International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:14, No:6, 2020

Image Haze Removal Using Scene Depth Based Spatially Varying Atmospheric Light in Haar Lifting Wavelet Domain

Prabh Preet Singh, Harpreet Kaur

Abstract**—**This paper presents a method for single image dehazing based on dark channel prior (DCP). The property that the intensity of the dark channel gives an approximate thickness of the haze is used to estimate the transmission and atmospheric light. Instead of constant atmospheric light, the proposed method employs scene depth to estimate spatially varying atmospheric light as it truly occurs in nature. Haze imaging model together with the soft matting method has been used in this work to produce high quality haze free image. Experimental results demonstrate that the proposed approach produces better results than the classic DCP approach as color fidelity and contrast of haze free image are improved and no over-saturation in the sky region is observed. Further, lifting Haar wavelet transform is employed to reduce overall execution time by a factor of two to three as compared to the conventional approach.

Keywords**—**Depth based atmospheric light, dark channel prior, lifting wavelet.

I. Introduction

HAZE is an atmospheric phenomenon that degrades the visual quality of an image thereby affecting the performance of many computer vision applications. Haze removal is a difficult task because thickness of haze depends upon depth, which is unknown. To estimate depth from a single image is an under constrained problem. Since the image dehazing model is an ambiguous problem, two strategies are available: Multiple image dehazing and single image dehazing. However, in many real applications, obtaining multiple images of the same scene is not possible; thus, single image dehazing has gained popularity. The success of various single image dehazing techniques depends on the accuracy and generality of their priors/assumptions.

Different single image dehazing methods have been used by authors for images and videos. He et al. [1] proposed the DCP for obtaining haze free image. Though simple and effective, the prior fails for the sky part of hazy images for which the results get oversaturated. In [2], Zhao improved the classical DCP method with a bright region filling process to remove color distortion in an aerial vehicle video signal. DCP together with the bright region filling process enhances the spatial consistency. They used a temporal filter between the adjacent frames to achieve better temporal coherence. To reduce computational complexity, they optimized the transmission calculation. Bi et al [3] proposed a brightness map that reflects the brightness information and light reflection ability of the scene for image dehazing. They also proposed a mathematical model that gives the relation between DCP and the brightness map. The advantage of their method is that it provides high quality haze free images. Qing et al. [4] used cluster segmentation for image dehazing. They used K-means clustering to segment the depth map into regions having different depths. They also estimated the attenuation coefficient based on intensity for each segmented region to improve the transmission accuracy. Nicholas et al. [5] estimated scene depth by exploiting attenuation differences among color channels in RGB color space. They then used this estimate to dehaze underwater images. Based on the fact that haze is low frequency noise, Yang et al. [6] employed Haar discrete wavelet transform (filter bank implementation) for image dehazing. They processed only the low frequency component of an image for haze removal. This led to a significant reduction in run time of the dehazing algorithm. Lifting scheme, developed by Sweldens [7]-[10] has several benefits over filter bank implementation of discrete time wavelets. Due to simple operations (split, predict and update), it is less complex and computationally less expensive. Inverse lifting transform can be easily obtained by just reversing the order and sign. Moreover, it is an in-place algorithm, i.e., does not require auxiliary memory. Considering the above benefits, in [11], we proposed the use of a lifting scheme to decompose the hazy image into approximation and detail coefficients.

In this paper, a method for image dehazing is presented inspired partly from the above stated works. The main contribution of this work is the increase in the accuracy of atmospheric light estimation. The expression for calculating atmospheric light at every pixel has been formulated. The formula is based on the fact that more the scene depth more is the thickness of haze and hence more is the atmospheric light. This ensures correct estimation even in the presence of Sun or any other light source which forms the reason for non-uniform atmospheric light. Apart from this, lifting Haar wavelet transform has been used to reduce computation runtime and memory requirements.

II. Preliminaries

The atmosphere scattering model widely used in image processing is:

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

Prabh Preet Singh and Harpreet Kaur are with the Delhi Technological University, India (e-mail: prabhpreet05@gmail.com, k.harpreet13@gmail.com).

x denotes the position of the pixel in the image, I denotes the observed hazy image intensity, J denotes the scene radiance, A is the atmospheric light and t is the transmission of the medium associated with the portion of light reaching the camera.

