

Underwater Image Enhancement Based on the Dark Channel Prior and Attenuation Compensation

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(Received August 8, 2016; revised September 30, 2016; accepted December 30, 2016)

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Abstract Aimed at the two problems of underwater imaging, fog effect and color cast, an Improved Segmentation Dark Channel Prior (ISDCP) defogging method is proposed to solve the fog effects caused by physical properties of water. Due to mass refraction of light in the process of underwater imaging, fog effects would lead to image blurring. And color cast is closely related to different degree of attenuation while light with different wavelengths is traveling in water. The proposed method here integrates the ISDCP and quantitative histogram stretching techniques into the image enhancement procedure. Firstly, the threshold value is set during the refinement process of the transmission maps to identify the original mismatching, and to conduct the differentiated defogging process further. Secondly, a method of judging the propagating distance of light is adopted to get the attenuation degree of energy during the propagation underwater. Finally, the image histogram is stretched quantitatively in Red-Green-Blue channel respectively according to the degree of attenuation in each color channel. The proposed method ISDCP can reduce the computational complexity and improve the efficiency in terms of defogging effect to meet the real-time requirements. Qualitative and quantitative comparison for several different underwater scenes reveals that the proposed method can significantly improve the visibility compared with previous methods.

Key words dark channel; image defogging; color cast; histogram stretching

1 Introduction

Obtaining a normal underwater image is a complex and important project. The imaging process suffers from serious light scattering and attenuation problems because of the extremely complex underwater imaging environment, which causes the image fogging and blue-green tone. Image fogging is produced by multiple reflections of the light by suspended particle, and the color cast is formed due to different degree of attenuation in different color channels. Based on the problems described above, some of the current existing defogging methods like DCP have been proposed. But they still have some shortcomings in the process of soft mapping such as mass calculation, low efficiency, large energy consumption and so on. Thus, we should not only improve the underwater imaging quality, but also reduce the process cost.

Currently, the technique of image enhancement focuses on two aspects, *i.e.*, image restoration technology and image enhancement technology. Image restoration technology is a process based on the physical model of image degradation. The relevant parameters of the degraded links are obtained by analyzing and solving the inverse process of image de-

gradation. Thereby, it can recover sharp images as realistic as possible. Schechner and Karpel (2004, 2005) and other researchers analyzed the physical effects of visibility degradation and proposed an image recovery algorithm based on a couple of images taken at different orientations with a polarizer. However, this algorithm is rather complex. Alessandro *et al.* (2003) proposed unsupervised digital image color equalization with simultaneous global and local effects. Trucco and Olmos-Antillon (2006) proposed a self-tuning image restoration filter, simplifying the underwater image construction model proposed by Jules (1990) and McGlamery (1979). These researchers suggested that under-water images can be represented as a linear superposition of three components, but the procedure is difficult to implement because of high-computing resources.

Image enhancement technology has wide applicability, which can effectively improve the image contrast and the image visual effects, though it causes some loss of information. Hitam *et al.* (2013) proposed a method called mixture contrast limited adaptive histogram equalization (CLAHE-Mix), reducing the noise effect caused by CLAHE method, and applied to the HSV color space. ICM (Integrated Color Model) developed by Kashif *et al.* (2007), and subsequent UCM (Unsupervised color Correction Model) proposed by Kashif *et al.* (2010), realized the

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equalization from histogram and HSV space. Further, Ahmad *et al.* (2015a) proposed an improved color model by means of Rayleigh-distribution. In the same year, Ahmad *et al.* (2015b) proposed a method called dual-image Rayleigh-stretched contrast-limited adaptive histogram specification. These methods can improve the visual effects well; however, some of them ignore the objective consideration of scene authenticity.

In addition to the traditional methods introduced above, He *et al.* (2011) proposed a creative solution to the mist caused by the light refraction, called DCP method (Dark Channel Prior). This method was derived from the observation about fog-free environment on land. Some researchers have employed it for repairing underwater images (Liu and Wang, 2010), some researchers presented a real time hardware accelerator for single image haze removal using dark channel prior (Liang *et al.*, 2014) and some other researchers tried to estimate inherent underwater optical properties for underwater image enhancement (Ahmad *et al.*, 2015b). Zhao *et al.* (2015) proposed a method of deriving inherent optical properties of water from the background color of underwater images based on an underwater image formation model. These methods can obviously improve computational efficiency in real-time transmission.

In order to solve the problem of image fogging preferably, we propose a superior method called improved segmentation dark channel prior to decrease the computational complexity of defogging process. Besides, the quantitative stretching based on attenuation amount was employed to solve the color cast. Specified steps for the method are described as follows. Firstly, the improved segmentation dark channel prior method was used to defog. Secondly, the perspective view obtained from the step above was used to estimate the distance between the camera and the object, and the depth of scene was determined using the attenuation difference of the background light. Finally, the quantitative compensation stretching was carried out according to the light attenuation in three channels, and the image was obtained in high quality. The remainder of this paper is organized as follows: in Section 2, underwater image defogging process is described. In Section 3, the underwater image color compensation technique is introduced. In Section 4 the experimental simulation results are analyzed. The conclusions and the summary are shown in Section 5.

