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# Single Image Dehazing for Robust Image Matching

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**Abstract:** The visibility of images of outdoor scenes is degraded by bad weather conditions. Atmospheric phenomena like haze and fog reduce significantly the visibility of the captured image. Haze is the atmospheric phenomenon that dims the clarity of an observed scene due to the particles such as smoke, fog, and dust. Due to these atmospheric particles there is a significant degradation in the color and contrast of the captured image in the bad weather conditions. If two or more images of same scene are given, then the process of image matching requires find valid corresponding feature points in images. Image matching is a fundamental aspect of many problems in computer vision. Besides the geometric and photometric variation, outdoor and aerial images that are subjected to the process of matching are often degraded by the atmospheric phenomenon of haze. In this paper we presented an efficient physics based method for recovering a haze-free image when a single photograph is available as an input. This technique restores the hazy images based on the estimated transmission (depth) map. Our method benefits from three main contributions. The first is a new constraint on the scene transmission. Second contribution is contextual regularization that enables us to incorporate a filter bank into image dehazing. Our final contribution is an efficient optimization scheme, enables us to quickly dehaze images of large sizes. Our method requires some general assumption and can restore a high quality haze free image. At final stage we have performed matching of images by SURF operator to show efficiency of our method and also demonstrate that our technique is suitable for the challenging problem of image matching based on local feature points.

**Keywords:** Single image dehazing; Haze; Air light; Transmission map; Image matching; Local feature detectors and descriptors; Speeded up Robust Feature (SURF).

## I. INTRODUCTION

Outdoor images are often suffered by suspended atmospheric particles such as haze, fog, smoke and mist that reduce the quality of the images taken in the scene. Visibility, contrast, and vividness of the scene are drastically degraded, which makes it difficult to distinguish objects. Enhancing the images acquired in poor weather conditions is called de-weathering and has been a very critical issue in applications such as aerial photography, image recognition, driving assistance and visual surveillance. Dehazing is a representative de-weathering problem especially for removing the weather effect caused by suspended aerosol and water drops. The goal of dehazing is to improve the contrast of the foggy images and restores the visibility of the scene.

If two or more images of same scene are given, then the process of image matching requires finding valid corresponding feature points in images. Image matching is a fundamental aspect of many problems in computer vision, including object or scene recognition, solving for 3D structure from multiple images, stereo correspondence, and motion tracking. Image matching plays a crucial role in many remote sensing applications such as change detection, cartography using imagery with reduced overlapping, fusion of images taken with different sensors.

Now a day, the task of image matching is done automatically. It is due to progress of local feature point detectors and descriptors. Many local feature point operators have been introduced.

Recent local feature operators are invariant to image transformations such as geometric (scale, rotation, affine) and photometric. Besides the geometric and photometric variation outdoor and aerial images that are subjected to the process of matching, are often degraded by the atmospheric phenomenon of haze.

The organization of this paper is as follows: Section 2 discusses the fundamentals of hazing and dehazing, Section 3 discusses about related work, Section 4 discusses proposed method, Section 5 shows our dehazing results and Section 6 gives the conclusion.

## II. FUNDAMENTALS OF HAZING AND DEHAZING

The visibility of images of outdoor scenes is degraded by bad weather conditions. Atmospheric phenomena like haze and fog reduce significantly the visibility of the captured image. This type of degradation in visibility of images is known as hazing effect. To remove effect of haze and enhancing the visibility of image is very challenging task in the area of image processing. Since the aerosol is misted by additional particles, the reflected light is scattered and as a result, distant objects and parts of the scene are less visible, which is characterized by reduced contrast and faded colors. Poor visibility in bad weather is a major problem for many applications of computer vision. Most automatic systems for surveillance, intelligent vehicles, outdoor object recognition, etc., assume that the input images have clear visibility.

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In almost every practical scenario the light reflected from a surface is scattered in the atmosphere before it reaches the device because aerosols such as dust, mist, and fumes deflect light from its original course of propagation. In long distance photography or foggy scenes, this process has a significant effect on the image in which contrasts are reduced and surface colors become low. Such degraded photographs often lack visual vividness and appeal, and moreover, they offer a poor visibility of the scene contents. This may also be the case for satellite imaging, land-use planning, archeology, and environmental studies.

