain the global atmospheric light $A$. This simple and effective approach of calculating global atmospheric lighting avoids overdoing of de-hazing model and hence reduces false color and prevents excessive contrast to the restored image. The global atmospheric light for the input hazy images given in Fig 1(a) and 1(c) are estimated to be 220 and 221 respectively. The estimated global atmospheric light is used to normalize the RGB channels of the input hazy image $I(x)$:

$$I'(x) = \frac{I_c(x)}{A}, c \in (R, G, B)$$  \hspace{1cm} (5)

### 3. Estimating the Transmission Map

A new and much simpler method of computing transmission map is presented in this paper. Transmission map implies the amount of light transmitted through haze from the object point to the camera and hence it is inversely related to depth map. For an object at a far distance from the camera, the transmission value will be lesser; while for a closer object, the transmission value will be closer to 1. In order to make the computation of transmission map easy and effective, we propose a new way of computing the transmission map using HSV color space. In the RGB space, a ‘true color’ is defined as a color in which one of R, G and B values is either zero or very close to zero. Our approach is to restore the closest true color to every pixel in the image is affected by haze. First, the method transforms the normalized image $I'(x)$ into its HSV color space and then uses the computed saturation ($S(x)$) and intensity values ($V(x)$) of the transformed image to compute the transmission map as given in equation (6):

$$T(x) = 1 - q \cdot V(x) \odot (1 - S(x))$$  \hspace{1cm} (6)

‘$\odot$’ indicates pixel to pixel multiplication.

Where ‘$q$’ is the multiplication factor which influences the quantum of haze to be removed from the input image. For the present study, $q$ is assumed to be 0.95. In order to avoid the transmission map in the sky or saturated region exceeding unity, the transmission values in those regions are made to 0.95. A low level smoothing is carried out over the computed transmission map to smooth out high variations between neighboring pixels. It is done by dividing the transmission map into patches and assigning the minimum of transmission values in the patch to every pixel inside the patch. This low level smoothing of the transmission map is then followed by intense smoothing using the guided filter approach. For all example images presented in this paper, the patch size used for low level smoothing is a 3x3 window. Fig. 2(a) & 2(c) show the results of low level smoothing of images shown in Fig. 1(a) and 1(c). Fig 2 clearly shows the maximum transmission values in the less hazy region and minimum transmission values in the regions far from the camera.

### 4. Guided Filter

He et al. [14] proposed an explicit image filtering technique called Guided Filtering technique which is effective than Bilateral filter to preserve edges while removing small fluctuations in the transmission map. We use this approach to smooth the transmission map. The guided filtering technique preserves the edges by considering local linear model between the content of the guidance image and the input image. In the present study, transmission map before ($T(x)$) and after low level smoothing ($L(x)$) are considered as the guidance image and input image respectively. Thus the smoothed transmission map $T'(x)$ is given as

$$T'(x) = a_k T(x) + b_k$$  \hspace{1cm} (7)

Here $a_k$ and $b_k$ are the linear coefficient for a subset $\omega$ of transmission map, centered at pixel $k$. The cost function that minimizes the difference between $T'(y)$ and $L(y)$ is considered as follow:

$$E(a_k, b_k) = \sum_{x \in \omega} ((a_k T(x) + b_k - L(x))^2 + \mu^2)$$  \hspace{1cm} (8)

$E$ is the regularization parameter which is considered as 0.01 in the current work. The given cost function (8) is minimized for $a_k$ and $b_k$ and derives out to be

$$a_k = \frac{1}{|\omega|} \sum_{y \in \omega} T(y) L(y) - \mu_T \mu_L$$  \hspace{1cm} (9)

$$b_k = \mu_L - a_k \mu_T$$  \hspace{1cm} (10)

Figure 2. Transmission map for the given input images computed after low level filtering (a & c) and guided filtering technique (b & d).
Where, $\mu_T$ and $\sigma_T$ are the mean and standard deviation of $T(y)$ within the subset $\omega$ centered at pixel $k$ and $\mu_L$ is the mean of $L(y)$ within the considered subset. Since $a_k$ and $b_k$ are computed for pixel $k$ continue to vary and get updated when computed with different window; the average value of $a_k$ and $b_k$ for various window are computed and is used in Equation(7) for smoothing the transmission value at pixel $k$. For the example images given in this paper, a subset size of 5×5 pixels is used.