2 Image Defogging

2.1 Underwater Environment

Underwater imaging environment is extremely complex, as well as variable. When the light wave propagates underwater, each color channel rapidly loses its intensity in different degrees. As a consequence, the blue-green tone is formed. In this paper, the quantitative compensation based on the degree of attenuation was conducted. Another problem to be solved here is image blurring caused by light scattering. Image defogging and color cast are the

two focus of the underwater image enhancement in the previous works. An underwater imaging model is necessary for the underwater image enhancement process (Webb, 2002). The equation in the model is as follows:

$$I^c(x) = J^c(x) \cdot t(x) + (1 - t(x)) \cdot B^c(x),$$

$$c \in \{\text{blue, red, green}\}, \quad (1)$$

where x represents a point in underwater scene, and $I^c(x)$ is the final scene captured by camera. $J^c(x)$ denotes the non-attenuated light, which comes from the water surface and is reflected to form the scene. $t(x)$ is the residual rate of energy. $B^c(x)$ is the homogeneous underwater environment light. Its components are complex which contain background light and the lights refracted from other points in the scene.

As to the problem of underwater image blurring caused by light refraction, the blurry part of the imaging result should be removed. In the paper, we adopt and improve the dark channel prior technology proposed by He *et al.* (2011). The reason that the defogging algorithm on land could be used underwater is that the fog is formed by the light refraction whether on land or underwater. Underwater, a variety of suspending particles cause a lot of light refraction, leading to fog effect. Compared with the background light in atmosphere, the underwater background light with color cast is a little weaker. In the following, we use the improved dark channel principles to defog.

2.2 Dark Channel Principles

In the most non-sky area, a certain pixel has at least one color channel having a low gray value. In other words, the minimum light intensity of the area has a very small value. This principle can also be applied to underwater. Mathematical definition is given below. As for any image $J(y)$, its dark channel can be expressed:

$$J^{\text{dark}}(x) = \min_{y \in \Omega(x)} [\min_{c \in \{r, g, b\}} J^c(y)], \quad (2)$$

where $\Omega(x)$ is an x -centered local patch, $J^{\text{dark}}(x)$ is the dark channel that is determined from two minimum calculation in $\Omega(x)$ for three channels in $J(y)$.

We can obtain Eq. (3) in RGB color channel perspective from Eq. (1) to get the function of $t(x)$:

$$\frac{I^c(x)}{B^c(x)} = t(x) \cdot \frac{J^c(x)}{B^c(x)} + 1 - t(x), c \in \{\text{blue, red, green}\}. \quad (3)$$

Suppose the transmission $t(x)$ in each small window is a constant, defined as $\tilde{t}(x)$, and the value $B^c(x)$ will be given in paragraph 5. Then we compute minimum twice for both sides of Eqs. (2) and (3), and the following equation is obtained:

$$\min_{y \in \Omega(x)} [\min_c \frac{I^c(y)}{B^c(x)}] = \tilde{t}(x) \min_{y \in \Omega(x)} [\frac{J^c(y)}{B^c(x)}] + 1 - \tilde{t}(x), \quad (4)$$

where $J(y)$ is the fog-free image to be solved. According to the previous dark channel prior principles, there is:

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

Bring the results of Eq. (5) into the original Eq. (4), we can get:

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

where $\tilde{t}(x)$ is the estimated transmission value. The light on land is different from that in the underwater environment, so image brightness should be improved while a certain concentration of fog occurred and the change of the underwater environment with the increase of the water depth is taken into account (He *et al.*, 2011). High

concentration of fog has a significant impact on image brightness, as shown in Fig.1. We adopt a factor changing with the increasing water depth to retain a dynamic concentration of mist. Set the water depth as $d(x)$, then

$$\omega = \log_{\partial} \frac{d(x)}{3} (0 < \partial < 1). \tag{7}$$

Eq. (6) is converted to:

$$\tilde{t}(x) = 1 - \omega \min_{y \in \Omega(x)} \left[\min_c \frac{I^c(y)}{B^c(x)} \right]. \tag{8}$$

Background light $B^c(x)$ can not be the brightest region or spot in one image. However, there are highlights in the actual image obtained. In order to make $B^c(x)$ more robust, the maximum of the minimum brightness values of all lumi-

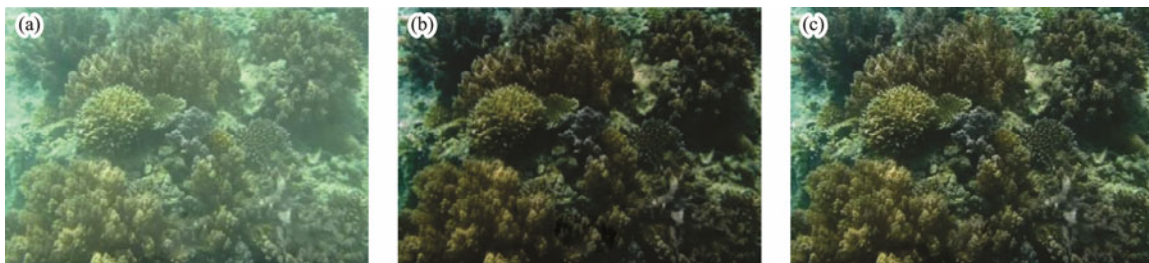


Fig.1 (a) Original image. (b) Result when $\omega=0.95$. (c) Result when $\omega=0.8$.

nance image areas was chosen, that is,

$$B^c(x) = \max_{x \in I} \min_{y \in \Omega(x)} I^c(y). \tag{9}$$

Considering that the small transmission t can lead to a large value of $J(y)$ and there will be too large white area existing in the image, we set a threshold value t_0 . When the value of t is less than t_0 , we set $t=t_0$, and subsequently use $t=0.1$ based on statistical results of experimental data. Thus, the final recover equation obtained is as follows:

$$J(x) = \frac{I(x) - B^c(x)}{\max[t(x), t_0]} + B^c(x). \tag{10}$$

However, the transmission map is rough, because $\Omega(x)$ is the region adjacent to the x -centered square and $I_m(u, v)$ is assumed as the point with the luminance value in the region of $\Omega(x)$. When $\Omega(x)$ covers a non-uniform area, DCP uses a fixed value with a larger deviation in the same area for the transmission map, and a mismatch will be caused. Therefore, a refinement of the process is necessary to eliminate the mismatch.

