SINGLE UNDERWATER IMAGE RESTORATION BY BLUE-GREEN CHANNELS DEHAZING AND RED CHANNEL CORRECTION

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ABSTRACT

Restoring underwater image from a single image is know to be ill-posed, and some assumptions made in previous methods are not suitable for many situations. In this paper, we propose a method based on blue-green channels dehazing and red channel correction for underwater image restoration. Firstly, blue-green channels are recovered via dehazing algorithm based on an extension and modification of Dark Channel Prior algorithm. Then, red channel is corrected following the Gray-World assumption theory. Finally, in order to resolve the problem which some recovered image regions may look too dim or too bright, an adaptive exposure map is built. Qualitative analysis demonstrates that our method significantly improves visibility and contrast, and reduces the effects of light absorption and scattering. For quantitative analysis, our results obtain best values in terms of entropy, local feature points and average gradient, which outperform three existing physical model available methods.

Index Terms— Underwater image restoration, image dehazing, image enhancement, visibility recovery

1. INTRODUCTION

Since the mysterious underwater world contains abundant resources, the study of underwater image enhancement and restoration is meaningful, and thus desired in both consumer photography and computer vision applications. However, capturing clear underwater images is challenging due to physical properties of the underwater environment. The effects of absorption and scattering as well as the varying attenuation of light in different wavelengths cause the degradation of underwater images. Therefore, single underwater image enhancement and restoration have become a hot spot of research given its wider application range.

An underwater image can be represented as a linear superposition of a direct component, a forward scattering component and a back scattering component [1]. Such a forward scattering causes blurring of the image features while the back scattering masks the details of the scenario. As shown in Fig. 1, the light intensity decreases with the distance from objects in water by light attenuation depending on the wavelength of light [2]. Such a varying attenuation of light in different wavelengths causes color casts. The overall poor visibility caused by the above-discussed effects limits to the applications of underwater images, such as marine biology and archaeology [3], marine ecological research [4] and aquatic robot inspection [5].

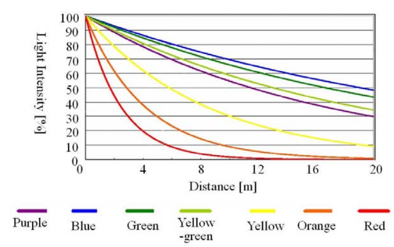


Fig. 1. Light intensity in water.

Numerous approaches are proposed to process the degraded underwater images and can be described from two different perspectives. One is based on image restoration technique. Trucco and Olmos [6] devised a self-tuning image restoration filter based on a simplified version of Jaffe [7] and McGlamery [8] underwater imaging formation model. Optimal filter parameter are estimated by optimizing a quality criterion based on a global contrast measure. Carlevaris *et al.* [9] proposed a simple prior that exploits the strong difference in attenuation among the three color channels of an underwater image in water to estimate the depth of the scene. As a result, the effects of light scattering in underwater images can be removed. Yang *et al.* [10] proposed an efficient and low complexity underwater image restoration method based on the Dark Channel Prior algorithm [11]. The median filter is used to estimate the depth map of image instead of the soft matting procedure. Moreover, a color correction algorithm is adopted to enhance the color contrast of underwater images. Chiang and Chen [12] restored underwater images by com-

This work was supported by the National Key Basic Research Program of China (2014CB340400) and the Natural Science Foundation of Qinghai Province of China (2015-ZJ-721).

bining a dehazing algorithm with wavelength compensation. The haze effects from color scatter are removed by the Dark Channel Prior algorithm [11]. According to the amount of attenuation of each wavelength, reverse compensation is conducted to restore the distortion from color casts. Galdran *et al.* [13] proposed a Red Channel method, where color associated with short wavelength is recovered and leads to a recovery of the lost contrast. In sum, the image restoration technique can remove the haze in underwater images to some extent. However, those techniques are limited by the accuracy of the assumption, optical model and estimated parameters.

Another kind of technique is based on image enhancement. Ancuti *et al.* [14] proposed a novel strategy to enhance visual quality of underwater images and videos based on the fusion principles. Chani and Isa [15] improved the contrast and reduced the noise of underwater images through integrated color model with Rayleigh distribution. Li and Guo [16] proposed an underwater image enhancement method based on dehazing and color correction. However, underwater image enhancement technique usually produces under-enhanced or over-enhanced regions because this kind of technique is not based on the underwater imaging model.