For a point in an image situated at a distance (depth) d from the camera, relation between transmission and depth is given by:

$$t(x) = e^{-\beta d(x)} \tag{2}$$

where, β is the ‘scattering coefficient.

As discussed above, recovering haze free image J from (1) is an under constrained problem due to unknown depth. To solve this problem, [1] proposed the DCP. The prior is based on the observation that in a large portion of the outdoor haze free images, no less than one color channel has a negligible intensity in a patch. They computed the dark channel for an image using a window Ω of size $15x15$ as:

$$I^{dark}(x) = \min_{y\in\Omega(x)}\left(\min_{c\in\{R,G,B\}} I^c(y)\right) \tag{3}$$

c denotes the color channel.

Normalizing the haze imaging equation by atmospheric light A gives:

$$\frac{I^c(x)}{A^c} = t(x)\frac{J^c(x)}{A^c} + 1 - t(x) \tag{4}$$

Now, assuming that the dark channel of haze free image is zero, i.e.

$$J^{dark}(x) = \min_{y\in\Omega(x)}(\min_c J^c(y)) = 0 \tag{5}$$

Transmission can be computed from (4) as:

$$\tilde{t}(x) = 1 - \min_{y\in\Omega(x)}\left(\min_c \frac{I^c(x)}{A^c}\right) \tag{6}$$

Atmospheric light required to estimate transmission is estimated as the average of the pixel intensities in the hazy image corresponding to 0.1% of the bright pixels in the dark channel. Thus, in the method proposed by [1], atmospheric light is assumed to be constant throughout the image. This, however, is not true because of the following reasons:

1) Haze density is different for different image regions and therefore atmospheric light also varies accordingly.
2) Due to the presence of sky region or say sunlight, atmospheric light is more in one part of the image than others.
3) When localized light sources are present in the image like a streetlight, vehicle headlights, and lamps, etc. atmospheric light is more near the center of these sources.

The impact of keeping atmospheric light constant can be seen in Fig. 1. To deal with this issue, in the proposed method, spatially varying atmospheric light is computed for each pixel on the basis of scene depth. This change in atmospheric light computation implicitly solves the sky saturation problem and leads to significant improvement in the visual quality of haze free image.

Fig. 1 (a) Input image (b) He's dehazed result [1]

III. Proposed Method

The proposed technique can be summarized as: Input hazy image is divided into approximate and detail coefficients using lifting haar wavelet transform. Only the approximate image is further processed for haze removal. Rough estimates of atmospheric light and transmission are obtained from the method discussed in Section II. Scene depth is determined from the rough transmission using (2). The rough estimate of atmospheric light computed above is then varied according to the scene depth to obtain pixel based spatially varying atmospheric light. Next, an improved transmission estimate is obtained using new atmospheric light. It is then refined using soft matting technique [12]. Scene radiance is recovered back using the atmosphere scattering model. Finally, the haze free image is reconstructed by applying inverse wavelet transform on haze free approximate image and detail coefficients.

In this section, two steps which are different from the conventional DCP approach are discussed in detail – lifting haar wavelet and depth based atmospheric light estimation.

A. Lifting Haar Wavelets

In the proposed method, lifting haar wavelet has been employed to decompose hazy image into four sub images. This renders benefits of lifting scheme to the proposed algorithm – speed, simplicity and memory efficiency.

Approximate ($\lambda(z)$) and detail coefficients ($\gamma(z)$) of haar have been obtained using:

$$\begin{bmatrix}\lambda(z)\\ \gamma(z)\end{bmatrix} = P(z)^{-1}\begin{bmatrix}f_e(z)\\ z^{-1}f_o(z)\end{bmatrix} \tag{7}$$

where, $f_e(z)$ and $f_o(z)$ refers to the even and odd samples of input discrete data sequence respectively and $P(z)$ refers to a poly-phase matrix with the value of its inverse as:

$$P(z)^{-1} = \begin{bmatrix}\sqrt{2} & 0\\ 0 & \frac{1}{\sqrt{2}}\end{bmatrix}\begin{bmatrix}1 & \frac{1}{2}\\ 0 & 1\end{bmatrix}\begin{bmatrix}1 & 0\\ -1 & 1\end{bmatrix} \tag{8}$$

Implementation of discrete wavelet transform (DWT) using traditional filter bank technique and the lifting scheme is shown in Figs. 2 and 3.