2.3 MDCP

To reduce the effect of the mismatch without large calculations a method called MDCP (Median-DCP) (Kristofor *et al.*, 2011) was proposed. DCP algorithm can make the halo phenomenon in the image, mainly because the dark-channel value $I^{\text{dark}}(x)$ is the minimum of the three color channels (R, G, B) in a local x -centered area $\Omega(x)$.

When there is a far and near junction in the local neighborhood, the boundary dark color value will be underestimated. The transmission could be overestimated, leading to the halo phenomenon. MDCP changes the Eq. (8), proposing the mid-value instead:

$$\tilde{t}(x) = 1 - \omega \text{med}_{y \in \Omega(x)} \left[\frac{I^c(y)}{B^c(x)} \right]. \tag{11}$$

This MDCP method can protect the edges of the subject better than the method of DCP, and it can achieve better results without using the refinement process. However, it cannot completely smooth the edges of the subject, which may lead to white edge phenomenon. At the same time, a new problem is introduced that over-estimating the value of the dark colors may leads to the black edge phenomenon of the scene.

2.4 Improved Dark Channel Prior

2.4.1 The reason for halo phenomenon

In the calculation the dark channel operation is block-based, namely the neighborhood $\Omega(x)$ based on pixel x -centered. Since the $\tilde{t}(x)$ obtained does not consider the non-homogeneity, a halo effect is caused. When the foreground $\Omega^f(x, y)$ and the background $\Omega^b(x, y)$ exist in the same image at the same time (Kristofor *et al.*, 2011), the distance gap can result in different concentrations of fog. Then if the fog was removed according to the same basis, the fog with high concentration will not be cleared out, leading to the mismatch transmission. In the DCP method,

when the background takes up larger area than the fore-ground, there will appear a little white edge in the image obtained and vice versa. While MDCP methods are used, the dark color value $I^{\text{dark}}(x)$ obtained will be $\Omega^f(x)$ or $\Omega^b(x)$. Whichever occupies a large area, halo phenomenon will appear.

2.4.2 The segmentation dark channel processing method

Based on the analysis above, we can get a conclusion that white or black edge will appear in one image block based on either MDCP or DCP method without considering that foreground $\Omega^f(x)$ and the background $\Omega^b(x)$ may exist at the same time because these two methods manage the image block as a whole. In this paper, we will consider the foreground and the background separately. The non-homogeneous block $\Omega(x, y)$ is divided into two sets, a foreground set $\Omega^f(x, y)$ and a background set $\Omega^b(x, y)$. Thus, there exist $\Omega(x, y) = \Omega^f(x, y) \cup \Omega^b(x, y)$ and $\Omega^f(x, y) \cap \Omega^b(x, y) = \phi$. Moreover, the idea of scanning all the pixels containing image block center is proposed. By defining these pixels as the image block set $\Omega^s(x, y)$, the following estimation is proposed:

$$t_s(x, y) = 1 - w \min_{(u, v) \in \Omega^s(x, y)} I_m(u, v). \quad (12)$$

In Eq. (12), $\Omega^s(x, y)$ is the set of pixels in the same region with the center of the image block (u, v) . The area is either the foreground or the background, and the rest is included in an additional set of pixels. Therefore, the method with the process of segmentation is called the ISDCP (Improved Segmentation Dark Channel Prior). A

simple and fast segmentation logic formulation is adopted as follows:

$$\text{if } \left| \frac{I_m(u, v) - I_m(x, y)}{I_m(x, y)} \right| < \epsilon, (u, v) \in \Omega^s(x, y), \\ \text{else } (u, v) \in \Omega^r(x, y), \quad (13)$$

where ϵ is a segmentation threshold value, and is given as 0.2 to make the segmentation more effective and avoid emerging undersized region. The value of $\epsilon = 0.2$ is a statistical result that will get a better effectiveness for most underwater images. In addition, we adopt the dark channel mid-value in terms of the rest area:

$$t_r(x, y) = 1 - w \text{med}_{(u, v) \in \Omega^r(x, y)} I_m(u, v). \quad (14)$$

Finally, the different transmission values are assigned to the modified transmission map in the two areas obtained after segmented.

2.5 Image Defog Implementation

For a clear boundary ϵ can perform well. When it comes to a blurring boundary, ϵ is also effective; though some pixels are wrongly assigned to $\Omega^s(x, y)$, the mismatch is very little. Therefore, the ϵ value can either define boundaries well or be applied to any foggy image without causing serious halo.

