# **Underwater Image Dehazing Using Modified Dark Channel Prior**

Bowen Yao<sup>1</sup>, Ji Xiang<sup>1</sup>

1. College of Electrical Engineering, Zhejiang University, Hangzhou 310027, China E-mail: jxiang@zju.edu.cn

**Abstract:** In an underwater environment, light always scatters and absorbs as it travels from the object to the camera, seriously affecting image quality. As a result, underwater images have poorer contrast, like a haze covering them. In this paper, a modified method for images restoration based on the dark channel prior (DCP) is presented. Firstly, the ambient light is estimated according to the difference between the blue and red channel. Then, attenuations of three RGB channels are obtained separately. Finally, a color collection is used to compensate the remaining color distortion. The experiments carried out at last demonstrate the good performance of this method for improving the visibility of underwater images.

Key Words: Underwater Image, Haze Removal, Dark Channel Prior

#### 1 INTRODUCTION

In recent years, the attention of autonomous underwater vehicles (AUVs) has been greatly developed. Despite the wide usage of sonar to detect and recognize objects under the water, we must use vision sensors as well, to get more high-quality images especially when short-range objects should be observed [1, 2].

Unfortunately, the images captured by a camera under the water are often degraded, mostly due to the distortion of light as it travels in water. Firstly, because of the suspended particles' scattering, underwater images often have poor contrast and a foggy appearance covering them [3]. Secondly, color often changes due to varying degrees of light absorption for different wavelengths [4]. Thus, it is indispensable to recover underwater images and enhance their visibility before using them for object observation and other image processing.

There are a number of methods aiming to improve the visibility of these degraded images. Polarization filter is used in [5] and [6] to remove degradation effects, which needs a couple of images taken through a polarizer at different orientations. Kopf *et al.* [7] exploits a scene depth to solve the ambiguities, which is calculated through an existing model of the scene. However, it is difficult to obtain a underwater scene's model. Iqbal *et al.* [8] proposes a technique utilizing histogram equalization in both RGB and HSI color space to correct the color of underwater images.

Recently, some haze removal strategies [9–12] based on the single image have been developed to improve image's visibility, mostly using some statistical prior knowledge of intrinsic characteristics of natural images. Moreover, with the advantages of no additional information required and good performance on visibility enhancement, these methods inspire lots of researchers. One of the most representative strategies is the Dark Channel Prior (DCP) initially proposed by He *et al.* [11], aiming to dehaze for outdoor

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images. It's a method based on the physical model of the imaging process in foggy weather, using the estimation of ambient light and light's attenuation to recover hazy images. Because of the great similarities of imaging process between underwater and outdoor with foggy weather, DCP has been widely applied to the field of underwater image restoration by many researchers. For instance, Chiang [4] uses DCP to enhance underwater images and compensate color distortion, taking into account the influence of artificial light source and changes of light color when lights travel from water surface to image scene as well. Drews [13] aims to improve the robustness of DCP and proposes a new method that uses only green and blue channel to calculate dark channel, considering the predominance of them in underwater images. However, these methods focus little attention on ambient light, mostly using the same way as on the land to estimate it, resulting in large deviations with real ambient light.

To improve performance, a modified method is proposed in this paper, with a new approach to estimate ambient light. What's more, considering the characteristics of underwater images, we separate the attenuations of three RGB channels and use an extra color collection algorithm to compensate distortion. The remainder of this paper is assigned as follows. The imaging model of underwater images is introduced in the second section. And in the third, the original DCP is illustrated. Then, the modified method is proposed in the fourth. Experiment results are shown in the fifth section and finally, a conclusion is given in section six.

# 2 Imaging Model

According to a widely used model presented by McGlamery [14] and Jaffe [15], light received by the camera has three main components: direct attenuation, forward scattering, and back scattering. Its specific process is shown in Figure 1.