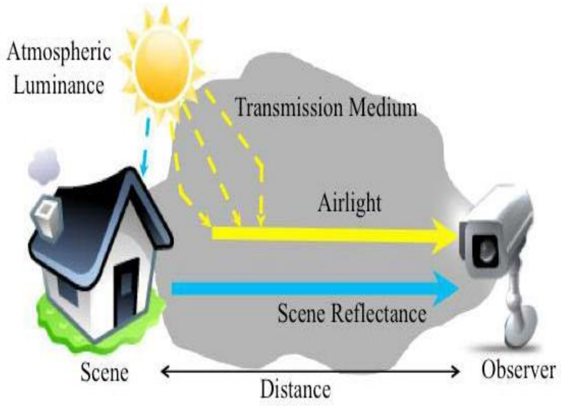


Fig.1. Atmospheric scattering model

Haze removal (or dehazing) is very important in both consumer/computational photography and computer vision applications and has been a challenging task especially when only a single degraded image is available. Dehazing or defogging is the strategy to enhance images degraded by bad weather condition. The first dehazing approaches employ multiple images of same scene taken from different weather condition. This approach requires additional information such as depth map and specialized hardware. But these strategies are limited to offer a reliable solution for dehazing problem because unavailability of such additional information to the users.

The second approach is single image dehazing approach. This method only requires a single input image. This method relies upon statistical assumptions and or the nature of the scene and recovers the scene information based on the prior information from a single image.

Therefore most constraint-based defogging methods from a single image are computationally too demanding to fulfill the requirement of a wide range of practical applications. Several single image based techniques have been introduced in this paper. In general these techniques can be divided in two major classes: physically based and contrast-based techniques.

(i) Physically based technique
Physically based techniques restore the hazy images based on the estimated transmission (depth) map. Independent component analysis (ICA), Dark channel prior, Bayesian probabilistic method etc are physics based method in which the author restore the hazy image by estimating the transmission map and global air light also.

Hazy image

Dehazed image

Fig. 2 Physics based method

(ii) Contrast based technique
Contrast-based techniques enhance the hazy images without estimating the depth information. Contrast based techniques enhance visibility of images by restoring the contrast of degraded imges.

Hazy image

Dehazed image

Fig. 3 Contrast based method

## III. RELATED WORK

Early haze removal methods are mainly depend on additional depth information or multiple observations of the same scene. These methods require multiple images of same scene. Representative works include [25], [24], [22], [21]. Schechner et al. [25] notice that the air light scattered by atmospheric particles is partially polarized. Based on this observation, they develop a quick method to reduce hazes by using two images taken through a polarizer at different angles. Narasimhan et al. propose a physics-based scattering model [24], [22]. By this model, the scene structure can be recovered from two or more weather images. Kopf et al. [18] proposed to dehaze an image by

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using the scene depth information directly accessible in the geo-referenced digital terrain or city models.

The second approach is single image dehazing, which requires single input image and is a more challenging problem, because fewer information about the scene structure is available. Fattal (2008), He et al. (2011) and Nishino et al. (2012) have employed physically based single image dehazing techniques. Fattal [16] formulated the refined image formation model that relates to the surface shading and the transmission function. Fattal grouped the pixel belonging to the same surface having the same reflectance and the same constant surface albedo. The basic key idea of his work is to resolve the airlight albedo ambiguity and assuming that the surface shading and the scene transmission are uncorrelated. This approach is physically valid and can produce good results, but may be unreliable because it does not work well for dense haze.

He et al. [9] dark channel prior is based on the prior assumption. They have observed that in most of the local regions which do not cover the sky, some pixels have very low intensity in at least one color (RGB) channel and these pixels are known as the dark pixels. In hazy images the intensity of the dark pixels in that color channel is basically contributed by the air light and these dark pixels are used to estimate the haze transmission. After estimation of the transmission map for each pixel, combining with the haze imaging model and soft matting technique to recover a high quality haze free image. The dark channel prior does not work efficiently when the surface object is similar to the atmospheric light.

Nishino et al. [6] employs a Bayesian probabilistic model. Their key approach is to model the image with a Factorial Markov Random Field (FMRF) in which the scene albedo and depth are two statistically independent latent layers and to jointly estimate them. They derive a novel joint estimation method based on a Bayesian formulation to factorize a single foggy image into its scene albedo and depth.

Tarel and Hautière (2009), Tan (2008) and Ancuti et al. (2014) have employed contrast based single image dehazing. In [15] Robby T. Tan has introduced an automated method that only requires a single input image. Two observations are made based on this method, first, clear day images have more contrast than images afflicted by bad weather; and second, airlight whose variant mostly depends on the distance of objects to the observer tends to be smooth. Tan develops a cost function in the framework of Markov random fields based on these two observations. The results have larger saturation values and may contain halos at depth discontinuities.

