Single Image Dehazing with Varying Atmospheric Light Intensity

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***Abstract*—Images taken in bad weather conditions like haze and fog suffer from loss of contrast and color shift. The object radiance is attenuated in the atmosphere and the atmospheric light is added to the scene radiance creating a veil like semi-transparent layer called airlight. The methods proposed till now assumes that the atmospheric light is constant throughout the image domain, which may not be true always. Here we propose a method that works under the relaxed assumption that the color of atmospheric light is constant but its intensity may vary in the image. We use the color line model to estimate the contribution of airlight in each patch and interpolate at places where the estimate is not reliable. We apply reverse operation to recover the haze free image.**

***Index Terms*—image enhancement, dehazing, color line**

I. Introduction

Adverse weather conditions like fog and haze greatly reduce the visibility of the scene. This occurs mainly due to existence of small particles in the atmosphere. These particles deviate the light reflected off an object from its path of propagation. Also the environmental illumination incident on these particles gets scattered in the direction of the observer creating a semi-transparent layer. For these reasons images lose contrast and their color shifts towards the color of the atmospheric light.

Image dehazing methods try to recover scene radiance by removing the effect of haze from the image. Recovering the scene radiance from a single image is challenging since the amount of haze depends on the distance of the object from the camera. So, any global enhancement methods does not work well and recovering depth from a single image is under-constrained. So, the earlier methods tried to solve this problem by using more than one image. Method by Narasimhan and Nayar [1] require multiple image of the same scene taken under different weather condition. Polarization based method [2] requires images with different degree of polarization.

More recent methods tackle this problem using stronger priors. Tan's method [3] is based on the observation that clear day images have more contrast compared to images in bad weather. So it tries to remove haze by maximizing the local image contrast under MRF framework. The results offer increased visibility but the colors tend to get saturated. The first work by Fattal [4] estimates the medium transmittance assuming the surface shading and medium transmission functions are locally statistically uncorrelated. This produces better result, but can't handle regions where shading component does not vary significantly compared to noise. He et al. [5] proposed Dark Channel Prior to estimate transmission. The method is simple and produces quite good results. But the step to refine the transmission estimate using soft matting procedure tends to underestimate the transmission. The second work on dehazing by Fattal [6] is based on local color line prior. The method estimates transmission based on the shift of the local color line from the origin in the direction of atmospheric light. Unlike other methods this assumes global atmospheric light is known. The unique feature of this method is the testing of the validity of the assumptions when estimating transmission thus providing better results.

Our method builds upon the color line based dehazing by Fattal [6]. We modify this method to solve the problem when the imaging model is relaxed. However, unlike this method, we do not assume that atmospheric light is known. Second, unlike others, we do not try to estimate the transmission of medium. Instead we estimate the added airlight and remove that to clear the haze. In the rest of the paper, section II presents problem formulation, section III the proposed method of dehazing, and section IV present concise algorithm. Experimental results and concluding remarks are placed in section V and VI respectively.

II. Background

Irradiance of a scene point from a point of observation is given by following imaging model due to Koschmeider [7]:

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

where $I(\mathbf{x})$ is the observed irradiance. $J(\mathbf{x})$ is the scene radiance. $\mathbf{x}$ denotes pixel position. A is the intensity of the atmospheric light, and $0 \leq t(\mathbf{x}) \leq 1$ is the transmittance of the medium describing how much of the scene radiance reaches the observer without being scattered. When we consider RGB color images, this equation takes the form of a 3D vector equation where $I(\mathbf{x})$, $J(\mathbf{x})$, and A are vectors and $t(\mathbf{x})$ still is a scalar. This is valid because in haze and fog the transmittance $t(\mathbf{x})$ does not vary much with wavelength. The first part of the equation, called *direct transmission*, provides the amount of radiance reaching the observer without being scattered. The second part, called *airlight*, describes how much of the

This is a pre-print version of a paper accepted to NCVPRIPG 2015, IIT Patna

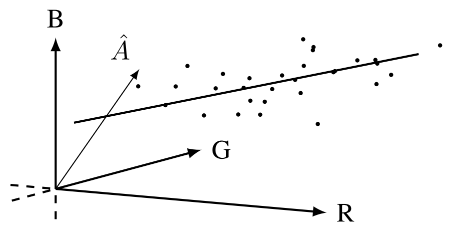

Fig. 1. Colors in a patch as points in RGB space. The color line formed by them is shifted in the direction of $\hat{A}$.

