Edge-Preserving Decomposition Based Single Image Haze Removal

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Abstract—Single image haze removal is under-constrained because the number of freedoms is larger than the number of observations. In this paper, a novel edge-preserving decomposition based method is introduced to estimate transmission map for a haze image so as to design a single image haze removal algorithm from the Koschmiedars law without using any prior. Particularly, weighted guided image filter is adopted to decompose simplified dark channel of the haze image into a base layer and a detail layer. The transmission map is estimated from the base layer, and it is applied to restore the haze-free image. Experimental results on different types of images including haze images, underwater images, and normal images without haze show the performance of the proposed algorithm.

Index Terms—Single image haze removal, Edge-preserving smoothing, Weighted guided image filtering, Minimal color channel

I. INTRODUCTION

Images of outdoor scenes often suffer from bad weather conditions such as haze, fog, smoke and so on. The light is scattered and absorbed by the aerosols in the atmosphere, and it is also blended with air-light reflected from other directions. This process fades the color and reduces the contrast of captured objects, and the degraded images often lack visual vividness. Haze removal can significantly increase both local and global contrast of the scene, correct the color distortion caused by the air-light, and produce depth information. As such, the dehazed image is usually more visually pleasing. The performance of computer vision algorithms and advanced image editing algorithms can also be improved. Therefore, haze removal is highly demanded in image processing, computational photography and computer vision applications [1].

Since the amount of scattering depends on the unknown distances of the scene points from the camera and the air-light is also unknown, it is challenging to remove haze from haze images, especially when there is only a single haze image. Many methods were presented by using multiple images or additional information [2], [3], [4]. For example, in [2], the depth boundary is detected from multiple images captured under different atmospheric or weather conditions, and a haze-free image is then recovered. Haze is removed by using a polarization based method in [3] through two images taken with different degrees of polarization. The scene depth was measured from the difference between the two images. Depth information either from user inputs or from 3D models is required by a depth based method in [4]. Although these methods work well in presence of multiple images capturing the same scene with haze, applications of the methods are limited because of their requirements on the inputs.

Recently, haze removal through single image attracted much interest and made significant progresses due to its broad applications. Many single image haze removal algorithms were proposed. Based on an observation that a haze-free image has higher contrast than its haze image, an interesting single image haze removal algorithm was proposed in [5] by maximizing the local contrast of the restored image. The results are visually compelling while they might not be physically valid. A haze image is interpreted in [6] through a refined image formation model that accounts for both surface shading and scene transmission. Under an assumption that the transmission and the surface shading are locally uncorrelated, the air-light-albedo ambiguity is resolved. The algorithm proposed by Fattal [6] sounds reasonable from the physical point of view and it can also produce impressive results. However, this algorithm could fail in presence of heavy haze. Novel dark channel prior based haze removal algorithms were proposed in [7], [10]. The dark channel prior is based on an observation of haze-free outdoor images, i.e., in most of the local regions which do not cover the sky, it is very often that some pixels have very low intensity in at least one color (RGB) channel. The algorithm is physically valid and can handle distant objects even in images with heavy haze. However, noise in the sky could be amplified and color in sky regions could be distorted by using the algorithm in [7], [10] even though a lower bound was introduced for the transmission map in [7], [10]. The dark channel prior was simplified in [11], [15] by using the minimal color component of a haze image. An adaptive sky region compensation term was also proposed to avoid the amplification of noise in the sky region. Beside the above haze removal algorithms, many other interesting single image haze removal algorithms were recently proposed such as [8], [9], [16], [17], [18], [19], [20], [21], and similar ideas were applied to enhance underwater images [22], [23], [24]. The estimation of the transmission map is crucial for single image haze removal algorithms. There are two steps in most of the above algorithms. In the first step, an initial value of the transmission map is given using a prior. In the second step, the transmission map is refined by using a local edge-preserving filter. The accuracy of the priors is verified using extensive experimental results in the corresponding algorithms. One natural question is “Why is the second step required given the accurate prior?” A further question is “Is it possible to design a single image haze removal algorithm from the Koschmiedars law [28] without
using any prior?” The major objective of this paper is to answer the latter question.