The transmission map and defogging results of DCP, MDCP and ISDCP are shown in Fig.2. Obviously the effects of DCP underwater are different from that on land. The uneven color phenomenon appeared and the transmi-

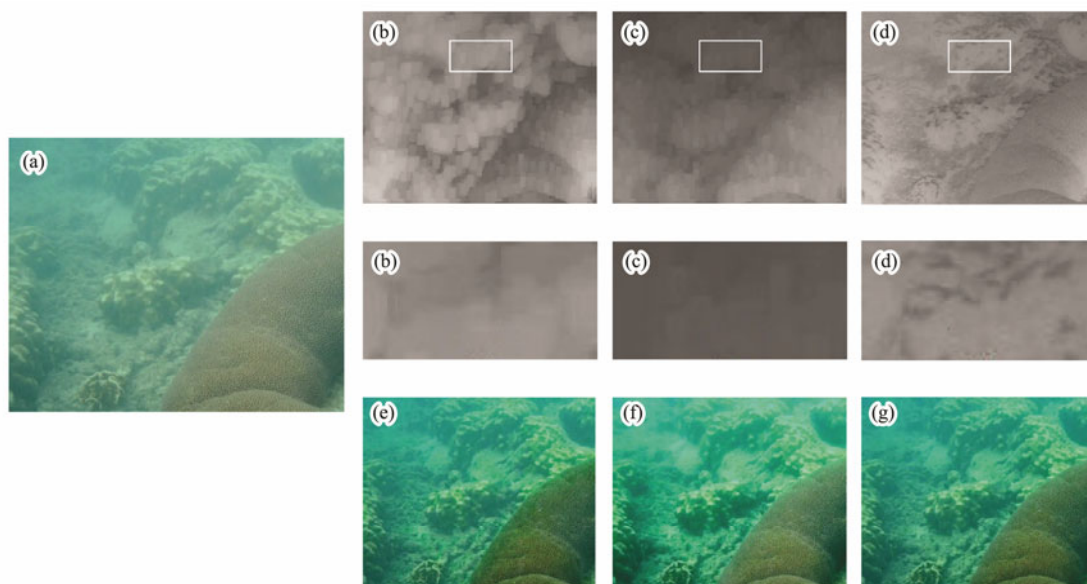


Fig.2 Results of three methods. (a) Original image. (b) Transmission map of DCP. (c) Transmission map of MDCP. (d) Transmission map of ISDCP. (e) Defogging image from DCP. (f) Defogging image from MDCP. (g) Defogging image from ISDCP.

ssion map seemed to be under-refined. MDCP can lessen uneven color distribution, yet the image contrast is low

compared with the other two methods. However, ISDCP can not only solve the problem of uneven color but also

improve the contrast, and the effects are close to that of Guide-filtering.

3 Color Correction

Images obtained underwater usually have a blue-green color cast, even more serious after defogging, as shown in Fig.1 and Fig.2. Hence, a color correction procedure is necessary to solve color cast of underwater imaging. Because the attenuation of three color channels varies with the depth, a quantitatively histogram stretching method was proposed to perform at three channels based on the propagation distance of light underwater. In addition, before the attenuation is determined, the scene depth and the distance between camera and target scene should be obtained first.

3.1 The Propagation Distance of Light Underwater

3.1.1 The distance $d(x)$ between camera and scene

The usual way to estimate scene depth is to seek the parallax of two images (Robby, 2008), but it is complex to implement. In this paper, we adopt dark channel prior method to achieve the distance. It is known that the image $I^c(x)$ consists of the reflection of the scene $J^c(x) \cdot t(x)$ and the fog $(1-t(x)) \cdot B^c(x)$ from Eq. (1). With the increase of the distance between camera and scene, the proportion of fog increases. Thus the fog concentration can be an index to the distance. Indeed $t(x)$ is a function of $d(x)$, and it can be expressed as:

$$t(x) = 10^{-\beta(c) \cdot d(x)} = Res(c)d(x),$$

$$c \in \{\text{blue, red, green}\}, \quad (15)$$

where $\beta(c)$ denotes the attenuation coefficient of one color channel, $Res(c)$ is the residual attenuation of light, whose value varies with different seawater transparency. In this paper, the seawater transparency is set as $Res(\text{red})=0.75$, $Res(\text{green})=0.86$, $Res(\text{blue})=0.93$ the values being reasonable in most cases (Jerlov, 1968). Therefore, the estimated dark channel transmission map can be used to predict distance $d(x)$ in one image. By Eq. (8), we can know:

$$t(x) = 1 - \omega \min_{y \in \Omega(x)} [\min_c \frac{I^c(y)}{B^c(x)}] = \min(Res(c)^{d(x)}),$$

$$c \in \{\text{blue, red, green}\}, \quad (16)$$

Among all color channels, the red one retains the lowest rate of residual energy, thus $\min_c(Res(c)^{d(x)})$ is approximately equal to $Res(\text{red})^{d(x)}$. Finally, we can deduce:

$$d(x) = \log_{Res(c)}(1 - \omega \min_{y \in \Omega(x)} [\min_c \frac{I^c(y)}{B^c(x)}]). \quad (17)$$

Since the image is captured underwater, $d(x)$ value is set as the scene foreground distance. Part of the blue tone in the background is retained, in order to retain some characters underwater. Since $d(x)$ is the distance for part of light propagation underwater, it is necessary to derive

the depth for another part $D(x)$.

3.1.2 Estimate the scene depth $D(x)$

As for the homogeneous light A , B^A denotes primary energy of the background light, and the energy of three colors above the water surface is the same, namely $B^A_{\text{red}} = B^A_{\text{green}} = B^A_{\text{blue}}$. After propagating in the water for depth D , the energy of each color channel shall decay. In other words, the background light of underwater $B^c(x)$, $c \in \{\text{blue, red, green}\}$, is different and can be presented as $B^c_{\text{red}}, B^c_{\text{green}}$ respectively. In order to estimate the depth $D(x)$, the corresponding intensity of each color channel is firstly detected. Then, the least square method is used to obtain depth $D(x)$ by means of seeking the difference values, between the original energy distribution and the version after attenuating of three color channels, as follows:

$$\min_{D(x)} \sum_{\lambda} \|(B^c - B^A \cdot (Res(c))^{D(x)})\|^2,$$

$$\lambda \in \{\text{blue, red, green}\}. \quad (18)$$

After obtaining the distance between the camera and the scene $d(x)$ and water depth $D(x)$, we give the light propagation channel a determined distance $\omega(x) = d(x) + D(x)$. Since the light energy is decaying at an exponential rate with the increasing light propagation distance under water, there exists a positive correlation between the image stretching compensation and energy attenuation:

$$e_c(x) = \frac{E_c^r(x)}{E_c^i(x)} = Res(c)^{\omega(x)}, c \in \{\text{blue, red, green}\}, \quad (19)$$

where $e_c(x)$ is the energy residual rate, and $E_c^r(x)$ denotes light wave residue. $E_c^i(x)$ represents the original energy before the light enters the water.