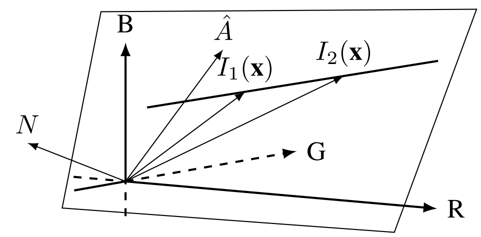

Fig. 2. The plane containing the color line and $\hat{A}$ can be computed from $I_1(\mathbf{x})$ and $I_2(\mathbf{x})$.

atmospheric light gets added due to scattering in the direction of the observer.

Note that in equation (1) the atmospheric light $A = m\hat{A}$ is assumed to be constant, where m denotes the magnitude and $\hat{A}$ is the direction. But in general case it may not remain so. So, here we try to solve a relaxed version of equation (1). We assume that in the image the direction of the atmospheric light vector is constant but its magnitude may vary. So, the equation (1) becomes,

$$I(\mathbf{x}) = J(\mathbf{x})t(\mathbf{x}) + a(\mathbf{x})\hat{A}; \quad a(\mathbf{x}) = (1 - t(\mathbf{x}))m(\mathbf{x}) \tag{2}$$

To recover haze free image using this equation, we estimate $\hat{A}$ and the magnitude of airlight component ($a(\mathbf{x})$) at each position instead of estimating A as in earlier works. Then by subtracting the airlight from the recorded image we get $J(\mathbf{x})t(\mathbf{x})$. Finally, we enhance the contrast of this new image to get haze free image.

III. Proposed Approach

In this section we describe our proposed approach and justify it through geometrical interpretation of the equation (2) in RGB color space.

A. Color line model

Considering colors as points in the RGB space, Omer and Werman [8] showed that for natural images colors in a small patch should lie on a line passing through the origin. But due to noise and camera related distortions they form an elongated color cluster. In case of hazy images, due to the additive airlight component, the line gets shifted from the origin by an amount $a(\mathbf{x})$ in the direction of $\hat{A}$ (Fig.1). It is assumed that $t(\mathbf{x})$ varies smoothly and slowly in the scene except at depth discontinuities. The magnitude of atmospheric light also varies smoothly. So, for a small patch the equation (2) becomes

$$I(\mathbf{x}) = J(\mathbf{x})t + (1 - t)m\hat{A} \tag{3}$$

So, if we can estimate the line formed by the color points of a patch and the direction of atmospheric light, then by moving the line in the direction opposite to the atmospheric light vector, we can neutralize the effect of airlight by making it pass through the origin.

The problem in this approach is that the line in the RGB space can be obtained only under certain assumptions. First, it is assumed that the patch contains pixels from an object with single reflectance value that would provide the direction of the line. Second, within the patch the surface normal and consequently the shading component varies sufficiently, otherwise the pixels will not form elongated cluster. So estimating the color line direction due to the reflectance value will be error prone. Now these assumptions may not hold in all the patches. So, we test the validity of these assumptions on each patch and ignore the patch if the assumptions don't hold. Therefore it is quite likely that for all the patches an estimate may not be obtained. For those patches we need to interpolate the estimate.

B. Estimating $\hat{A}$

As already discussed we are supposed to get a line from the color points of pixels of a patch in the RGB space, which may have been shifted in the direction of the airlight. This color line and $\hat{A}$ lie on a plane (Fig.2). The normal to this plane can be obtained from cross product of two vectors representing the points lying on the line. The lines corresponding to different reflectance value ($\hat{J}$) will form different planes with $\hat{A}$. Since airlight direction $\hat{A}$ is constant throughout the image, we can compute $\hat{A}$ as the intersection of all the planes formed by the origin and the color line of each patch where airlight component is nonzero.

IV. Proposed Algorithm

Here we present the implementation of our method through algorithmic steps. Note that this method is a modification of color line based method of Fattal [6] (denoted by dehazeCL subsequently) to work under relaxed imaging equation (2).

A. Computing $\hat{A}$

As already stated, to compute $\hat{A}$ we need the planes containing the fitted line for each patch and the origin. Similar to what is done in dehazeCL [6], to fit a line in each patch, we apply RANSAC [9] to the points in RGB space and get two points $\vec{p}_1$ and $\vec{p}_2$ lying on the line and a set of inliers. The estimated equation of the line is $\vec{P} = \vec{P}_0 + \rho\vec{D}$, where ρ is line parameter, direction ratio $\vec{D} = \frac{\vec{p}_2 - \vec{p}_1}{\|\vec{p}_2 - \vec{p}_1\|}$ and $\vec{P}_0 = \vec{p}_1$. The normal to the plane containing the line and the origin is computed as $\vec{N} = \frac{\vec{p}_1 \times \vec{p}_2}{\|\vec{p}_1 \times \vec{p}_2\|}$. We test the estimated line with conditions namely, significant number of inliers, positive slope of $\vec{D}$ and unimodality similar to [6] and discard the unreliable ones.