The direct component is the light reflected directly by objects to the camera. And its intensity is related to the radi-

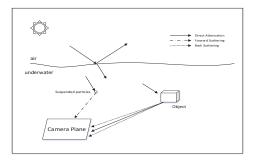


Figure 1: The imaging process of the underwater image

ance of object and the attenuation of light when propagating from target object to camera, respectively, as follows:

$$E_D(x) = J(x)e^{-cd(x)} = J(x)t(x)$$
 (1)

where  $E_D(x)$  is the intensity of direct light received by the camera, J(x) is the object radiance which represents the clear image without attenuation and haze, d(x) is the distance between object and camera, and c is the attenuation coefficient. Here,  $e^{-cd(x)}$  is also known as transmission t(x) which represents the remainder rate of light energy after propagation.

Scattering is the phenomenon that light deviates from different directions due to the irregular change of suspended particles or the density of medium itself in the process of media propagation.

In our imaging model, the light produced by small-angle scattering of object reflected light is forward scattering. And it can be expressed by convolution of the direct reflected light and the point spread function, specifically, as follows:

$$E_F(x) = E_D(x) * g(x)$$
 (2)

where  $E_F(x)$  is the forward scattering intensity,  $E_D(x)$  is the direct light intensity, and g(x) is the point spread function.

The backscattered light is the light that enters the camera after scattering of the ambient light by the suspended particles in the medium. Mathematically, it is often expressed as:

$$E_B(x) = B_{\infty}(1 - e^{-cd(x)}) = B_{\infty}(1 - t(x))$$
 (3)

where  $E_B(x)$  is backscattered light intensity and  $B_{\infty}$  is ambient light.

So considering three parts mentioned earlier, the total light intensity received by the camera  $E_T(x)$  can be specifically expressed as:

$$E_T(x) = E_D(x) + E_F(x) + E_B(x)$$
 (4)

Generally, when the distance between target object and camera is small, we can neglect the influence of forward scattering. And then, (4) can be simplified as:

$$E_T(x) = E_D(x) + E_B(x) \tag{5}$$

Therefore image captured by the camera can be presented as follow:

$$I(x) = J(x)t(x) + B_{\infty}(1 - t(x))$$
 (6)

Just as we said above, J(x) presents the clear image, and our goal is to obtain an image which is close to J(x) as much as possible. In order to achieve our goal, it is important to estimate the value of t(x) and  $B_{\infty}$  correctly.

#### 3 Dark Channel Prior

Dark Channel Prior is a statistical conclusion firstly proposed by He *et al.* [11] in 2009, aiming to obtain a method to remove the haze from foggy images. Its main point is that in patches on an outdoor haze-free image, there is always one channel at least having some pixels whose intensity are very low and close to zero. Its rationality lies in a universal phenomenon that three factors are always existing in images: (1) shadows, e.g., the shadow of buildings, creatures and plants; (2) colorful objects or surfaces, e.g., green glass, red or yellow flowers; and (3) dark objects or surfaces, e.g., dark creatures and stone. Mathematically, it can be expressed as:

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) \tag{7}$$

where  $J^{dark}$  is the dark channel image,  $J^c$  is a color channel of J, and  $\Omega(x)$  is a patch of image centered at pixel  $\mathbf{x}$ . In order to restore the hazy image,  $B_\infty$  should be estimated first. And there are some ways to get the ambient light  $B_\infty$  already. In He's paper [11], a method which chooses pixel's intensity in most hazed area as the value of ambient light. Tan [9] regards it as the brightest pixel in the image. After  $B_\infty$  is obtained, transmission t(x) can be calculated as well. First, the (6) can be rewritten as follow when its both sides are divided by  $B_\infty$ :

$$\frac{I(x)}{B_{\infty}} = \frac{J(x)t(x)}{B_{\infty}} + (1 - t(x)) \tag{8}$$

Then dark channels of both sides of equation (8) are calculated simultaneously:

$$\min_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} \frac{I^{c}(y)}{B_{\infty}} \right)$$

$$= \min_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} \frac{J^{c}(x)t(x)}{B_{\infty}} \right)$$

$$+ \min_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} (1 - t(x)) \right)$$
(9)

where transmission t(x) is considered to be a constant in a small patch and in three channels. Besides, according to dark channel prior,  $\min_{y \in \Omega(x)} (\min_{c \in \{r,g,b\}} \frac{J^c(x)t(x)}{B_{\infty}})$  tends to zero, that is:

$$\min_{y \in \Omega(x)} (\min_{c \in \{r,g,b\}} \frac{J^c(x)t(x)}{B_{\infty}}) \to 0$$
 (10)

So transmission t(x) can be expressed as follow:

$$t(x) = 1 - \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} \frac{I^{c}(y)}{B_{\infty}})$$
 (11)

Because regarded as a constant in a small patch, t(x) is a coarse transmission with obvious block artifacts. The initial rough t(x) obtained by (11) should be refined. He [11] uses a method called soft matting to refine coarse transmission t(x).

