Underwater Image Color Correction based on Surface Reflectance Statistics

Hui Liu and Lap-Pui Chau
Nanyang Technological University, Singapore
E-mail: {hui.liu,elpchau}@ntu.edu.sg

***Abstract*—Underwater image processing has attracted much interest during the past decades. Most of the underwater images suffer from the problems of backscattering and color distortion. In this paper, we focus on solving the problem of color distortion. Due to the light attenuation, which is caused by absorption and scattering, different colors of light will disappear gradually with the increase of water depth according to their wavelengths. The blue color has the shortest wavelength, so it can reach the largest depth, which results in the bluish tone of the underwater images. Our main contribution is that we proposed a new color correction scheme based on a local surface statistical prior. Our work mainly contains two steps. Firstly, we segment the underwater image into several non-overlapped blocks. Secondly, for each block, we estimate its illuminant based on the image formation model and the local surface statistical prior. By dividing the image block by its illuminant, the true reflectance can be obtained. Our experimental results demonstrate that our proposed method can achieve comparable or even better results than some state of the art approaches.**

I. Introduction

Obtaining high quality underwater images is very important in marine scientific research and ocean engineering, such as analyzing marine geological environment, studying marine organisms and assisting in offshore oil drilling or marine rescue. However, it is a challenging task to get a clear underwater image. Due to the existence of dust-like particles known as “marine snow” in the water, underwater images always suffer from backscattering effect in various degrees, which leads to the loss of contrast. Besides due to the light attenuation which is caused by absorption and scattering, different colors of visible light will disappear gradually with the increase of water depth according to their wavelengths. The longer the wavelength is, the shorter the distance it can penetrate. As illustrated in Fig.1, the red color disappears firstly at about 5 m depth in the water. The green color can travel about 30 m. The blue color is able to travel the longest distance because it has the shortest wavelength, so the underwater images always show a greenish or bluish tone. In summary, backscattering and color distortion are two major problems of distortion for underwater images. In this paper, we only focus on correcting color distortion. We aim to restore the true color (the color of the scene illuminated by a natural light source in air) of the underwater images.

The rest of the paper is organized as follows: Section II introduces several state of the art color correction algorithms. Section III describes the proposed method in detail. Section IV presents the experiments result and analysis. Section V concludes this paper.

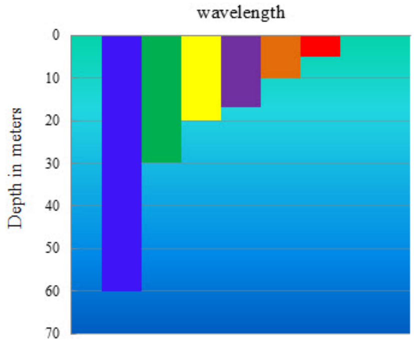


Fig. 1. Penetration of light with different wavelengths in the open ocean.

II. Related Work

Up to date, many color correction methods have been proposed to modify the distorted underwater images. The classic one is the physical model-based method. Chiang *et al*. [1] proposed a method based on wavelength compensation. Their method is based on the Jaffe-McGlamery image formation model. Due to the fact that different wavelengths of light are attenuated at different rates in water, to restore the color balance, they applied the wavelength compensation to adjust the bluish-greenish tone to a natural color. Galdran *et al*. [2] proposed a red-channel underwater image restoration method where the colors associated to short wavelengths are recovered. In this method, they amended the dark channel prior to make it adapt to the underwater environment. Though the aforementioned approaches should achieve the most correct results in theory, they all require the assistance of the hardware to measure some key parameters such as the absorption coefficient, scattering coefficient, or the energy. Torres-Mendez and Dudek [3] proposed a method from another point of view. The underwater image color distortion problem was translated into an energy minimization problem using learned constrains. Another effective method is based on some priori information, such as the most popular Grey-World (GW) assumption and the White-Patch (WP) criteria. The GW theory assumes that the average color of the R, G and B channel of the natural images tends to be grey based on statistics [4], [5], [6]. While