In terms of solving the color cast, the previous image enhancement methods mainly focus on the histogram stretching, which enhances the red channel and weakens the blue and the green channels. In fact, though specifying the color distribution can get better color performance, it is not a real reflection of scenes. Thereby, we adopt a method to compensate its red, green and blue channels on the basis of different light attenuation, which can restore the realistic scenes.

3.2 The Histogram Stretching of Color Channel

The red channel has the highest decay rate because it is normally the lowest intensity color channel, whereas the blue and green channels have the lowest and normal decay rate respectively. Therefore, the different color channel should be stretched toward the upper side on a discrepant intensity level. Since we have known the residual rate of each channel in Eq. (19), the corresponding stretching amount $E_c^{cmp}(x)$ is:

$$E_c^{cmp}(x) = \frac{E_c^r(x)}{e_c(x)} - E_c^r(x), c \in \{\text{blue, red, green}\}. \quad (20)$$

The minimum value of the original histogram p_0^{\min} is set to be $p_0^{\min} \cdot e_c(x)$, and the maximum value p_0^{\max} is set to be $p_0^{\max} \cdot e_c(x)$ if the final value does not exceed the maximum gray level 255. Otherwise the maximum value p_0^{\max} is set to be 255. For the histogram of three channels, the values p_0^{\min} and p_0^{\max} are stretched to be the values of p_d^{\min} and p_d^{\max} , respectively, as the stretching procedure illustrated in Fig.3.

$$p_d^{\max} = \begin{cases} p_0^{\max} \cdot e_c(x) & p_0^{\max} \cdot e_c(x) < 255 \\ 255 & \text{otherwise} \end{cases} \quad (21)$$

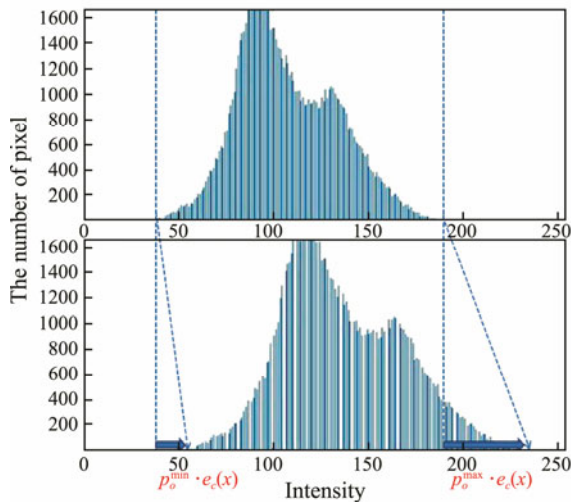


Fig.3 Histogram stretching of color channel toward the upper sides within the limits of (0, 255).

4 Simulation Results and Analysis

In this section, the results are evaluated both qualitatively and quantitatively. The simulation results of the proposed

method in this paper and, for the comparison, those of other methods, *i.e.*, the basic Histogram Equalization (HE), ICM, DCP used in underwater (UDCP) and the latest Rayleigh Distribution method of stretching (RD-HIS) were presented. The results indicated that the proposed method can solve some problems mentioned above, and has achieved better results for both defogging and color correction. Besides, it can obtain better values of MSE and PSNR. In Section 4.2, the quantitatively analysis will be shown.

4.1 Qualitative Comparison

The method is simulated on the platform with CPU i5-4210U, memory of 4G DDR3 and graphics card of AMD Radeon R7 M265, and MATLAB 2015b. As for the comparison of images obtained from different methods, two aspects, *i.e.*, image contrast and the effects of solving color cast, are discussed.

Fig.4 shows the results for a scene of two colored fish and some marine plants. It is easy to find the presence of fog and color cast in the first original image. The second one is the result by means of direct defogging based on UDCP, with strong green tone but improved contrast. The result using HE is shown in the third one. The color of the processed fish becomes darker, whereas the background color is too bright, leading to serious polarization though eliminating partial fog effects. The fourth one is the result of ICM, in which the fish color seems more natural and overall contrast is further improved, yet the impact of a single blue-green tone still exists. The effect of RD-HIS is obviously good in ameliorating color cast, but is poor in the contrast reducing. The performance of the method in this paper is presented in the last one, which not only displays the background clearly, but also removes the color cast well.