Once ambient light  $B_{\infty}$  and refined transmission t(x) have been estimated, the hazy image can be recovered as:

$$J(x) = \frac{I(x) - B_{\infty}}{t(x)} + B_{\infty}$$
 (12)

Dark channel prior has very significant effect on image dehazing and has been welcomed since it appeared. However, it can not be applied to underwater image directly owing to unique characteristics of underwater imaging. In the next section, a modified dark channel prior fitting to underwater condition will be introduced.

## 4 Proposed Method

Although the imaging process under the water is much similar to the process in the air, it has obvious differences which include attenuation coefficient of light, light source and other distinguishing features in the water. The ambient light  $B_{\infty}$  and transmission t(x) will be incorrect if dark channel prior is applied directly. In this section, we analyze the specifics of these differences and propose a modified method to estimate the ambient light  $B_{\infty}$  and transmission t(x).

#### 4.1 Estimating the Ambient Light

According to the imaging model expressed as (6), one can see that when transmission t(x) tends to zero, the pixel obtained in the original image I(x) can be regarded as the ambient light  $B_{\infty}$ . And the area where transmission t(x)tends to zero often locates at the thickest haze area or at the area having farthest distance from camera. He et al. [11] puts forward that in dark channel images pixels' intensities of haze-opaque areas are often larger than other areas and their values can indicate the thickness of haze. Then dark channel can be used to detect the most haze-opaque region. The top 0.1% brightest pixels in the dark channel are selected as the most haze-opaque area. And pixels with the highest intensity among these pixels are selected as the ambient light  $B_{\infty}$  [11]. Though the method has a good accuracy of ambient light estimation, it loses its correctness when applied to underwater images.

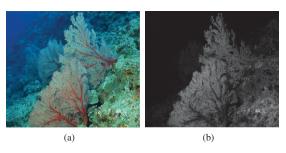


Figure 2: (a)The original image. Red point is selected as ambient light by dark channel prior. (b)Dark Channel

Figure 2a is a typical underwater image with hazing and bluish effects. It is obvious that the ambient light  $B_{\infty}$  should be located in regions with the largest concentration of medium (in the air it's haze and now it's water). However, as the red point in the figure 2a shows, the ambient light obtained by He's [11] method does not agree with the expectation. The reason can be find on the dark channel of this original image (see Figure 2b). Areas with the farthest distance from camera often have the lower intensity than others, due to a phenomenon that the value of red channel in a distance may be very small after attenuation, causing an incorrect estimation of ambient light.

It is clear that the vision of these areas often saturates with water and has no other objects. In these areas, the difference of pixel intensities between the blue and red channels is almost related to their different attenuation. Without the influence of other colorful objects, this difference in these areas is often larger than in others and has lower variance among the neighborhood.

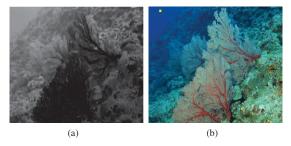


Figure 3: (a)Difference between B channel and R channel. (b)Yellow point is selected as ambient light by our method.

So the difference between blue channel and red channel is used to estimate the ambient light as follow:

$$Differ = \max\{G, B\} - R \tag{13}$$

where the green channel is also taken into account because sometimes underwater image is greenish and utilizing the difference between green channel and red is more effective. Figure 3a shows the result of this difference. Based on this difference, some steps are carried out to estimate the ambient light, concretely as follows:

- step 1 Remove the top 0.1% largest pixels in the difference image, considering the existence of blue objects in the camera vision which may have a bad effect on our result.
- step 2 Select the top 1% largest pixels in the remaining as our rudimentary result.
- step 3 Classify pixels obtained in *step 2* according to their spatial position in the original image, gathering them to an identical area if they are adjacent each other.
- step 4 Choose the largest area as our last selected region which has the farthest distance from the camera. In this region, the pixels with the highest intensity are selected as the ambient light  $B_{\infty}$ .