The guided filtered transmission map corresponding to Fig. 2(a) and 2(c) are shown in the Fig. 2(b) and 2(d).

5. MODEL BASED IMAGE DE-HAZING

The image hazing model given in Equation 2 is rewritten appropriately in the current work to incorporate the computed transmission map $T'(x)$ and normalized RGB values $I'(x)$ of hazy image for de-hazing:

$$D(x) = \frac{(I'(x) - 1 + T'(x))}{T'(x)}$$  \hspace{1cm} (11)

This rewritten model minimizes the lowest of the RGB values for each pixel to produce true color. For the input images in Fig. 1, the resultant images obtained using the proposed de-hazing model is given in the Fig. 3.

![Figure 3: Resultant images corresponding to input images in Fig. 1(a) & 1(c) using the proposed algorithm](image)

6. RESULTS AND DISCUSSIONS

The proposed algorithm was developed in Matlab™ on a 3 GB RAM, 2.40 GHz Intel CORE™ i3 processor. The images and visible edge segmentation technique source code used for comparing the results are taken from the webpage of Gibson et al. [12] and Hautiere et al. [15]. The eight input hazy images used in our study are shown in Fig. 4. The entire process of removing haze from the input images is completely automatic. The de-hazed test images obtained from different algorithms along with smoothed transmission map are given in the Fig. 5-12. In comparison with the other methods, the proposed algorithm is able to remove the varying amount of haze (i.e., mild to dense) effectively. The performance of the proposed method is quantified using the visibility edge segmentation technique indicators $e$, $r$ and $sigma$. These technique converts the input and restored images into gray scale value and compares to compute the mentioned indicators. The parameter $e$ describes the rate of newly visible edges after restoring the visibility. The visible edges are computed using Weber contrast calculator and contrast below 5% are exempted from the calculation. Fig. 13 shows the comparison of $e$ for different test images restored using considered algorithms. It is evident from the plot that the proposed algorithm performs exceedingly well in restoring visible edges. The descriptor $r$ demonstrates the geometric mean ratios of visibility level in the image before and after de-hazing. The plot in Fig. 14 displays the results of various test images de-hazed using mentioned algorithms. From the plot, it is shown that the proposed restoration algorithm is better in visibility enhancement of the hazy images. The last descriptor $sigma$ denotes the number of saturated pixels created during visibility restoration.

![Figure 4: Input Sample Images](image)

The plot of $sigma$ for various test images is given in Fig.15. The plot implies that the number of saturated pixels created from the proposed method is lesser than some of the considered algorithms for comparison.

By observing Fig. 5(h) -12(h), one can notice that a good amount of haze has been removed from the input images using the proposed approach. For a 600×400 image the algorithm takes 26.8 seconds for execution using Matlab™. It is to be noted that out of the 26.8 seconds, 26.1 seconds is taken for smoothing the transmission map. Both subjective and quantitative analysis ascertain the enhanced restoration performance of our proposed method.
7. **CONCLUSIONS**

This work presents a model based automatic image dehazing algorithm using the HSV color space. It attempts to map every pixel affected by haze into its nearest true color value in the RGB space; thereby restoring the image. We have proposed an effective way of computing the global atmospheric light. A new method of computing transmission map using saturation and intensity value of hazy image is also presented. The modified haze removal model works well to reliably restore the perceptual visibility of hazy image. Quantitative results using the visible edge segmentation technique demonstrates that the current algorithm is either better or at par with available state of the art methods in removing haze.

![Figure 5: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h)](image)

![Figure 6: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h)](image)

![Figure 8: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h)](image)

![Figure 10: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h)](image)
Figure 7: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h).

Figure 9: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h).

Figure 11: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h).

Figure 12: Smoothed transmission map and de-hazed images from the algorithm: He et al. [9] (a & b), Tarel [11] (c & d), Gibson et al. [12] (e & f) and present method (g & h).
Figure 13. Comparison plot of new visible edge descriptor $e$ for different test images restored using different algorithms.

Figure 14. Comparison plot of ratio of visible gradient $r$ for different test images restored using different algorithms.

Figure 15. Comparison plot of saturated pixel percentage $\sigma$ for different test images restored using different algorithms.

8. References