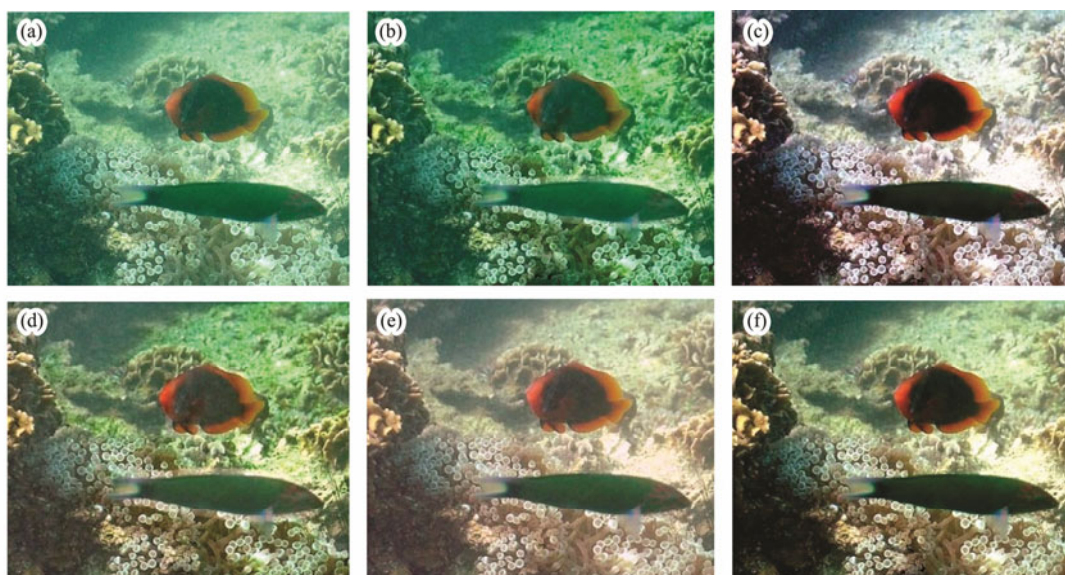


Fig.4 The scene with fish and plants. (a) the initial image, and the images after processing by (b) UDCP, (c) histogram equalization, (d) ICM, (e) RD-HIS and (f) proposed method.

Fig.5 shows a more clear underwater environment. It is easy to find the method of UDCP with an improved con-

trast but an obvious blue-green tone. The result of HE displays saturated color effect, too strong contrast, but does not eliminate blue-green tone well. At the same time, the result of ICM shows a clear outline of coral and stone far and near respectively, yet there still appears blue-

green tone. Result of RD-HIS does eliminate the effect of blue-green tone, and achieves clear outline of scenes near the camera, but blurs distant scenes. However, the proposed method in this paper can yield better effects in both blue-green hue elimination and contrast improvement.

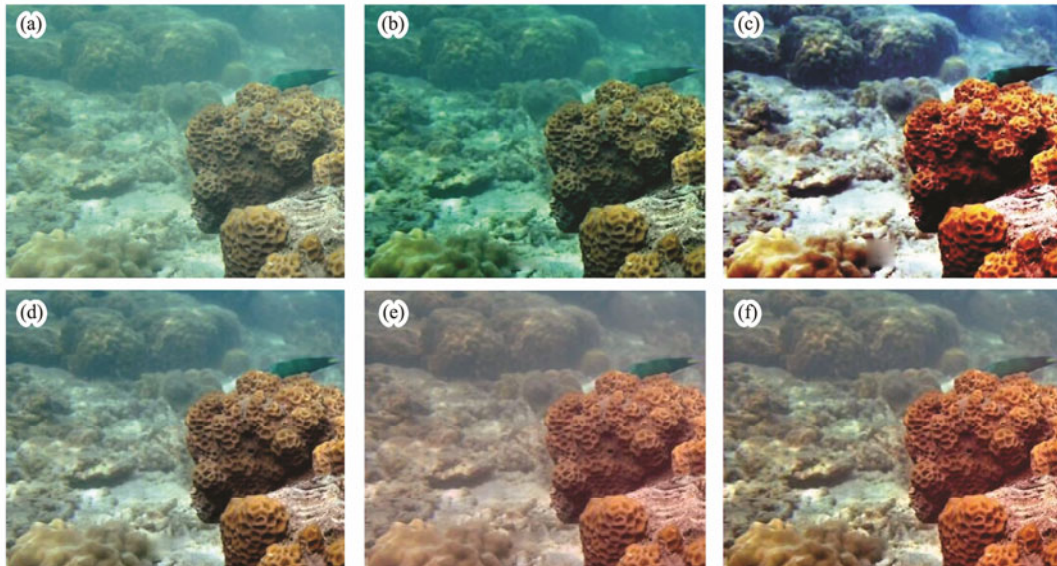


Fig.5 Comparison of results for images obtained in the clear underwater environment. (a) original image. (b) image produced by UDCP. (c) by histogram equalization. (d) by ICM. (e) by RD-HIS and (f) by the proposed method in this paper.

When the sunshine is strong outside and there are ripples, the surface of water will play a role as convex lens. In this case as shown in Fig.6, it is necessary to consider both the presence of sun and the impact of the sun on surrounding scenes. The result of UDCP shows a serious blue impact on both stone and background. Compared with UDCP, HE performs better in these two aspects, but it causes too blue seawater in the distance due to too strong sunshine.

At the same time, ICM deals with the sunlight well, yet there exists overall impact of blue-green tone. The result of RD-HIS weakens the sunlight, and handles the blue-green tone effect well, but the overall effect of defogging is not ideal. The proposed method here can make use of the sunlight well, and performs better in terms of defogging, handling the blue-green tone effect, and improving the overall contrast respectively.