Figure 3b shows the ambient light estimated by our method.

#### 4.2 Estimating the Transmission

Once ambient light  $B_{\infty}$  has been obtained, a rough transmission t(x) can be estimated through (11). However, the process of light attenuation under the water is much different from it in the air. Due to the different absorption of water, lights with different wavelengths have their own respective attenuation coefficients. Generally, the longer wavelength owns a worse attenuation and has a smaller transmission. Naturally, for the three channels of red, blue and green, we can get:

$$\min_{\lambda \in \{r,g,b\}} t_{\lambda}(x) = t_r(x) \tag{14}$$

So the transmission obtained directly by (11) is actual a transmission of red channel, that is:

$$t_r(x) = 1 - \min_{y \in \Omega(x)} \left( \min_{\lambda \in \{r, g, b\}} \frac{I_{\lambda}(y)}{B_{\lambda, \infty}} \right)$$
 (15)

In order to restore the image successfully, transmissions of the blue and green channel should be estimated as well. However, it is difficult for us to acquire all three channel transmission through the image directly [16]. Fortunately, there are other ways to estimate them. Equation (1) shows that the transmission t(x) is rated with attenuation coefficient  $c(\lambda)$  and distance d(x). For each pixel, the distance is always fixed, and if we know the relationship between these attenuation coefficients of the three channels, we can get the blue and green channels' transmissions through the red. Mathematically, it can be expressed as follow:

$$t_g = e^{-c_g d(x)} = (e^{-c_r d(x)})^{c_g/c_r} = t_r^{c_g/c_r}$$
 (16)

$$t_b = e^{-c_b d(x)} = (e^{-c_r d(x)})^{c_b/c_r} = t_r^{c_b/c_r}$$
 (17)

where  $c_r$ ,  $c_g$ ,  $c_b$  are the attenuation coefficients of three colors. These coefficients are the inherent characteristics of lights, and they cannot be estimated through image only [16].

Fortunately, some works for evaluating attenuation of lights with different wavelengths have been done already. Duntley [17] and Jerlov [18] had done much work of light propagation in the water. In light of these observations, the sea water can be divided into three types roughly [4]. Type-I water represents the extremely clear water and the water on most clear coastal with a higher attenuation coefficient is Type-II water. Type-III is the turbid water [4]. And a parameter called  $Nrer(\lambda)$  proposed by Duntley [17] is used to weigh the attenuation of different lights, with the meaning of energy residual proportion for each unit distance propagation. For Type-I water, the energy residual ratio is as follow:

$$Nrer(\lambda) = \begin{cases} 0.80 \sim 0.85, & if \ red \\ 0.93 \sim 0.97, & if \ green \\ 0.95 \sim 0.99, & if \ blue \end{cases}$$
 (18)

Using these values, we can obtain the relationship between three channels. And then, transmissions of green and blue channel can be estimated by (16) and (17). After ambient light and transmissions of all three channels have been estimated, we can get the recovery image through (12) finally. The transmissions of three channel and the result of recovery image by our method are shown in Figure 4.

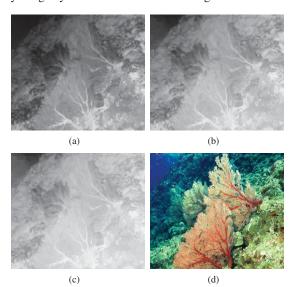


Figure 4: (a) Transmission of R channel. (b) Transmission of G channel. (c) Transmission of B channel. (d) Image after dehazing

#### 4.3 Color Correction

It can be found that the image still has color distortion after dehazing, because our estimation of three channels' transmissions can not offset the discrepancy absorption of different lights by water exactly, and light source color isn't quite true to the white after propagating from water surface to the scene [19].