Proceedings of APSIPA Annual Summit and Conference 2015 16-19 December 2015

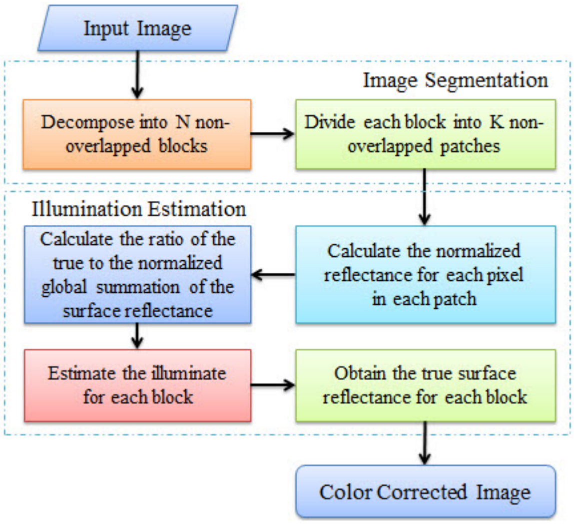


Fig. 2. The flowchart of the proposed scheme.

the WP theory assumes that the points with the maximum light intensity in natural images are white points, and uses these white points to estimate the environmental illumination [7]. These two criteria have been widely used in many methods and can often achieve satisfactory results. However, they also have limitations when processing some kinds of images. For example, the GW assumption is very suitable to deal with colourful images, but cannot handle images with a single color. The WP based methods cannot remove the color cast for images with complex colors or images without points with maximum light intensity. Therefore, many improved algorithms have been proposed, such as the GW/WP hybrid method [8], [9], [10].

Recently an efficient color constancy method based on local surface reflectance statistics [11] was proposed to remove the light source color for the color-biased natural images. These natural images are taken under the light source with certain spectral power distribution in air. For our underwater images, due to the attenuation of light source with different wavelength, the illumination is filtered by the water between the light source and the object and by the water between the object and the camera.Therefore they can be deemed to be taken under the light source with certain spectral power distribution in air. Inspired by this idea, this color constancy method can be used to do color correction for the underwater images. In this paper, we propose a new scheme based on the local surface reflectance statistics to remove the color cast for underwater images.

III. Proposed Method

Our proposed scheme mainly contains two steps: image segmentation and illumination estimation. The details are described in the following subsections and the flowchart of our proposed scheme is shown in Fig.2.

A. Image Segmentation

The aforementioned color constancy method can only deal with the scenes under the illumination with constant intensity. The depth map for the underwater image is a matrix with different element values. Therefore different points on the scene correspond to different light intensities. So the color constancy method based on local surface reflectance statistics cannot be directly applied to our underwater images. To adapt to this statistics, we need to segment the image into different regions according to its depth map. However there is no accurate approach to estimate the depth map for underwater images.Thus we simply decompose the original image into N non-overlapped blocks for further processing and we assume the light intensity in each block to be the same. The size of N is determined empirically in experiment. Each block can be considered as a small and separate image for the following processing.

B. Illumination Estimation

In this section, each block of the original underwater image is treated as an input image and is processed seperately in turn. According to the classic Retinex theory [7], the image can be decomposed into two separate parts: the illumination part and the reflectance part. The image formation model can be simplified with the following linear equation:

$$F_i(x, y) = I_i(x, y)R_i(x, y), \tag{1}$$

where each coordinate location (x, y) corresponds to a point in the image domain, $F_i(x, y)$ represents the input color-biased image, $i \in R, G, B$ are the three color channels of the sensor. $I_i(x, y)$ represents illumination which describes the intensity of the light source, $R_i(x, y)$ is the surface reflectance. From equation(1), if we can estimate the illumination, the surface reflectance $R(x, y)$ can be easily obtained by dividing the original image $F_i(x, y)$ by the illumination $I_i(x, y)$. However, this is an ill-posed problem in mathematics, because in Eq 1, only $F_i(x, y)$ is known and the other two terms are unknown.

The input image $F_i(x, y)$ is divided into K non-overlapped patches of the same size. We define:

$$N_i, k(x, y) = \frac{F_{i,k}(x, y)}{F_{i,k}(x_{k,max}, y_{k,max})}, \tag{2}$$

where $(x_{k,max}, y_{k,max})$ is the spatial coordinate of the maximum intensity pixel within the $k-th$ local region:

$$\begin{aligned}&(x_{k,max}, y_{k,max})\\&= \arg\max\{F_{i,k}(x, y), x = 1, 2, ...m, y = 1, 2, ...m\},\end{aligned} \tag{3}$$

$Ni, k(x, y)$ is actually the normalized pixel value of each point (x, y) by the maximum pixel value within the $k-th$ patch of the image domain. If we substitute Eq 1 into Eq 2, we get:

$$N_i, k(x,y) = \frac{I_i(x,y)R_{i,k}(x,y)}{I_i(x,y)R_{i,k}(x_{k,max}, y_{k,max})} = \frac{R_{i,k}(x,y)}{R_{i,k}(x_{k,max}, y_{k,max})}, \tag{4}$$