Fig. 5 illustrates the four components of the image shown in Fig. 4 obtained subsequent to wavelet decomposition. The approximation image contains the haze component and is the one which needs to be further processed by the dehazing algorithm.

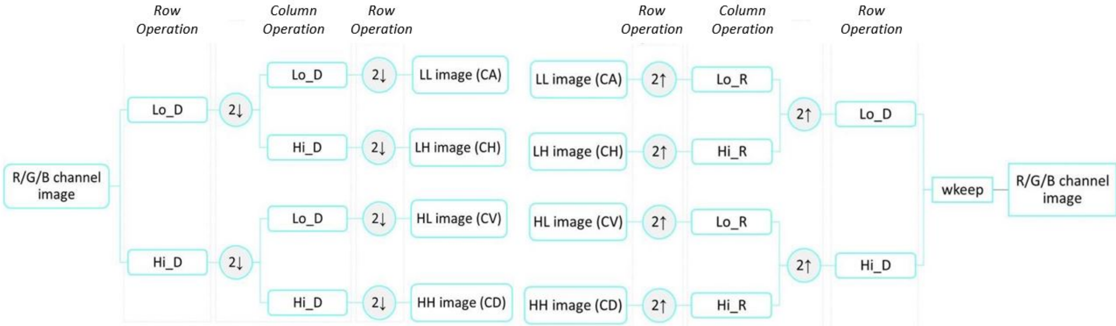

Fig. 2 DWT and inverse DWT implementation using filter bank for images

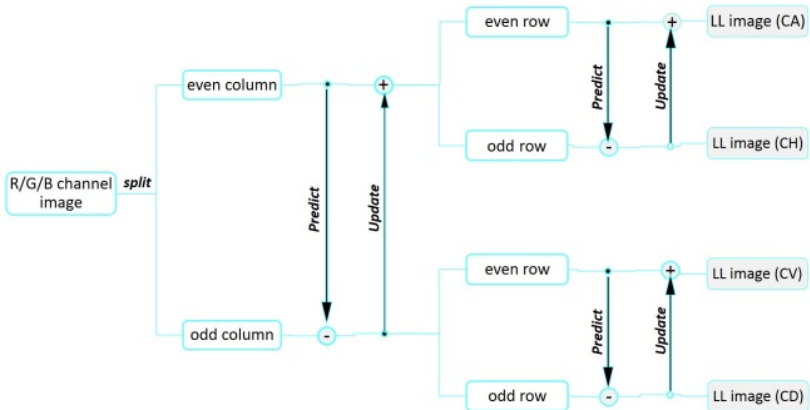

Fig. 3 DWT implementation using lifting wavelet scheme for images

Fig. 4 Hazy image

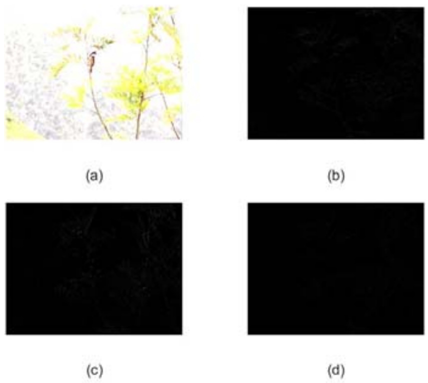

Fig. 5 Wavelet decomposition (a) Approximation image (b) Horizontal details (c) Vertical details (d) Diagonal details

B. Optimizing Atmospheric Light Estimation

To compute atmospheric light that varies with scene depth for each pixel, first the rough estimates of transmission t_{old} and atmospheric light A_{old} are obtained using the conventional DCP approach (Section II). Depth is computed using the following expression obtained by rearranging (2),

$$d(x) = \frac{1}{\beta}\ln\left(\frac{1}{t_{old}(x)}\right) \tag{9}$$

β has been taken as 1.

For points located too far from the camera, the transmission value is very low. Due to this, the depth for these location points is overestimated. To deal with this, an upper limit $depthul$ has been set on depth value. Similarly, to deal with unreasonably low depth values, a lower limit $depthll$ has also been set on depth value.