Inspired by an observation in [11] that single image haze removal can be regarded as a type of spatially varying detail enhancement, a neat single image haze removal algorithm is proposed in this paper by introducing an edge-preserving decomposition technique to estimate the transmission map for a haze image. The proposed algorithm is based on the concepts of minimal color channel [12], [13], [14], [15] and simplified dark channel in [15]. A new insight is provided on the simplified dark channel, i.e., the major function of the simplified dark channel is to reduce the variation of the direct attenuation. As such, the simplified dark channel of the haze image can be decomposed into a base layer and a detail layer via an existing edge-preserving smoothing technique. The base layer is composed of the transmission map. To avoid introducing artifacts to the dehazed image, the structure of the base layer is required to be similar to the structure of the haze image. Based on the observation, the weighted guided image filter (WGIF) in [11] is applied to decompose the simplified dark channel of the haze image. The guidance image is computed using the minimal color channel of the haze image. This is because the structure of the haze image is preserved better by the minimal channel of the haze image than the simplified dark channel of the haze image. To avoid amplifying noise in the haze image, the adaptive compensation term in [11] is adopted to constrain the transmission map, especially in the sky region. The estimated transmission map is finally used to recover the haze image. Experimental results show that the proposed algorithm is applicable to haze images, underwater images and normal images without haze. It should be pointed out that the proposed algorithm is a new framework for signal image haze removal which is from the Koschmieder's law without using any prior.

The rest of this paper is organized as follows. Existing works on guided image filtering (GIF) are summarized in Section II. A new model is proposed in Section III to decompose the simplified dark channel of a haze image into a base layer and a detail layer. Section IV includes details on the proposed haze removal algorithm. Experimental results are given in Section V to illustrate the efficiency of the proposed algorithm. Concluding remarks are provided in Section VI.

II. RELATED WORKS ON GUIDED IMAGE FILTERS

In this section, existing edge-preserving smoothing techniques are summarized with the emphasis on the GIF in [10] and the WGIF in [11].

One of the most popular edge-preserving smoothing techniques is based on local filtering. The bilateral filter (BF) is widely used due to its simplicity [25], [26]. However, the BF could suffer from “gradient reversal” artifacts which refer to the artifacts of unwanted sharpening of edges despite its popularity [10], and the results may exhibit undesired profiles around edges, usually observed in detail enhancement of conventional low dynamic range images or tone mapping of high dynamic range images. The GIF was introduced in [10] to overcome this problem. In the GIF, a guidance image $G$ is used which could be identical to an image $X$ to be filtered. It is assumed that a reconstructed image $Z$ is a linear transform of the guidance image $G$ in a window $\Omega_{\zeta_1}(p')$ [29], [30]:

$$ Z(p) = a_{p'} G(p) + b_{p'}, \forall p \in \Omega_{\zeta_1}(p'), $$

where $\Omega_{\zeta_1}(p')$ is a square window centered at the pixel $p'$ of a radius $\zeta_1$, $a_{p'}$ and $b_{p'}$ are two constants in the window $\Omega_{\zeta_1}(p')$.

The values of $a_{p'}$ and $b_{p'}$ are obtained by minimizing a quadratic cost function $E(a_{p'}, b_{p'})$ which is defined as

$$ E = \sum_{p \in \Omega_{\zeta_1}(p')} [(a_{p'} G(p) + b_{p'} - X(p))^2 + \lambda a_{p'}^2], $$(2)

where $\lambda$ is a regularization parameter penalizing large $a_{p'}$. The value of $\lambda$ is fixed for all pixels in the image. Even though the “gradient reversal” artifacts are overcome by the GIF, the GIF and the BF have a common limitation, i.e., they may exhibit halo artifacts near some edges where halo artifacts refer to the artifacts of unwanted smoothing of edges. As indicated in [10], the GIF would concentrate blurring near edges and introduce halos while global optimization based filters such as the weighted least squares (WLS) filter in [31] would distribute the blurring globally. It was observed in [11] that the Lagrangian factor is adaptive in the WLS filter and it is fixed in the GIF. This could be another reason that halo artifacts are avoided by the WLS filter. Based on the observation, an edge-aware weighting is incorporated into the GIF in [10] to form the WGIF [11].

In human visual perception, edges provide an effective and expressive stimulation that is vital for neural interpretation of a scene [32]. Larger weights are thus assigned to pixels at edges and introduce halos while global optimization based filters such as the weighted least squares (WLS) filter in [31] would distribute the blurring globally. It was observed in [11] that the Lagrangian factor is adaptive in the WLS filter and it is fixed in the GIF. This could be another reason that halo artifacts are avoided by the WLS filter. Based on the observation, an edge-aware weighting is incorporated into the GIF in [10] to form the WGIF [11].
It was shown in [11] that the WGIF can be applied to reduce/avoid halo artifacts from appearing in final images. In this paper, the WGIF will be applied to decompose the simplified dark channel of a haze image into two layers.