We assume that the plane containing the line and the origin also contains $\hat{A}$. This assumption is not valid if the estimated line goes through origin. In that case the computed normal cannot be useful. We check this by checking the angle between D and P_0. If this angle is less than a given threshold (θ), we ignore the normal.

Now we have the normals ($\vec{N}$), we may compute $\hat{A}$. To make our estimate for $\hat{A}$ more robust we discard some of the normals from our selection based on the dark channel value [5] of the patch. The dark channel value of a patch Ω is given by

$$Dark(\Omega) = \min_{\mathbf{x}\in\Omega}\Big(\min_{c\in\{R,G,B\}} I_c(\mathbf{x})\Big) \tag{4}$$

Note that the normal corresponding to patch Ω_i is discarded if the following condition holds

$$Dark(\Omega_i) \leq \lambda \max_{\Omega_j} Dark(\Omega_j) \tag{5}$$

Next from the remaining normals we compute $\hat{A}$ by minimizing the following error

$$E(\hat{A}) = \sum_i (N_i \cdot \hat{A})^2 \tag{6}$$

which boils down to solving

$$\frac{\partial E}{\partial \hat{A}} = 2\Big(\sum_i N_i N_i^T\Big)\hat{A} = 0 \tag{7}$$

As $\hat{A}$ is known to be a non-null vector, we need non-trivial solution of equation (7). So, we compute covariance matrix from the normals, and then find the eigen vector of the covariance matrix corresponding to the smallest eigen value as the solution.

B. Estimation of Magnitude of Airlight Component $a(\mathbf{x})$

$\hat{A}$ is estimated and the color line corresponding to a patch is found, we obtain airlight component ($a(\mathbf{x})$) by minimizing the following error

$$E_{line}(\rho, s) = \min_{\rho,s} \|P_0 + \rho D - s\hat{A}\|^2 \tag{8}$$

where s denotes of airlight component. The solution of equation (8) is obtained as described in [6]. The computed airlight component is then validated with the following conditions, namely large intersection angle, close intersection, valid range and shading variability. Out of them large intersection angle and close intersection is done the same way as reported in [6]. Test for valid range and shading variability conditions are described below.

Valid Range. The magnitude of airlight is $(1-t(\mathbf{x}))m(\mathbf{x})$, where $t(\mathbf{x})$ varies between 0 and 1, and $m(\mathbf{x})$ between 0 and $\sqrt{3}$ (when $m(\mathbf{x})\hat{A}$ is $[1,1,1]^T$). But this bound allows some undesirable estimates which leads to overestimation. So, we use the smallest intensity present in the patch as the upper limit of the airlight component. If the estimate goes beyond this value then it is ignored.

Shading Variability. The color clusters in the RGB space are expected to be distributed along a line. If the points do not spread much in a linear direction, the fitted line becomes sensitive to noise. To discard such potentially bad patches we project the inlier points on the estimated line and compute the standard deviation. If this standard deviation falls below a certain threshold we discard the patch.

If a patch passes all the tests, its estimated value is assigned to all of its inlier pixels. As we consider overlapping patches, is case a pixel may receive more than one estimate we combine the estimates using max rule.

C. Interpolation of Estimate

In the process of estimating the airlight component $a(\mathbf{x})$ we discard quite a few patches. But to recover the haze free image we require the airlight component at every pixel. So, we need to interpolate the value of airlight at every pixels. This is done by minimizing the following function

$$\psi(a(\mathbf{x})) = \sum_{\Omega}\sum_{\mathbf{x}\in\Omega}\frac{(a(\mathbf{x})-\tilde{a}(\mathbf{x}))^2}{(\sigma_a(\Omega))^2} + \alpha\sum_{\mathbf{x}}\sum_{\mathbf{y}\in L(\mathbf{x})}\frac{(a(\mathbf{x})-a(\mathbf{y}))^2}{\|I(\mathbf{x})-I(\mathbf{y})\|^2} + \beta\sum_{\mathbf{x}}\frac{a(\mathbf{x})}{\|I(\mathbf{x})\|} \tag{9}$$

where $\tilde{a}(\mathbf{x})$ is the estimated airlight component value, $L(\mathbf{x})$ is neighborhood of $\mathbf{x}$ and $a(\mathbf{x})$ is the acceptable airlight component to be computed. Ω denotes a patch and $\sigma_a(\Omega)$ is the error variance of the estimate within the patch. The first two terms constitute what is similar to the function used in [6]. To achieve better results, we add the last term which ensures that the airlight component would be a small fraction of $I(\mathbf{x})$. The last term of (9) is used to vary the airlight component with intensity of $I(\mathbf{x})$. Finally, to minimize the energy function given by equation (9), we convert this to the following form