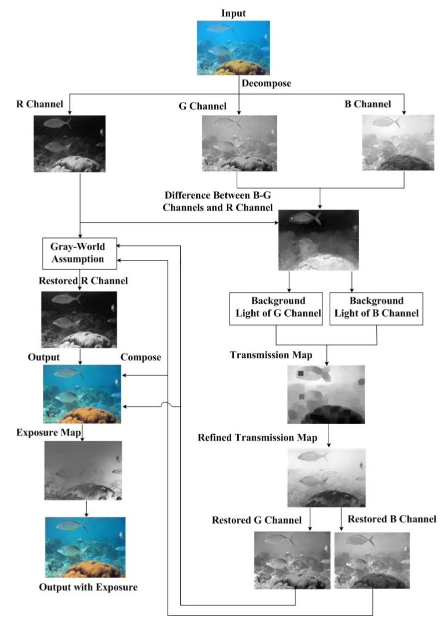


Fig. 2. Flowchart of the proposed method.

2. RELATION TO PRIOR WORK

According to the selective absorption theory of water, the red light is much easier to be absorbed than the blue light and the green light. Moreover, scattering intensity is inversely proportional to the fourth power of wavelength according to the Rayleigh scattering theory. The shorter wavelengths of the green light and the blue light will scatter much more than the longer wavelength of the red light [17]. Therefore, we can assume that the attenuation of the red light only results from absorption while the attenuation of the blue light and the green light only result from scattering. Unlike previous underwater image restoration works which apply original Dark Channel Prior algorithm to restore RGB three color channels with the same equation, we recover underwater images by blue-green channels dehazing and red channel correction. The blue-green channels are recovered using a dehazing algorithm based on an extension and modification of the Dark Channel Prior algorithm. Then, the red channel is corrected following the Gray-World assumption theory. In order to resolve the problem which some recovered image regions may look too dim or too bright, an adaptive exposure map is built for better visual quality. Fig. 2 shows the flow of the proposed method.

The rest of the paper is organized as follows: Section 3 describes our method. Section 4 evaluates and compares experimental results. Section 5 concludes the paper.

3. OUR METHOD

3.1. Blue-Green Channels Dehazing

As discussed above, the attenuation of the blue-green channels only results from scattering, which is similar to the hazy images [18]. Hence, we process the blue-green channels of an underwater image via a dehazing algorithm based on the remarkable progress on single image dehazing theory. The underwater imaging model can be described as:

$$I^c(x) = J^c(x)t(x) + B^c(1 - t(x)), c \in \{g, b\}, \qquad (1)$$

where x denotes a pixel, $I(x)$ is the observed image, $J(x)$ is the restored image, B is the background light, and $t(x) \in [0,1]$ is the medium transmission map which represents the percentage of the scene radiance reaching the camera. The purpose of dehazing is to recover $J^c(x)$, B^c and $t(x)$ from $I^c(x)$.

The background light B can be estimated based on the fact that red channel attenuates much faster than green and blue channels in an underwater image. To determine the differences among the three color channels, the maximum intensity of the red channel and that of the maximum one of the green and blue channels are compared as:

$$D(x) = \max_{x \in \Omega, c \in r} I^c(x) - \max_{x \in \Omega, c \in \{g,b\}} I^c(x), \qquad (2)$$

where $D(x)$ denotes the largest differences among three different color channels, $I^c(x)$ refers to a pixel x in the observed image, and Ω is a local patch in the image. The background light can be estimated as follows:

$$B^c = avg(I^c(\arg\min_x D(x))), c \in \{g, b\}. \qquad (3)$$

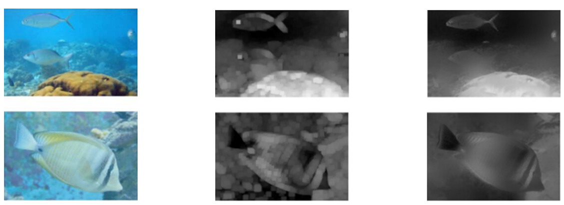
According to the Rayleigh scattering theory, the attenuating of the blue light and the green light is the same in water. Thus, we assume the medium transmissions map of the blue and green channels are identical. Furthermore, we also assume that the medium transmissions map in a local patch is constant. The Eq. (1) is rearranged and taken the minimum operation in a local patch:

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

The first term on the right side of the Eq. (4) should tend to be zero based on the Dark Channel Prior theory. Thus, the medium transmission map of the green and blue channels can be written as:

$$t(x) = 1 - \min_{c\in\{g,b\}}(\min_{x\in\Omega}(\frac{I^c(x)}{B^c})). \quad (5)$$

As shown in Fig. 3(b), there are some halos and block artifacts in the map *t(x)*. The halos and block artifacts are produced because *t(x)* is calculated over an image patch, which produces a coarse initial estimate of the map. To address the problem, the guided filter [19] is applied to refine the coarse map. Fig. 3(c) displays the refined medium transmission map.



(a) (b) (c)

Fig. 3. Medium transmission map. (a) Original underwater images with a size 600×400. (b) Coarse medium transmission maps. (c) Refined medium transmission maps.

With the refined medium transmission map and the obtained background light, we can restore the haze-free green and blue channels according to the Eq. (1). Specifically, the haze-free channel can be restored by:

$$J^c(x) = \frac{I^c(x) - B^c}{t^c(x)} + B^c, c \in \{g, b\}, \quad (6)$$

where $J^c(x)$ represents the restored channel.

3.2. Red Channel Correction

The absorption rate of red light is hard to be obtained for single underwater image. Inspired by the Gray-World assumption theory that the average value of object color in an ideal image is gray, we correct the red channel following the assumption. It can be written as:

$$(avgRr + avgBr + avgGr)/3 = 0.5, \quad (7)$$

where *avgRr*, *avgBr* and *avgGr* are the normalized average values of the recovered red channel, blue channel and green channel, respectively. The average value of the recovered red channel can be estimated as follows:

$$avgRr = 1.5 - avgBr - avgGr. \quad (8)$$

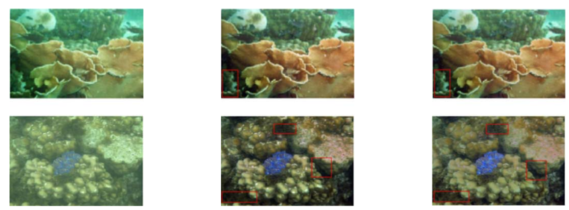
Then, the compensation coefficient δ can be calculated as:

$$\delta = avgRr/avgR, \quad (9)$$

where *avgR* is the normalized average value of the original red channel. The recovered red channel *Rrec* can be obtained by:

$$Rrec = R. * \delta, \quad (10)$$

where *R* is the normalized original red channel, and δ is the estimated compensation coefficient. As shown in Fig. 4(b), after blue-green channels dehazing and red channel correction processing, clarified visibility, calibrated color casts and enhanced contrast are achieved.



(a) (b) (c)

Fig. 4. Recovered results. (a) Original underwater images with a size 600×400. (b) The recovered results without an adaptive exposure map. (c) The recovered results with an adaptive exposure map. Red rectangles indicate the details.

3.3. Adaptive Exposure Map Estimation

Based on the observation that the dark or bright regions in underwater images become too dark or too bright after processing by our method, we take an adaptive exposure map [20] to adjust our results. The adaptive exposure map *s(x)* can be obtained by solving optimization problem:

$$\min_s \sum_x \{[1 - s(x)\frac{Y_{J(x)}}{Y_{I(x)}}]^2 + \lambda[s(x) - 1]^2\} + \Phi(s), \quad (11)$$

where *s(x)* is the adaptive exposure map, Y_J is the illumination intensity of the restored image, Y_I is the illumination intensity of input image, $\lambda = 0.3$ is a constant, and $\Phi(\cdot)$ is a smoothness regularization. The optimization problem can be approximately solved using a two-step approach. First, solve *s(x)* without the smoothness regularization, which has a closed-form solution. Then, apply guided filter GF_I [19] to smooth the solution. Therefore, we can get a fast approximate solution as:

$$s(x) = GF_I[\frac{Y_{J(x)}Y_{I(x)} + \lambda Y_{I(x)}^2}{Y_{J(x)}^2 + \lambda Y_{I(x)}^2}]. \tag{12}$$