III. EDGE-PRESERVING DECOMPOSITION OF A HAZE IMAGE

In this section, a new model is built up to decompose the simplified dark channel of the haze image into two layers. The decomposition will be adopted in the next section to design a simple single image haze removal algorithm which is from the Koschmiedars law without using any prior.

A. Modelling of haze images

According to the Koschmiedars law [28], a haze image is generally modeled by

\[ X_c(p) = Z_c(p)t(p) + A_c(1 - t(p)), \]

where \( c \in \{r, g, b\} \) is a color channel index, \( X_c \) is a haze image, \( Z_c \) is a haze-free image, \( A_c \) is the global atmospheric light, and \( t \) is the medium transmission describing the portion of the light that is not scattered and reaches the camera.

The first term \( Z_c(p)t(p) \) is called direct attenuation [5] and it describes the scene radiance and its decay in the medium. The second term \( A_c(1 - t(p)) \) is called air-light. Air-light results from previous scattered light and leads to the shift of the scene color. When the atmosphere is homogenous, the transmission \( t(p) \) can be expressed as:

\[ t(p) = e^{-\alpha d(p)}, \]

where \( \alpha \) is the scattering coefficient of the atmosphere. It indicates that the scene radiance is attenuated exponentially with the scene depth \( d(p) \). The value of \( \alpha \) is a monotonically increasing function of the haze degree.

Same as the existing haze removal algorithms [7], [10], [11], it is assumed that the value of \( t(p) \) is constant in a small patch. If the contrasts in the image are measured as the magnitude of its gradient field, it can be derived from Equation (5) that

\[ \|\nabla X_c(p)\| = \|t(p)\nabla Z_c(p) + (1 - t(p))\nabla A_c\| = t(p)\|\nabla Z_c(p)\|. \]

It can be derived from Equation (6) that

\[ 0 \leq t(p) \leq 1. \]

This implies that the haze-free image \( Z_c \) has higher contrast than the haze image \( X_c \). The contrast is attenuated exponentially with the scene depth. When the haze becomes heavier, the attenuation rate of the contrast is increased. As a result, the hazed image is smoother and the color fidelity of the hazed image is lost more.

The objective of haze removal is to restore the haze-free image \( Z \) from the haze image \( X \). It is a challenging problem because the haze is dependent on the unknown depth information \( d(p) \) as in Equation (6). In addition, it is under-constrained as the input is only a single haze image while all the components \( A_c \), \( t(p) \) and \( Z_c(p) \) are freedoms. To restore the haze-free image \( Z \), both the global atmospheric light \( A_c \) and the transmission map \( t(p) \) need to be estimated. The haze-free image \( Z \) is then restored as

\[ Z_c(p) = X_c(p) + \frac{1}{t(p)} - 1)(X_c(p) - A_c). \]

It can be observed from the above equation that single image haze removal is a type of spatially varying detail enhancement. The amplification factor is \( \frac{1}{t(p)} - 1 \) which is spatially varying, and the detail layer is \( (X_c(p) - A_c) \) [11]. Inspired by this observation, a new haze removal algorithm is introduced in this paper.

B. Decomposition of the simplified dark channel of a haze image

A new haze image model is derived by using the simplified dark channels of the haze image \( X \) and the haze-free image \( Z \). Let \( A_m \), \( X_m(p) \) and \( Z_m(p) \) be defined as [11]

\[ A_m = \min\{A_r, A_g, A_b\}, \]
\[ X_m(p) = \min\{X_r(p), X_g(p), X_b(p)\}, \]
\[ Z_m(p) = \min\{Z_r(p), Z_g(p), Z_b(p)\}. \]

\( X_m \) and \( Z_m \) are called the minimal color components of the images \( X \) and \( Z \), respectively [12], [13], [14], [15]. Because the transmission map \( t(p) \) is independent of the color channels \( r, g, \) and \( b \), it can be derived from the haze image model in Equation (5) that the relationship between the minimal color components \( X_m \) and \( Z_m \) is given as

\[ A_m - X_m(p) = (A_m - Z_m(p))t(p). \]