The constant value of atmosphere, A_{old}, is a 3-D vector containing values of atmospheric light corresponding to each color – Red, Green and Blue. In the proposed technique, each value of A_{old} is independently varied according to depth using:

$$delta = k - slope * exp^{-scale*depth} \tag{10}$$

$$A_{new}^{c} = A_{old}^{c} * delta \tag{11}$$

where k is constant, $slope$ decides the rate of rising of the exponential graph, $scale$ controls the extent of variation of new atmospheric light in accordance with depth (set to 3 in the proposed technique), $depth$ is a 2-d matrix obtained from (9) and c refers to the colour channel. Note that for each value of A_{old}^{c}, two dimensional matrix $A_{new}^{c}$is produced.

The parameter slope is calculated as:

$$delta_{min} = dark_{min}/A_{old}^{c} \tag{12}$$

$$slope = \frac{1 - delta_{min}}{exp^{-scale*depthll} - exp^{-scale*depthul}} \tag{13}$$

$dark_{min}$ is the average of the pixel intensities in the approximate hazy image corresponding to 0.1 % of the darkest pixels in the dark channel. $delta_{min}$ specifies the minimum amount of variation in A_{old}^{c}. It can be easily verified that when $delta_{min}$ is 1, $slope$ is 0 and $delta$ is 1, thus, in that case, A_{new}^{c} is same as A_{old}^{c}.

The value of constant k is computed as:

$$k = 1 + slope * exp^{-scale*depthul} \tag{14}$$

The atmospheric light calculated by the proposed method is depicted in Fig. 6.

Fig. 6 (a) Hazy image (b) Atmospheric light calculated using proposed method

C. Haze Free Approximation Image

In the proposed method, transmission is estimated using haze imaging model with the only difference that now atmospheric light is pixel based. Mathematically,

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_{c} \left(\frac{I^{c}(x)}{\max_{c}(A_{new}(x))} \right) \right) \tag{15}$$

After having calculated the atmospheric light and transmission, scene radiance can be calculated using haze imaging model with the only change of pixel based A.

$$J(x) = \left(\frac{I(x) - A_{new}(x)}{max(t(x), t_0)} \right) + A_{new}(x) \tag{16}$$

IV. Simulation and Results

In this section, the efficacy of the proposed algorithm over a set of different types of real images has been illustrated. The performance of the proposed algorithm is measured with two approaches: Objective evaluation and subjective evaluation.

A. Subjective Evaluation

Figs. 7-9 show that the output from the proposed algorithm reproduces natural sky shades without compromising on the non-sky region.

Figs. 10-15 show natural colors are well preserved in results obtained from the proposed technique. Despite color fidelity, the proposed method's results exhibit better contrast and brightness.

B. Objective Evaluation

In order to quantify the image quality produced by the proposed method, Structural Similarity Index (SSIM), entropy and contrast have been considered as performance parameters. Their physical significance to image dehazing along with formulation is as follows:

1. SSIM

It indicates the degree of structure retained in a processed image with respect to the reference image. In the proposed method, SSIM of output haze free image has been measured considering the hazy image as a reference. Formulation:

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{17}$$

2. Contrast

Higher contrast makes it easy to differentiate among objects in an image. In the present work, root mean square contrast has been used as a metric. This is the same as standard deviation. Formulation:

$$RMS\ Contrast = \sqrt{\frac{1}{MN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \left(I_{ij} - \bar{I}\right)^2} \tag{18}$$

3. Entropy

Entropy signifies randomness. A low value of entropy corresponds to homogenous regions of the image. Since haze is distributed all over the image, hazy image has low entropy as compared to haze free image. Thus, entropy is related to the amount of haze removed from the image. Formulation:

$$Entropy\ H = -\sum_{i} p_i (log_2 p_i) \tag{19}$$

Table I shows the run time comparison between the classic DCP approach and the proposed algorithm. For most of the cases, the proposed algorithm reduces the execution time by a factor of around three. Table II shows the comparison on the basis of entropy, RMS contrast and SSIM. As can be observed, the proposed algorithm produces better results.