$$\Psi(a) = (a-\tilde{a})^T\Sigma(a-\tilde{a}) + \alpha a^T L a + \beta b^T a \tag{10}$$

where a and $\tilde{a}$ are the vector form of $a(\mathbf{x})$ and $\tilde{a}(\mathbf{x})$. Σ is a covariance matrix of the pixels where estimate exists. L is the Laplacian matrix of the graph constructed by taking each pixel as one node and connecting the neighboring nodes. The weight of the edge between the nodes $\mathbf{x}$ and $\mathbf{y}$ is $\frac{1}{\|I(\mathbf{x})-I(\mathbf{y})\|^2}$. Each element of b is $\frac{1}{\|I(\mathbf{x})\|}$, and α and β are scalar controlling the importance of each term. The equation (10) is minimized by solving the following

$$(\Sigma + \alpha L)a = (\Sigma\tilde{a} - \beta b) \tag{11}$$

D. Haze-free Image Recovery

Airlight at each pixel can now be obtained by computing $a(\mathbf{x})\hat{A}$. So, the direct transmission may be recovered as follows

$$J(\mathbf{x})t(\mathbf{x}) = I(\mathbf{x}) - a(\mathbf{x})\hat{A} \tag{12}$$

As we do not have $t(\mathbf{x})$ explicitly, we enhance the contrast using the airlight and try to recover $J(\mathbf{x})$. Let's say the recovered image is $R_{im}(\mathbf{x})$, then

$$R_{im}(\mathbf{x}) = \frac{J(\mathbf{x})t(\mathbf{x})}{1 - Y(a(\mathbf{x})\hat{A})} \tag{13}$$

$$Y(I(\mathbf{x})) = 0.2989 I_R(\mathbf{x}) + 0.5870 I_G(\mathbf{x}) + 0.1140 I_B(\mathbf{x}) \tag{14}$$

where $Y(I(\mathbf{x}))$ computes the luma at the pixel. The idea is that a pixel is enhanced depending on how much intensity is

Fig. 3. Result comparison.(Left to Right) Top Row: Original image by böhringer friedrich via Wikimedia commons, results of He et al.(own implementation), dehazeCL(own implementation, airlight computed using He et al.), and our method. Bottom Row: Original Image, results of He et al., dehazeCL, and our method

removed from it. For many pictures the image stays dark even after this operation so we use gamma correction to restore the overall brightness.

V. Results

We have implemented our method using MATLAB® R2010b and generated the results. For the line fitting part with RANSAC, we use the code of Peter Kovesi [10]. The linear equations were solved using mldivide($\backslash$) operator. The threshold values used to check various conditions namely, significant number of inliers, unimodality, large intersection angle, and close intersection are kept as quoted in [6]. For θ (threshold of angle between D and P_0), λ (equation (5)), and shading variability condition we have used $15°$, 0.45 and 0.006 respectively as the threshold. The same values are used for all the images. α and β usually take small values (typically 2×10^{-4} and 1×10^{-5}) depending on the input image. Note that in our implementation we have taken image pixel values between 0 and 1.

In Fig.3 we show the output obtained using our method (rightmost image in both row) along with the output of other methods. On the first row it can be seen that in the output of He et al. the haze in not cleared properly, specially on the left side of the tree on the left. Also due to erroneous estimate of airlight the mid portion turns out reddish. The result of dehazeCL is slightly better but the result of our method is better than both the methods. These problems don't occur in our method because of relaxed imaging equation and more accurate calculation of airlight direction using multiple patches. For the train image the output of other methods have more contrast in some places but the colors obtained using our method is better. More results can be found in the website[1].

VI. Conclusion

In this paper we have proposed a image dehazing method using a relaxed haze imaging model. We use color line model to estimate $\hat{A}$ from multiple patches of the image, then we estimate the contribution of airlight in each patch and interpolate at places where the estimates are unreliable. We then use the image forming equation to recover haze free image. Here we have estimated the airlight contribution $(a(\mathbf{x})\hat{A})$ at each patch but not the scene transmission $t(\mathbf{x})$. So, unlike other methods we do not compute the depth map. Due to the unavailability of $t(\mathbf{x})$ we tried to recover $J(\mathbf{x})$ using eq. (13). So, we can't gurantee good results for all images. This part should be modified to improve the results. Our method assumes that within an image, $\hat{A}$ is constant but the magnitude of airlight varies. So, our method may fail to give satisfactory results where this is violated, e.g. nighttime haze images.

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