Let \( \Psi_{\zeta_2}(\cdot) \) be a minimal operation in the neighborhood \( \Omega_{\zeta_2}(p) \) and it is defined as

\[ \Psi_{\zeta_2}(z(p)) = \min_{p' \in \Omega_{\zeta_2}(p)} \{z(p')\}. \]

With the fast implementation in [27], the complexity of \( \Psi_{\zeta_2}(z(p)) \) is \( O(N) \) for an image with \( N \) pixels. The simplified dark channels of images \( X \) and \( Z \) are defined as [11]

\[ J_d^X(p) = \Psi_{\zeta_2}(Z_m(p)) ; J_d^Z(p) = \Psi_{\zeta_2}(X_m(p)), \]

where the value of \( \zeta_2 \) is set at 7 if it is not specified.

Since the value of \( t(p) \) is usually constant in the neighborhood \( \Omega_{\zeta_2}(p) \), it can be derived from Equation (13) that

\[ A_m - J_d^X(p) = (A_m - J_d^X(p))t(p). \]

Both the dark channel prior in [7], [10] and the simplified dark prior in [11] assume that the values of \( J_d^X(p) \)’s are zero’s. The transmission map \( t(p) \) is first estimated by using the prior and Equation (16), and it is refined via the GIF or the WGIF. The prior is not always satisfied. It was pointed out in [7], [10]
that the values of $J_d^Z(p)$'s are usually very small except for pixels in the sky-regions. Instead of using the prior as in [7], [10], [11], the proposed algorithm uses an important feature of $J_d^Z(p)$, i.e., the variation of $J_d^Z(p)$ is usually small even though the value of $J_d^Z(p)$ could be large in the sky region. This implies that the major function of the simplified dark channel is to reduce the variation of $(A_m - J_d^Z(p))$ such that the term $t(p)$ forms the base layer and the term $(A_m - J_d^Z(p))$ forms the detail layer.

IV. SINGLE IMAGE HAZE REMOVAL VIA 
EDGE-PRESERVING DECOMPOSITION

In this section, a simple single image haze removal algorithm is introduced by using the new decomposition model proposed in the previous section. The global atmospheric light $A_c(c \in \{r, g, b\})$ is first empirically determined by using a hierarchical searching method based on the quad-tree subdivision. The WGIF is then adopted to decompose the simplified dark channel of a haze image into two layers as in Equation (16) and the value of $t(p)$ is then obtained. Finally, the scene radiance $Z(p)$ is recovered by using the haze image model in Equation (5).

A. Empirical estimation of the global atmospheric light

The global atmospheric light $A_c(c \in \{r, g, b\})$ is usually estimated as the brightest color in a hazed image, since a large amount of haze causes a bright color. However, objects, which are brighter than the atmospheric light, could lead to undesirable selection of the atmospheric light. Based on the observations that the variance values of pixels are generally small while the intensity values are large in bright regions, the values of $A_c(c \in \{r, g, b\})$ are obtained by a hierarchical searching method on basis of the quad-tree subdivision [33].

The input image is firstly divided into four rectangular regions. Each region is assigned a value which is computed as the average pixel value subtracted by the standard deviation of the pixel values within the region. The region with the highest value is then selected and it is furthered divided into four smaller rectangular regions. The process is repeated until the size of the selected region is smaller than a pre-defined threshold which is selected as $32 \times 32$ if it is not specified. In the finally selected region, the pixel which minimizes the difference $\| (X_r(p), X_g(p), X_b(p)) - (255, 255, 255) \|$ is chosen and it is used to determine the global atmospheric light.

B. Estimation of the transmission map

Once the values of $A_c(c \in \{r, g, b\})$ are obtained, the value of $A_m$ can be computed via Equation (10). The decomposition model in Equation (16) is available. The WGIF in [11] is applied to decompose the image $(A_m - J_d^X(p))$ into two layers as in Equation (16). The guidance image $G$ is computed using the minimal color channel $X_m$ rather than the simplified dark channel $J_d^X$ as

$$G(p) = A_m - X_m(p).$$

This is because the structure of the haze image is preserved better by the minimal color component $X_m$ than the simplified dark channel $J_d^X$ as shown in Fig. 1.