The exposed output can be written as:

$$OutputExp = J^c(x). * s(x), c \in \{r, g, b\}, \tag{13}$$

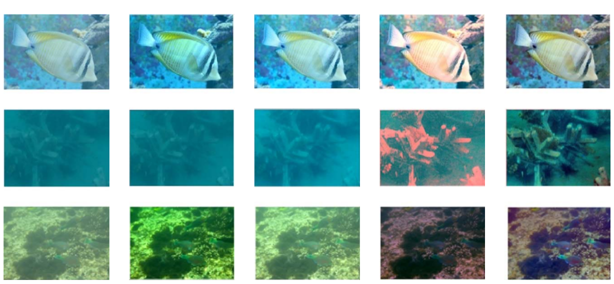
where J^c is the restored image and *s(x)* is the adaptive exposure map. Figure 4(c) shows the results of applying an adaptive exposure map.

4. EXPERIMENT RESULTS

In order to assess the performance of the proposed underwater image restoration method, we compared our method with three existing methods: Carlevaris *et al.* [9], Yang *et al.* [10] and He *et al.* [11], which are based on underwater imaging optical model and dehazing algorithm. The qualitative and quantitative evaluations are carried out to assess the performance of different methods. We just show some examples of the results owing to the limited space.

4.1. Qualitative result

Figure 5 shows that He's work has little or no effect on underwater images due to the distinction between the atmospheric scattering model and the actual underwater optical model. The method of Carlevaris can remove the haze. However, the solution of Carlevaris can unveil little details in the foreground. The results of Yang usually contain evident color casts and artifacts because the assumption of the color correction is unavailable in some cases. The proposed method produces aesthetically natural image versions and improved contrast and details without artifacts.



(a) (b) (c) (d) (e)

Fig. 5. Qualitative comparisons. (a) Original underwater images with a size 600×400: Image 1, Image 2 and Image 3 from top to bottom. (b) He results. (c) Carlevaris results. (d) Yang results. (e) Our results.

4.2. Quantitative result

Unlike the common image quality assessment or common image restoration areas, there is no easy way to have a reference image, which makes underwater images difficult to evaluate. We consider the main goal of image restoration as to emphasize the image features and information content. Table 1 shows the comparative values in terms of entropy, SIFT (Scale-Invariant Feature Transform) local feature points [21] and the average value of gradient (AVG) for the underwater images shown in Fig. 5. The value of entropy represents the valuable information contained in the recovered images. The SIFT local feature points indicate the global contrast and local features while the AVG denotes the contrast and details changes. The best results are represented by bold face values.

Table 1. Comparison in terms of entropy, SIFT and AVG.

Images	Method	entropy	SIFT	AVG
Image1	He	7.3727	198	0.1093
	Carlevaris	7.3425	208	0.0851
	Yang	7.5179	223	0.0818
	Our	**7.5801**	**234**	**0.1139**
Image2	He	5.0047	107	0.0125
	Carlevaris	5.4966	135	0.0112
	Yang	6.5463	240	0.0236
	Our	**6.7354**	**243**	**0.0253**
Image3	He	7.3706	639	0.1067
	Carlevaris	7.1155	599	0.0888
	Yang	6.8192	470	0.0399
	Our	**7.4268**	**642**	**0.1084**

Table 1 shows that the quantitative performance of our method stands out among the other methods in terms of entropy, SIFT and AVG. The results demonstrate that our method can increase the valuable information, global contrast, local features and details of the underwater images.

Therefore, the qualitative and quantitative evaluations prove that our method outperforms the three compared methods and can effectively improve the visual quality of underwater images.

5. CONCLUSION

An underwater image restoration method is proposed based on blue-green channels dehazing and red channel correction. The qualitative and quantitative evaluations show that the proposed method can effectively remove haze, restore natural appearance and increase contrast, gradient and local features of underwater images. Moreover, our method outperforms each of the three existing methods.

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