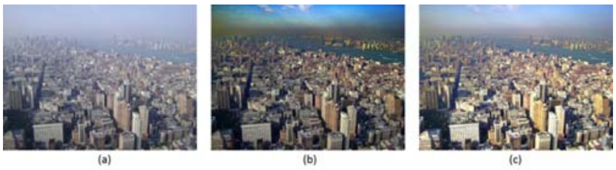

Fig. 7 New York - Sky saturation problem (a) Hazy image (b) Traditional DCP (c) Proposed method

Fig. 8 Mountain - Sky saturation problem (a) Hazy image (b) Traditional DCP (c) Proposed method

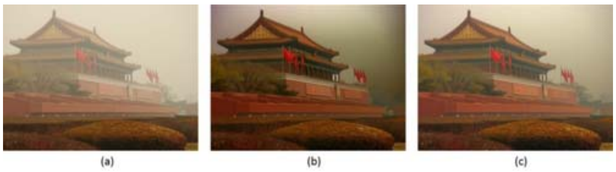

Fig. 9 Temple - Sky saturation problem (a) Hazy image (b) Traditional DCP (c) Proposed method

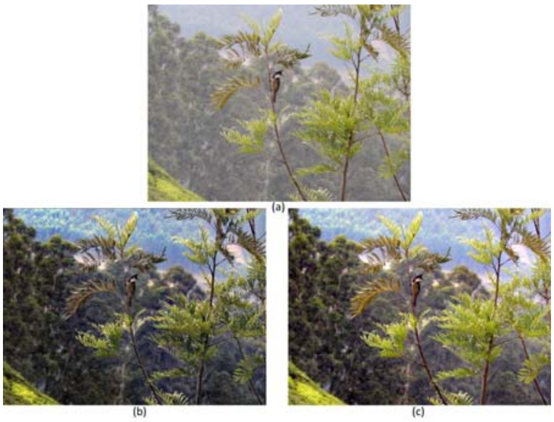

Fig. 10 Bird - Contrast and Color Fidelity Comparison (a) Hazy image (b) Traditional DCP (c) Proposed method

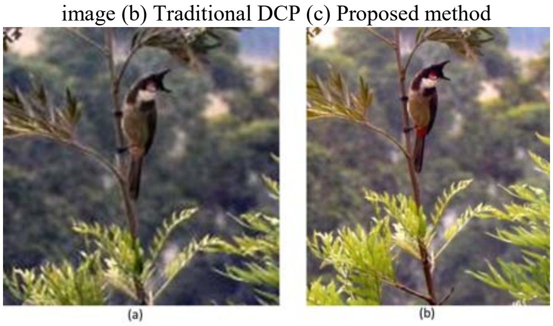

Fig. 11 Bird - Zoom in view (a) Traditional DCP (b) Proposed method

Fig. 12 Canon - Contrast and Color Fidelity Comparison (a) Hazy image (b) Traditional DCP (c) Proposed method

Fig. 13 Canon – Zoom in View (a) Traditional DCP (b) Proposed method

Fig. 14 Market - Contrast and Color Fidelity Comparison (a) Hazy image (b) Traditional DCP (c) Proposed method

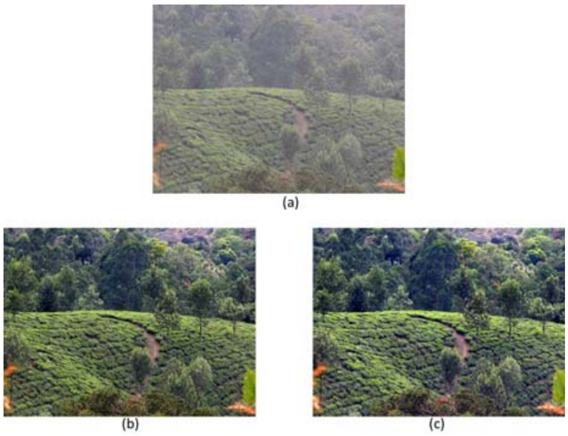

Fig. 15 Tea Garden - Contrast and Brightness Comparison (a) Hazy image (b) Traditional DCP (c) Proposed method

V. Conclusion

In the method, a single image dehazing method based on

DCP has been proposed. Atmospheric light has been calculated for each pixel on the basis of its depth. This accurate estimation of atmospheric light further leads to the accuracy of transmission and scene radiance. The effectiveness of the proposed method can be observed from the results produced. Accurate estimation of atmospheric light enables the algorithm to implicitly retain natural sky shades. Employment of haar lifting wavelet transform made the algorithm fast, simple, and memory efficient.