In [12] Tarel et al. have demonstrated algorithm for visibility restoration from a single image that is based on a filtering approach. The algorithm is based on linear operations and needs various parameters for adjustment. It is advantageous in terms of its speed. This speed allows visibility restoration to be applied for real-time applications of dehazing. They also proposed a new filter which preserves edges and corner as an alternate to the median filter. The restored image may be not good because there are discontinuities in the scene depth.

In [1] Ancuti and Ancuti presented a novel strategy to enhance images degraded by the atmospheric phenomenon of haze. This single-based image technique does not require any geometrical information and restoring the visibility of hazy image by enhancing the contrast of the degraded image. The degradation of the finest details and gradients is constrained to a minimum level. Using simple formulation that is derived from the lightness predictor contrast enhancement technique, restore lost discontinuities only in regions that insufficiently represent original chromatic contrast of the scene. The parameters of simple formulation are optimized to preserve the original colour spatial distribution and the local contrast. They compare their technique with Tarel and Hautiere (2009) by matching local feature points of hazy image and dehazed image. More number of good matches represents the efficiency of technique.

## IV. PROPOSED METHOD

The haze effect is both multiplicative as well as additive since the pixels are averaged together with a constant, the air light. Since in most of the cases the haze effect is non homogeneous and contrast based method works effectively in homogeneous haze affect and also does not estimate the air light and transmission map and recovered images are often oversaturated. The physical based method works in homogeneous as well as non homogeneous haze effect and recovers rich details of images, color information and scene radiance. Therefore we are using physical based method in our proposed method.

4.1 Haze image formation model

The model which is widely used in computer vision and computer graphics, to describe the formation of a haze image is as follows:

$$I(x) = J(x)t(x) + A(1 - t(x)) \qquad \ldots\ldots. (1)$$

where,

I is the observed intensity,

J is the scene radiance,

A is the global atmospheric light, and

t is the medium transmission which describes the portion of the light that is not scattered and reaches the camera.

The first term $J(x)t(x)$ on the right hand side of Equation (1) is called direct attenuation [15], and the second term $A\big(1 - t(x)\big)$ is called airlight [15]. Direct attenuation describes the scene radiance and its decay in the medium, while airlight results from previously scattered light and leads to the shift of the scene color. When the atmosphere is homogenous, the transmission t can be expressed as:

$$t(x) = e^{-\beta d(x)} \qquad \ldots\ldots.. (2)$$

Where β is the scattering coefficient of the atmosphere. It indicates that the scene radiance is attenuated exponentially with the scene depth d. Geometrically, the haze imaging Equation (1) means that in RGB color space, vectors A, I(x) and J(x) are coplanar and their end points are collinear. The transmission t is the ratio of two line segments:


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$$t(x) = \frac{\|A-I(x)\|}{\|A-J(x)\|} = \frac{A^c-I^c(x)}{A^c-J^c(x)} \quad ........(3)$$

where $c \in \{r,g,b\}$ is color channel index.

The goal of image dehazing is to recover the scene radiance J(x) from I(x) based on equation(1). This requires us to estimate the transmission function t(x) and the global atmospheric light A. Once t(x) and A are estimated, the scene radiance can be recovered by:

$$J(x) = \frac{I(x)-A}{[max(t(x),t_0)]^{\gamma}} + A \quad .......... (4)$$

where $t_0$ is a small constant (typically 0.0001) for avoiding division by zero, and the exponent $\gamma$, serving as the role of the medium extinction coefficient β is used for fine-tuning the dehazing effects.

4.2 Estimate Global Airlight

The airlight function is the multiplication of two factors: atmospheric luminance and the inverse of depth map. We can assume that a portion of the image contains pixels infinitely far away. The image points corresponding to scene points at infinity are regarded as the set of representative color vectors of atmospheric luminance and an average operation is applied to estimate the expected color vector of atmospheric luminance. To estimate A first pick up most hazy pixel in input hazy image and filter each color channel of an input image by a minimum filter with moving window. Then the maximum value of color channel is taken as estimate of A.