![Fig. 1: Minimal color component and simplified dark channel of the haze image in Fig. 8(a). The minimal color component (a) preserves the structure of the haze image better than the simplified dark channel (b).](image)

It is assumed that the base layer $t(p)$ is a linear transform of the guidance image $G(p)$ in the window $\Omega_{\zeta_1}(p')$:

$$t(p) = a_{p'} G(p) + \tilde{b}_{p'} \forall p \in \Omega_{\zeta_1}(p'),$$

where $a_{p'}$ and $\tilde{b}_{p'}$ are two constants in the window $\Omega_{\zeta_1}(p')$.

The values of $a_{p'}$ and $\tilde{b}_{p'}$ are obtained by minimizing the following cost function $E(a_{p'}, \tilde{b}_{p'})$:

$$\sum_{p \in \Omega_{\zeta_1}(p')} [(a_{p'} G(p) + \tilde{b}_{p'} - (A_m - J_d^X(p)))^2 + \frac{\lambda}{\Gamma_{C'}(p')} a_{p'}^2 ],$$

where the values of $\zeta_1$ and $\lambda$ are respectively set at 60 and 256 if they are not specified.

It should be pointed out that an optimization based approach was proposed in [34], [35]. Both the approach in [34], [35] and the proposed one assume that the global atmospheric light is empirically determined in advance. Two major differences between the approach in [34], [35] and the proposed one are: 1) the approach in [34], [35] is based on global optimization while the proposed one is based on local optimization; and 2) the proposed approach is explicitly based on edge-preserving smoothing techniques while the approach in [34], [35] is not. As such, the proposed algorithm is simpler than the approach in [34], [35]. The proposed formulation in Equation (18) also shares common points with the haze removal algorithms in [10], [11] in the sense that all of them are based on the GIF or the WGIF, and a linear relationship is built up between the transmission map and the original image. The major difference between the algorithms in [10], [11] and the proposed one is that the algorithms in [10], [11] are based on the dark channel prior while the proposed algorithm is based on an edge-preserving decomposition technique without any prior.
Defining \( \varphi(p) \) as \((A_m - t(p))\) and \( b_{p'} \) as \(((1 - a_{p'})(A_m - \bar{b}_{p'})\), it can be derived that
\[
\varphi(p) = a_{p'}X_m(p) + b_{p'}; \quad \Gamma_G(p') = \Gamma_{X_m}(p'),
\]
and the cost function \( E(a_{p'}, \bar{b}_{p'}) \) is equivalent to
\[
\sum_{p \in \Omega_{\xi_1}(p')} [(a_{p'}X_m(p) + b_{p'} - J_d^X(p'))^2 + \frac{\lambda}{\Gamma_{X_m}(p')}a_{p'}^2].
\]

The optimal values of \( a_{p'} \) and \( b_{p'} \) are computed as [11]
\[
a_{p'}^* = \frac{\mu_{X_m \odot J_d^X, \xi_1}(p') - \mu_{X_m, \xi_1}(p') \mu_{J_d^X, \xi_1}(p')}{\sigma^2_{X_m, \xi_1}(p') + \frac{\lambda}{\Gamma_{X_m}(p')}}, \quad b_{p'}^* = \mu_{J_d^X, \xi_1}(p') - a_{p'}^* \mu_{X_m, \xi_1}(p'),
\]
where \( \odot \) is the element-by-element product of two matrices. \( \mu_{X_m \odot J_d^X, \xi_1}(p'), \mu_{X_m, \xi_1}(p') \) and \( \mu_{J_d^X, \xi_1}(p') \) are respectively the mean values of \( X_m \odot J_d^X, X_m \) and \( J_d^X \) in the window \( \Omega_{\xi_1}(p') \).

The optimal solution \( \varphi^*(p) \) is then given as follows:
\[
\varphi^*(p) = \bar{a}_{p'}^*X_m(p) + \bar{b}_{p'},
\]
where \( \bar{a}_{p'}^* \) and \( \bar{b}_{p'}^* \) are the mean values of \( a_{p'}^* \) and \( b_{p'}^* \) in the window \( \Omega_{\xi_1}(p') \), respectively. Due to the box filter in [10], the complexity on the computation of \( \varphi^*(p) \) is \( O(N) \) for an image with \( N \) pixels.