In order to obtain better recovery images, another process for correcting image color is applied, using a traditional method named *Shades of Gray* proposed by Filayson and Trezzi [20]. It bases on a hypothesis that the average of all pixels in each channel is supposed to be equal [21], as follow:

$$\frac{\int S(x,\lambda)dx}{\int dx} = k \tag{19}$$

where  $S(x,\lambda)$  is the reflectivity of a point in space to the light with a wavelength of  $\lambda$ , and k is a constant between 0 and 1. Therefore, the intensity of each color channel can be calculated as follow:

$$\left(\frac{\int (I_{\lambda}(x))^{p} dx}{\int dx}\right)^{1/p} = ke(\lambda)$$
 (20)

where  $e(\lambda)$  is the intensity of each color channel, p is constant.

To eliminate the color distortion, the intensity of each channel should be equal. Thus, some processes are made to adjust the dehazing image. First, we calculate the average of three channels:

$$average = \frac{1}{3}(e(R) + e(G) + e(B))$$
 (21)

Then, with this average, each channel can be altered as follows:

$$R_{new} = R \times \frac{average}{e(R)} \tag{22}$$

$$R_{new} = R \times \frac{average}{e(R)}$$
 (22)  
 $G_{new} = G \times \frac{average}{e(G)}$  (23)  
 $B_{new} = B \times \frac{average}{e(B)}$  (24)

$$B_{new} = B \times \frac{average}{e(B)} \tag{24}$$

Figure 5 reveals the effect of color correction. It is obvious that image after collection looks more balanced.

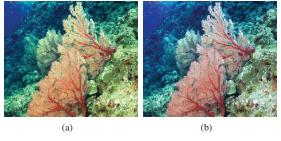


Figure 5: (a)Image before colour correction. (b)Image after colour correction.

## **Experimental Results**

To test our method proposed in this paper, we choose several images for experiment and compare with some widelyused algorithms. Figure 6a~6d shows four original images selected and the comparison with the standard dark channel prior in terms of the accuracy of ambient light estimation. The red point in the image shows estimation using dark channel prior [11], and the yellow point is estimated by our method. It is obvious that our method has a better performance. Figure 6e~6p illustrate the final processed images by different algorithms including dark channel prior (DCP) [11], underwater dark channel prior (UDCP) [13] and our method. From these results, we can see that the DCP proposed by He et al. [11] loses its effectiveness and still remains much haze in the processed images, while the technique of UDCP has bad color distortion. And our method restores the underwater images more effectively and has a better performance.

# 6 Conclusions

Compared with the imaging process on the land, the process under the water is much more complex, resulting in low contrast, blurring, color distortion and other problems. Due to the different absorption of light by water, the traditional dark channel prior cannot be applied to underwater images directly. In this paper, we proposed an algorithm based on modified dark channel prior and color correction to obtain the recovery image. Considering the characteristics of underwater images, this method improves the accuracy of estimation of the ambient light and three channels' transmissions. Moreover, we used a color correction to deal with the remaining distortion after dehazing. And the experiments illustrate the effectiveness of our method on underwater image dehazing.

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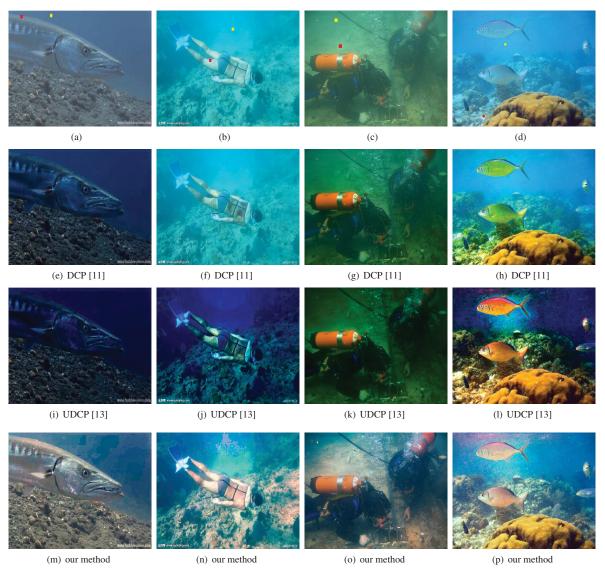


Figure 6: (a) $\sim$ (d)The original image with estimated ambient light by [11] and our method. Red point shows the ambient light estimated by [11] and yellow point is estimated by our method. (e) $\sim$ (p)The finial processed images by DCP, UDCP and our method.

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