4.3 Calculate Boundary Constraint

Here we are considering that the scene radiance J(x) of a given image is always bounded, that is,

$$C_0 \le J(x) \le C_1 \quad ....... (5)$$

where $C_0$ and $C_1$ are two constant vectors that are relevant to the given image. Consequently, for any x, a natural requirement is that the extrapolation of J(x) must be located in the radiance cube bounded by $C_0$ and $C_1$. The above requirement on J(x), in turn, imposes a boundary constraint on t(x). For given global atmospheric light A and for each x, we can compute the corresponding boundary constraint point $J_b(x)$. Then, a lower bound of t(x) can be determined and leading to the following boundary constraint on t(x):

$$0 \le t_b(x) \le t(x) \le 1 \quad ....... (6)$$

where $t_b(x)$ is the lower bound of t(x), given by

$$t_b(x) = min\left\{max_{c\in\{r,g,b\}}\left(\frac{A^c-I^c(x)}{A^c-C_0^c}, \frac{A^c-I^c(x)}{A^c-C_1^c}\right), 1\right\}. \quad (7)$$

where $I^c, A^c, C_0^c$ and $C_1^c$ are the color channels of I, A, $C_0$ and $C_1$, respectively.

4.4 Refining Estimation and Dehazing

In a local image patch, pixels share a similar depth value. Based on this consideration, we have derived a patch-wise transmission from the boundary constraint. But the situations where abrupt depth jumps occur, this contextual consideration often fails, and leading to significant halo artifacts in the dehazing results. A solution to overcome this problem is to introduce a weighting function W(x, y) on the constraints. Therefore we are here using Weighted $L_1$-norm based contextual regularization.

As we have noticed the facts that the depth jumps generally appear at the image edges and that within local patches, pixels with a similar color often share a similar depth value. Consequently, we can compute the color difference of local pixels to construct the weighting function.

$$W(x,y)(t(y) - t(x) \approx 0 \quad ........ (8)$$

Where x and y are two neighboring pixels.

Integrating the weighted contextual constraints in the whole image domain leads to the following contextual regularization on t(x):

$$\int_{x\in\Omega}\int_{y\in\Omega} W(x,y)|t(y)-t(x)|dxdy \quad ........ (9)$$

where $\Omega$ is the image domain.

It is also beneficial to use the high-order differential operators. This simple extension endows us with more flexibility in the use of the contextual constraints.

Introducing a set of differential operators,

$$\sum_{j\in w}\left\|W_j \circ (D_j \otimes t)\right\| \quad ....... (10)$$

Where $w$ is an index set.

This contextual regularization enables us to incorporate a filter bank into image dehazing. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners.

To estimate optimal transmission function t(x), minimizing the following function:

$$\frac{\lambda}{2}\|t-\hat{t}\|_2^2 + \sum_{j\in w}\left\|W_j \circ (D_j \otimes t)\right\| \quad ....... (11)$$

To optimize above equation, an efficient method based on variable splitting is employed. We introduce the following auxiliary variables, denoted by $u_j (j \in w)$ and convert above equation to a new cost function as below:

$$\frac{\lambda}{2}\|t-\hat{t}\|_2^2 + \sum_{j\in w}\left\|W_j \circ u_j\right\| + \frac{\beta}{2}\left(\sum_{j\in w}\left\|u_j(D_j \otimes t)\right\|_2^2\right)..(12)$$

Where β is a weight. As $\beta \to \infty$ the solution of equation (12) will converge to that of equation (11).

Minimizing equation (12) for a fixed β can be performed by an alternating optimization with respect to $u_j$ and t.

Finally we estimate the transmission function using following formula,

$$t(x) = F^{-1}\left(\frac{\frac{\lambda}{\beta}F(\hat{t}) + \sum_{j\in w}\overline{F(D_j)} \circ F(u_j)}{\frac{\lambda}{\beta} + \sum_{j\in w}\overline{F(D_j)} \circ F(D_j)}\right) \quad ........ (13)$$

Finally we get the dehaze image using equation (4) by using values of estimated Airlight and estimated transmission function.

4.5 Matching using SURF

After getting result of dehaze image we are applying matching of feature points of hazy images and dehazed

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image. For this matching operation we are using here SURF (Speeded up Robust Features) operator. In a hazy image the matched feature points will be very less. After dehazing of image it is possible to also match those feature points which are not able to detect in the hazy image. Since, after the image enhancement more numbers of image feature points are detectable therefore there are efficient increments in the matched feature points in the dehazed image which reflect efficiency of our dehazing method.