Suppose that \((A_m - \varphi^*(p), A_m - J_d^{Z^*}(p))\) is an optimal solution. For any given positive \( \beta, (\beta(A_m - \varphi^*(p)), (A_m - J_d^{Z^*}(p))/\beta) \) is also an optimal solution. Fortunately, \( \varphi^*(p) \) is usually smaller than \( A_m \). The ambiguity can thus be avoided by using Equation (6). The optimal value of the transmission map \( t(p) \) is computed as
\[
t^*(p) = 1 - \frac{\varphi^*(p)}{A_m}.
\]

The base and the detail layers of the simplified dark channel of the haze image in Fig. 8(a) are shown in Fig. 2. It is observed that the value of \( t^*(p) \) is almost zero if the pixel \( p \) belongs to the sky region.

**Fig. 2:** The base layer (a) and the detail layer (b) decomposed from the simplified dark channel of the haze image in Fig. 8(a) using the proposed edge-preserving decomposition method. The transmission map is almost zero in the sky region.

### C. Recovery of the scene radiance

Once the values of the global atmospheric light \( A_c(c \in \{r, g, b\}) \) and the transmission map \( t(p) \) are available, the scene radiance \( Z(p) \) is recovered by
\[
Z_c(p) = \frac{1}{t^*(p)}(X_c(p) - A_c) + A_c.
\]
Consider the case that the input image \( X_c(p) \) includes noise, i.e.,
\[
X_c(p) = \hat{X}_c(p) + e_c(p),
\]
where \( e_c(p) \) is the noise. Equation (26) is equivalent to
\[
Z_c(p) = \frac{1}{t^*(p)}(\hat{X}_c(p) - A_c) + A_c + \frac{1}{t^*(p)}e_c(p).
\]
It is shown in Inequality (8) that the value of \( t^*(p) \) is always less than or equal to 1. The value of \( t^*(p) \) approaches 0 if the pixel \( p \) belongs to a sky region as shown in Fig. 2(a). Clearly, the value of \( \frac{1}{t^*(p)} \) is very large if the pixel \( p \) belongs to a sky region. Subsequently, the noise in the sky region is amplified too much and it becomes visible in the image \( Z \) as shown in Fig. 3(a). To address the problem, a simple method is adopted in [11] to detect the sky region in the haze image according to the brightness and a non-negative compensation term was added to the transmission map \( t(p) \) in the sky region. The compensation term is adaptive to the haze degree of the input image \( X \) which is determined by the histogram of the input image \( X \). The compensation term is also adopted in the proposed algorithm to adjust the transmission map \( t(p) \) in the sky region. As such, amplification of noise can be avoided in the sky region as illustrated in Fig. 3(b).

**Fig. 3:** Reduction of noise amplification by the adaptive compensation term. (a) A dehazed image without the adaptive compensation term; and (b) A dehazed image with the adaptive compensation term.

### V. EXPERIMENTAL RESULTS

In this section, the proposed algorithm is compared with existing haze removal algorithms in [4], [5], [6], [7], [10], [11] by testing haze images, underwater images and normal images without haze. Since the proposed algorithm is most relevant to the haze removal algorithms in [10], [11], this section is focused on comparing the proposed algorithm with the algorithms in [10], [11]. Readers are invited to view the
A. Different choices of parameters

There are four parameters in the proposed algorithm and they are $\zeta_1$ and $\lambda$ in Equation (21), $\zeta_2$ in Equation (15), and the predefined threshold for the estimation of the global atmospheric light. Four different choices of $\zeta_1$ are tested and they are 15, 30, 60, and 120. It is demonstrated in Fig. 4 that halo artifacts are visible if the value of $\zeta_1$ is small and visibility of halo artifacts is reduced as the value of $\zeta_1$ is increased. Halos are reduced as the value of $\zeta_1$ is increased.

As indicated in [10], halo artifacts refer to the artifacts of unwanted smoothing of edges. A small $\zeta_1$ would concentrate the blurring near these edges and make halos visible while a large $\zeta_1$ would distribute such blurring more globally and make halos unnoticeable. The smoothness of the transmission map is controlled by $\lambda$. The transmission map is smoother if the value of $\lambda$ is larger. Four different choices of $\lambda$ are tested and they are 16, 256, 4096, and 65536. It is demonstrated in Fig. 5 that leafs become under-exposed if the value of $\lambda$ is too large. Some leafs become under-exposed if the value of $\lambda$ is too large.

The variation of the detail layer is controlled by $\zeta_2$. The variation is reduced if the value of $\zeta_2$ is increased. Color saturation is reduced when the value of $\zeta_2$ is increased.