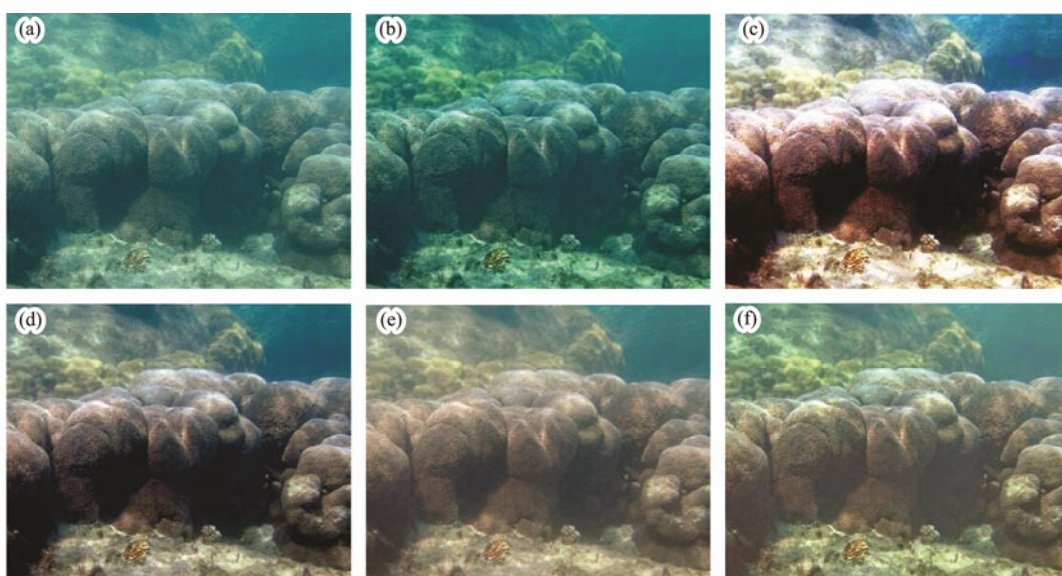


Fig.6 The processed results of images taken under strong sunshine. (a) initial image and processed images with (b) UDCP, (c) histogram equalization, (d) ICM, (e) RD-HIS and (f) proposed method in this paper.

It is difficult to process when the water quality is poor as shown in Fig.7. Due to the severe scattering and poor

light, the results are all not ideal. The result of UDCP does not remove most fog, though it can achieve better effect for some objects in the foreground. The HE method performs poor. Though this method bursts into gorgeous bloom, it distorts the color severely. However, ICM is able to improve the contrast effectively, and deal with

scenes in the foreground well, yet the blue tone appears. RD-HIS solves the problem of the color shift, but the clarity is not improved. The proposed method here has a better solution to the color cast, and improves the contrast to a certain extent, resulting in better performance compared with other methods.

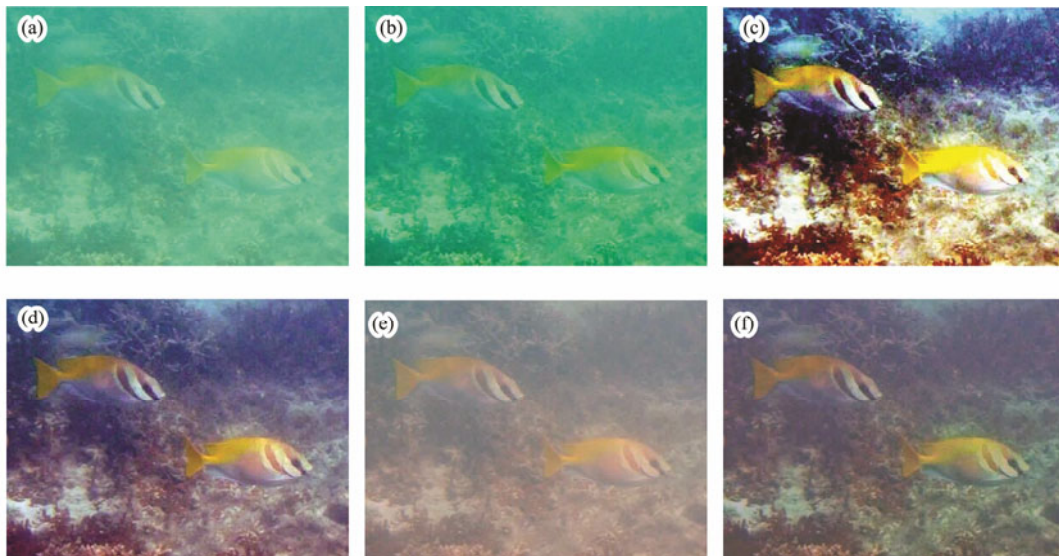


Fig.7 Scenes with poor water quality. (a) initial image and the processed images by (b) UDCP, (c) histogram equalization, (d) ICM, (e) RD-HIS and (f) proposed method in this paper.

4.2 Quantitative Analysis

Mean square error (MSE) and peak signal to noise ratio (PSNR), the two error metric functions, are used to measure the quality of processed image and estimate the image noise. MSE is used to evaluate the variance between the original image and the resulting image. MSE is calculated using the following expression,

$$MSE = \frac{1}{M \times N} \sum_{M,N} [I_1(m,n) - I_2(m,n)]^2, \quad (22)$$

where $I_1(m, n)$ and $I_2(m, n)$ are of original image and resulting image respectively; $M \times N$ represents the size of the image block; m and n denote the position of pixel x and y

respectively. By comparison, PSNR indicates the ratio of the maximum pixel value to noise. PSNR is represented as follows,

$$PSNR = 20 \log_{10} \frac{(2^B - 1)}{\sqrt{MSE}}. \quad (23)$$

In general, a good picture is characterized by low MSE and high PSNR. The comparison of MSE is listed in Table 1, and that of PSNR is shown in Table 2.