SURF algorithm is scale and rotation invariant. SURF (Speed Up Robust Features) algorithm, is based on multi-scale space theory and the feature detector is base on Hessian matrix. Since Hessian matrix has good performance and accuracy. In image I(x,y), x and y is the given point, the Hessian matrix $H(x,\sigma)$ in x at scale σ, it can be defined as,

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}$$

Where $L_{xx}(x,\sigma)$ is the convolution result of the second order derivative of Gaussian filter $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I(x,y) in point x and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$.

SURF creates a “stack” without 2:1 down sampling for higher levels in the pyramid resulting in images of the same resolution. Due to the use of integral images, SURF filters the stack using a box filter approximation of second-order Gaussian partial derivatives. Since integral images allow the computation of rectangular box filters in near constant time. In Figure (4) show the Gaussian second orders partial derivatives in y-direction and xy-direction.

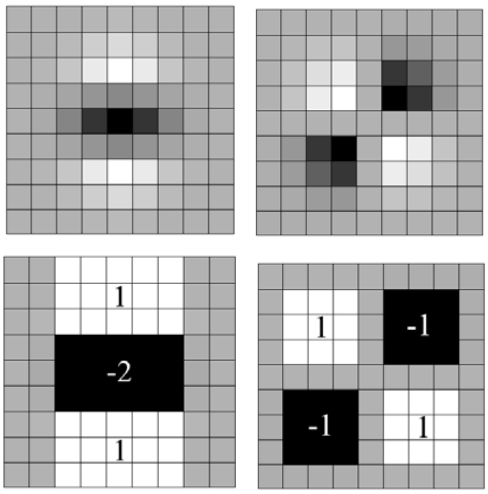



Fig. 4 The Gaussian second orders partial derivatives in y-direction and xy direction [34].

## V. RESULTS AND DISCUSSION

Some examples of our dehazing results are illustrated in figure. We are also including their boundary constraint map and recovered scene transmission function.

**Image1:**

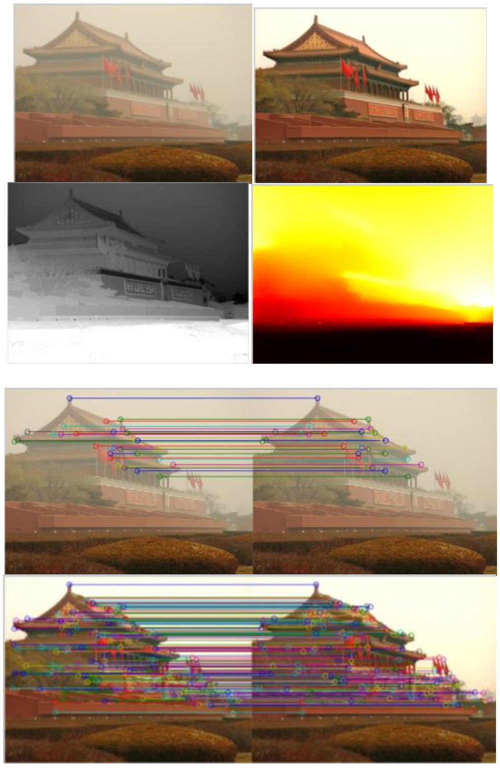
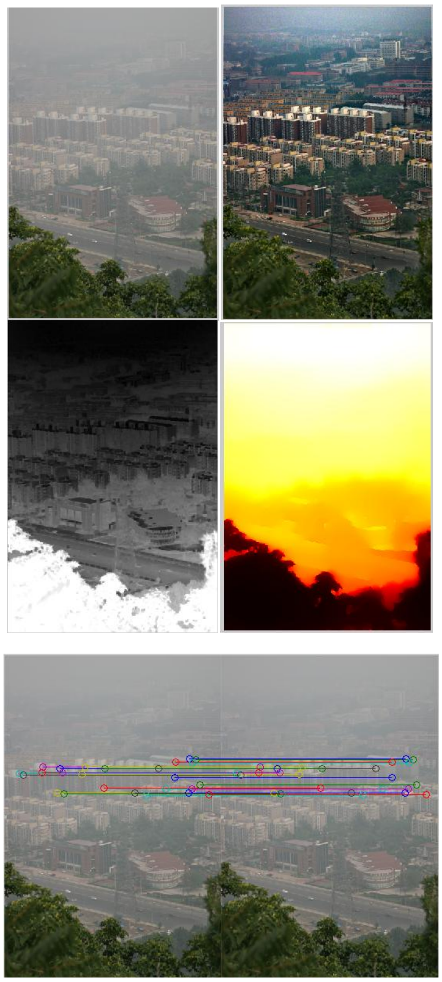