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Four different choices of $\zeta_2$ are tested and they are 1, 3, 7, and 15. It is shown in Fig. 6 that color saturation of the dehazed image is reduced if the value of $\zeta_2$ is increased. Four different choices of the pre-defined threshold are also tested and it is demonstrated in Fig. 7 that the proposed algorithm is not sensitive to the pre-defined threshold.

B. Comparison among different haze removal algorithms

The proposed algorithm is first compared with the haze removal algorithms in [10], [11] by testing four haze images. Since the main contribution is a new edge-preserving method for the estimation of the transmission map, the refined transmission maps of the haze removal algorithms in [10], [11] and the proposed algorithm for one haze image are shown in Fig. 8. As can be seen from Fig. 9, both the proposed algorithm and the algorithm in [11] neither amplify noise in sky regions nor produce halo artifacts as opposed to those from [10]. The algorithm in [10] also introduces color distortion in the sky regions. As shown by the zoom-in regions in Fig. 9, the dehazed images by the proposed algorithm are slightly sharper than the dehazed images by the haze removal algorithm in [11]. The resolutions of the images are $600 \times 450$, $1600 \times 1200$, $2592 \times 1944$, and $2144 \times 1424$, respectively. The running times of the algorithms in [10], [11] and the proposed one via Matlab 2008b on DELL Precision M6700 are given in Table I. The speed of the proposed algorithm is slightly faster than those of the haze removal algorithms in [10], [11].

The proposed algorithm is then compared with the haze removal algorithms in [10], [11] by testing two normal images...
without haze. It is expected that a haze removal algorithm will not make any noticeable change to an image without haze. The two images without haze and their enhanced images are demonstrated in Fig. 10. The proposed algorithm and the haze removal algorithm in [11] introduce less color distortion than the haze removal algorithm in [10]. The quality of the enhanced images by the proposed algorithm and the haze removal algorithm in [11] is better than the quality of the dehazed images by the haze removal algorithm in [10].

The proposed algorithm is finally compared with the algorithms in [4], [5], [6], [7], [10], [11] by testing two haze images. The results for the algorithms in [4], [5], [6], [7] are downloaded from the website [36]. As illustrated in Fig. 11, the images de-hazed by the proposed algorithm are comparable to those using the algorithms in [6], [7] while the proposed algorithm is much simpler than the algorithm in [7]. The colors of the images dehazed by the algorithms in [5], [10] are over saturated.

C. Enhancement of underwater images

Underwater images and haze images share common features, i.e., individual droplets are too small to be visible to a camera,
and the intensity produced at a pixel is due to the aggregate effect of a large number of droplets within the pixels solid angle. The model (5) can also be used to adequately represent the underwater images. Based on the observation, the proposed algorithm and the haze removal algorithms in [10], [11] are applied to enhance two underwater images. It is illustrated in Fig. 12 that the algorithms in [10], [11] and the proposed algorithm can be adopted to improve the visibility of the underwater images. The color of the water is slightly distorted by both the haze removal algorithm in [10] as shown in Fig. 12(b) and the haze removal algorithm in [11] as shown in Fig. 12(c). The problem is overcome by the proposed algorithm.

D. Limitation of the proposed algorithm

One possible problem for the proposed algorithm is that the estimation of haze level is not accurate. An example is given in Fig. 13. Clearly, the haze is not removed well. The problem could be solved by introducing an interactive mode to the proposed algorithm which allows a user to removal haze according to her/his preference.

VI. Conclusion and Discussion

A simple single image haze removal algorithm has been proposed in this paper by introducing an edge-preserving decomposition technique to estimate the transmission map for a haze image. Experimental results demonstrate that the proposed algorithm is applicable to haze images, underwater images, and normal images without haze. The proposed algorithm is a new framework for single image haze removal which is from the Koschmiedars law without using any prior. It also introduces a new application for existing edge-preserving smoothing techniques.

It should be pointed out that the proposed algorithm has its own limitation. Particularly, the estimated haze degree affects the performance of the proposed algorithm. It is interesting to design a more sophisticated method to detect the haze degree of a haze image rather than using the histogram of a haze image to estimate the haze degree. Another interesting problem is to extend the proposed haze removal algorithm to remove haze from a video sequence. Both problems will be studied in our future research.
REFERENCES