Based on data in Table 1 and Table 2, and for the image to be processed being complex and blurring, the proposed method here can yield a higher MSE value compared with other methods. On the contrary, the MSE value is lower as for the clear image.

Table 1 The comparison of MSE of different methods for various scenes

	UDCP	HE	ICM	RD-HIS	Proposed
Fish and plants	790.075	729.731	456.512	375.221	60.811
Clearer environment	1.178e+03	1.612e+03	312.3318	74.599	238.600
Scenes with sunshine	427.0478	1.296e+03	442.150	67.596	179.961
Poor water quality	383.7008	1.231e+03	1.713e+03	18.712	3.545e+03

Table 2 Comparison of PSNR of different methods for various scenes

	UDCP	HE	ICM	RD-HIS	Proposed
Fish and plants	19.154	19.499	21.536	22.387	30.290
Clearer environment	17.416	16.057	23.185	24.354	29.403
Scenes with sunshine	21.826	17.003	21.675	29.831	25.579
Poor water quality	17.228	12.634	15.792	35.409	22.291

It is because the contrast and color saturation of the image with poor quality are improved a lot after process-

ing, resulting in a higher MSE value. Similarly, original image with high quality can be reserved mostly, yielding

a lower MSE value. As for PSNR value, for some scenes, the results are lower than those of ICM and RD-HIS. However, in most cases, it performs better. Altogether, the method is superior to other methods.

5 Conclusions

In this paper, an improved method is proposed for underwater image defogging and color cast elimination. By improving the DCP method and applying the quantitative stretching method according to the amount of attenuation of light propagating in water, the technology greatly reduces the impact of blurring and the distortion of imaging process. Besides, quantitative and qualitative evaluation show that the image contrast has been improved as well. Further, compared with other methods, the proposed method significantly reduces the noise and the impact of blue-green tone, and enhances the image color. Consequently, the sharpness of scenes is improved, resulting in high degree recognition. The method can contribute to the future work of underwater exploration.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (No. 61401413).

References

- Alessandro, R., Carlo, G., and Daniele, M., 2003. A new algorithm for unsupervised global and local color correction. *Pattern Recognition Letters*, **24** (11): 1663-1677.
- Ahmad, S. A. G., and Nor, A. M. I., 2015a. Underwater image quality enhancement through integrated color model with Rayleigh distribution. *Applied Soft Computing*, **27**: 219-230.
- Ahmad, S. A. G., and Nor, A. M. I., 2015b. Enhancement of low quality underwater image through integrated global and local contrast correction. *Applied Soft Computing*, **37** (C): 332-344.
- He, K. M., Sun, J., and Tang, X., 2011. Single image haze removal using dark channel prior. *Transactions on Pattern Analysis and Machine Intelligence*, **33** (12): 2341-2353.
- Hitam, M. S., Yussof, W. N., Awalludin, E. A., and Bachok, Z., 2013. Mixture contrast limited adaptive histogram equalization for underwater image enhancement. *International Conference on Computer Applications Technology*, January 20-22, Sousse, Tunisia, 1-5.
- Jerlov, N. G., 1968. *Optical Oceanography*. Aberdeen University Press, Amsterdam, Netherlands, 63-69.
- Jules, S. J., 1990. Computer modeling and the design of optimal underwater imaging systems. *Journal of Oceanic Engineering*, **15** (2): 101-111.
- Kristofor, B. G., Dung, T. V., and Truong, Q. N., 2011. An investigation of dehazing effects on image and video coding. *Transactions on Image Processing*, **21** (2): 662-673.
- Kashif, I., Michael, O., Anne, J., and Rosalina, A. S., 2010. Enhancing the low quality images using unsupervised color correction method. *International Conference on System Man and Cybernetics (SMC)*, October 10-13, Istanbul, 1703-1709.
- Kashif, I., Rosalina, A. S., Azam, O., and Abdullah, Z. T., 2007. Underwater image enhancement using integrated color model. *International Journal of Computer Science*, **34** (2): 239-244.
- Liu, C., and Wang, M., 2010. Removal of water scattering. *International Conference on Computer Engineering and Technology*, April 16-18, Chengdu, China, 35-39.
- Liang, Z., Liu, H., Zhang, B., and Wang, B., 2014. Real-time hardware accelerator for single image haze removal using Recovery of underwater visibility and structure by polarization analysis dark channel prior and guided filter. *IEICE Electronics Express*, **11** (24): 1-12.
- McGlamery, B. L., 1979. A computer model for underwater camera systems. *Proceeding of the SPIE*, **208**: 221-231.
- Robby, T. T., 2008. Visibility in bad weather from a single image. *IEEE Conference on Computer Vision and Pattern Recognition*, June 23-28, Anchorage, AK, USA, 1-8.
- Schechner, Y. Y., and Karpel, N., 2004. Clear underwater vision. *Conference on Computer Vision and Pattern Recognition*, June 27-July 2, Washington, D. C., USA, 536-543.
- Schechner, Y. Y., and Karpel, N., 2005. Recovery of underwater visibility and structure by polarization analysis. *Journal of Oceanic Engineering*, **30** (3): 570-587.
- Trucco, E., and Olmos-Antillon, A. T., 2006. Self-tuning underwater image restoration. *Journal of Oceanic Engineering*, **31** (2): 511-519.
- Webb, W. L., 2002. *The Physics of Atmospheres*. Cambridge University Press, Texas, USA, 417pp.
- Zhao, X., Jin, T., and Qu, S., 2015. Deriving inherent optical properties from background color and underwater image enhancement. *Ocean Engineering*, **94**: 163-172.

(Edited by Chen Wenwen)