**Image2:**

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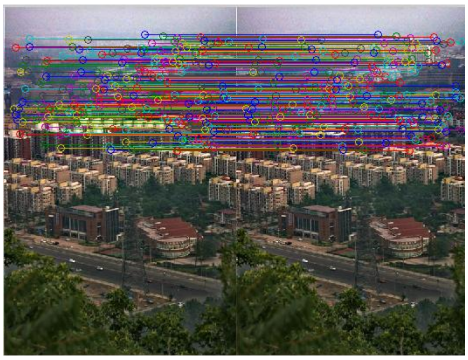

**Image3:**

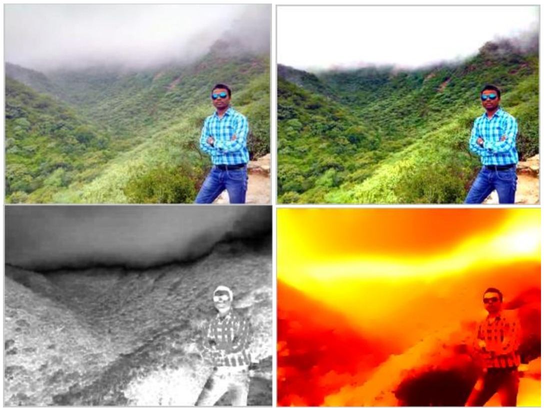

Fig.5. Dehazing and matching results: Image1, Image2 and Image3.

Left to right: (top) Hazy image, Dehazed image, (bottom) Boundary constraint map and Recovered scene transmission.
Bottom: (Up) Haze image matching points and (Down) Dehazed image matching points.

In our experiment we are taking Bitmap image as a input image (Hazy image). In our results we are showing input hazy image, their boundary constraint map and recovered scene transmission function (color map) and dehazed image. After dehazing operation we are also performing image matching of haze image and matching of dehazed image which are also shown in our result.

As can be seen from the results, our method can recover rich details of images with vivid color information in the haze regions. It should be pointed out that the estimated transmissions of the images in the figure cannot be regarded as a scaling version of the depth map, since the hazes in the images are not homogeneous. Actually, the transmission function reflects the density of the hazes in the captured scene.
In refining estimation process we performed six iterations for different values of β. We keep this values same for all images. The below table shows our iterations and respective values of β.

TABLE I VALUES OF β FOR DIFFERENT ITERATIONS

| **Iterations** | Iter1 | Iter2 | Iter3 | Iter4 | Iter5 | Iter6 |
|---|---|---|---|---|---|---|
| **β** | 1 | 2.83 | 8 | 22.6 | 64 | 181 |

The air light values are highest intensity pixels value in the foggy image. Maximum value of each color channel (R, G, B) is taken as estimate of component A. The estimated air light values of images found in our experiments are listed in below table.

TABLE II VALUES OF GLOBAL AIR LIGHT OF HAZE IMAGES

| **Images** | **Air light** | | |
|---|---|---|---|
| | **R** | **G** | **B** |
| Images1 | 193 | 185 | 164 |
| Images2 | 162 | 162 | 162 |
| Images3 | 192 | 186 | 200 |

The below table gives the number of best matches in hazy and dehaze condition of respective image.

TABLE III NUMBER OF MATCHING POINTS

| **Images** | **Haze matching points** | **Dehaze matching points** |
|---|---|---|
| Image1 | 30 | 200 |
| Image2 | 25 | 192 |
| Image3 | 30 | 185 |

As seen from above table the number of matching points for hazy images are very less which are efficiently increased after dehazing process that shows our method can effectively dehaze the weather degraded images.

## VI. CONCLUSION

In this paper we presented an efficient method for recovering a haze-free image when a single photograph is available as an input. This technique restores the hazy images based on the estimated transmission (depth) map. Our method benefits from three main contributions. The first is a new constraint on the scene transmission. This simple constraint, which has a clear geometric interpretation, shows to be surprisingly effective to image dehazing. Our second contribution is contextual regularization that enables us to incorporate a filter bank into image dehazing. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners. Our final contribution is an efficient optimization scheme, which enables us to quickly dehaze images of large sizes. And at the last stage we have performed image matching

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operation by using SURF operator to show the efficiency of our method. The more the Number of good matches more is the efficiency of the algorithm. This also shows that our technique is suitable for task of matching using local feature points.

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