TABLE I
EXECUTION TIME COMPARISON

Image name	Image Dimensions	He's method	Proposed method
New York	1024x768	117.723s	42.530s
Temple	600x450	29.042s	15.133s
Canon	400x600	46.307s	12.313s
Mountain	512x384	24.787s	10.890s
Bird	1152x864	162.504s	55.959s
Tea Garden	1152x864	161.940s	55.046s
Market	332x500	23.546s	9.491s

TABLE II
PARAMETER COMPARISON

Parameter	Entropy			SSIM		Contrast		
Image	Hazy image	Classical DCP	Proposed Algorithm	Classical DCP	Proposed Algorithm	Hazy image	Classical DCP	Proposed Algorithm
Canon	6.89	7.23	7.2	0.58	0.66	6.28	6.02	5.66
Tea Garden	6.34	7.33	7.37	0.61	0.61	2.92	5.81	6.64
Bird	6.99	7.52	7.78	0.67	0.78	4.77	7.48	8.72
Market	7.3	7.84	7.89	0.61	0.65	6.74	9.44	10.07
Mountain	7.48	7.53	7.65	0.76	0.77	5.64	5.59	5.96
New York	7.61	7.64	7.77	0.7	0.78	7.69	7.67	8.88
Tiananmen	7.64	7.61	7.79	0.77	0.93	8.95	7.59	8.85

REFERENCES

[1] Kaiming He, Jian Sun, and Xiaoou Tang, Fellow IEEE, "Single Image Haze Removal Using Dark Channel Prior", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 12, December 2011

[2] X. Zhao, W. Ding, C. Liu and H. Li, “Haze Removal For Unmanned Aerial Vehicle Aerial Video Based On Spatial-Temporal Coherence Optimisation.”, IET Image Processing, vol. 12, no. 1, pp. 88-97, 2017.

[3] G. Bi, J. Ren, T. Fu, T. Nie, C. Chen and N. Zhang, “Image Dehazing Based On Accurate Estimation Of Transmission In The Atmospheric Scattering Model”, IEEE Photonics Journal, vol. 9, no. 4, pp.1-18, 2017.

[4] C. Qing, Y. Hu, X. Xu, W. Huang, “Image Haze Removal Using Depth-Based Cluster And Self-Adaptive Parameters”, 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), pp. 1070-1075, 2017.

[5] Nicholas Carlevaris-Bianco, Anush Mohan and Ryan M. Eustice, "Initial Results in Underwater Single Image Dehazing", IEEE Oceans Mts, September 2010

[6] Yanjing Yang, Zhizhong Fu, Xinyu Li, Chang Shu and Xiaofeng Li, “A Novel Single Image Dehazing Method” , IEEE International Conference on Computational Problem-solving (ICCP), October 2013Kaiming He, Jian Sun, “Fast Guided filter”, Microsoft.com, arXiv:1505.00996v1(cs.CV), 5 May 2015

[7] W. Sweldens, "The Lifting Scheme: A Construction of second generation wavelets," SIAMJ. Math. Anal 1997

[8] W. Sweldens, "The Lifting Scheme: A Custom Design construction of Biorthogonal," Wavelets Appl. Comput. Harmon. Anal. 3(2); 1996

[9] I. Daubechies and W. Sweldens "Factoring wavelet transform into lifting steps" Technical report, Bell Laboratories, Lucent Technologies, 1996

[10] W. Sweldens “Wavelets and the lifting scheme: A 5 minute tour“, ZAMM - Journal of Applied Mathematics and Mechanics, vol. 76 (Suppl. 2), pp. 41-44, 1996

[11] “Image Dehazing Using Dark Channel Prior and Fast Guided Filter in Daubechies Lifting Wavelet Transform Domain”, World Academy of Science, Engineering and Technology, International Journal of Computer and Information Engineering Vol:12, No:3, 2018

[12] A. Levin, D. Lischinski, and Y. Weiss, “A Closed Form Solution to Natural Image Matting,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. 1, pp. 61-68, 2006