Define FR_i as the ratio between the summation of pixel value of the whole image and the summation of the normalized pixel value of the whole image in the $i-th$ color channel .

$$FR_i = \frac{\sum_{x=1}^{m}\sum_{y=1}^{m} F_i(x,y)}{\sum_{k=1}^{K}\sum_{x=1}^{m}\sum_{y=1}^{m} N_{i,k}(x,y)}, \tag{5}$$

where K signifies the total number of patches. If we substitute Eq 1 into Eq 5, we can get:

$$FR_i = \frac{I_i \sum_{x=1}^{m}\sum_{y=1}^{m} R_i(x,y)}{\sum_{k=1}^{K}\sum_{x=1}^{m}\sum_{y=1}^{m} N_{i,k}(x,y)} = I_i \frac{T_i}{E_i}, \tag{6}$$

where

$$T_i = \sum_{x=1}^{m}\sum_{y=1}^{m} R_i(x,y), \tag{7}$$

$$E_i = \sum_{k=1}^{K}\sum_{x=1}^{m}\sum_{y=1}^{m} N_{i,k}(x,y), \tag{8}$$

Where T_i signifies the global summation of the surface reflectance and E_i represents the global summation of the normalized surface reflectance. Based on exploring the Gehlershi image dataset, SFU indoor dataset, SFU HDR dataset and the SFU ball dataset, a local surface statistics prior [11] was found:

$$\frac{T_R}{E_R} \approx \frac{T_G}{E_G} \approx \frac{T_B}{E_B} \approx \rho, \tag{9}$$

Where ρ is a constant value which may be different for different images. If we substitute Eq 9 into Eq 6, we can obtain:

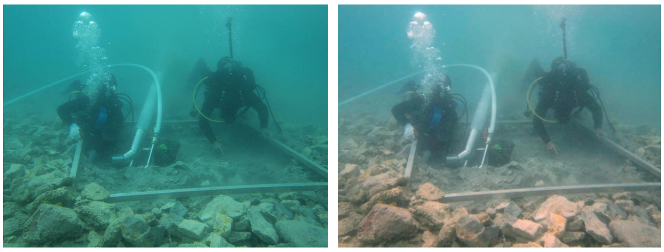
$$FR_i \approx \rho I_i, \tag{10}$$

Then the illumination can be estimated as:

$$I_i \approx \frac{1}{\rho} FR_i, \tag{11}$$

Based on Eq 11 and Eq 1, the surface reflectance can be obtained:

$$R_i(x,y) = \frac{F_i(x,y)}{I_i(x,y)} = \frac{\rho F_i(x,y)}{FR_i}, \tag{12}$$



(a) (b)

Fig. 3. (a)the original image. (b) the enhanced image by our proposed method

Thus the surface reflectance for each block on the image can be achieved by applying Eq 12. As we know, The color of an object is given by its wavelength dependent reflection which represents the fraction of incident power that is reflected. So the true color of the underwater image can be achieved by obtaining the surface reflectance of each block on the image.

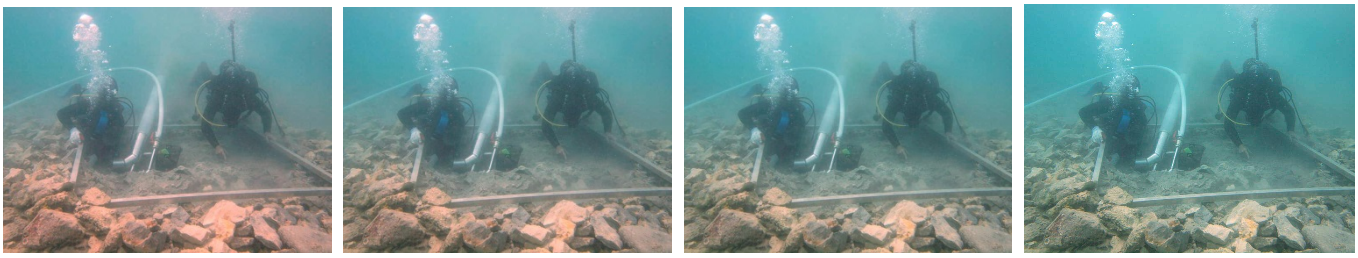
IV. Experimental Results and Analysis

In our experiments, we applied some of the aforementioned algorithms and our proposed method to several test images downloaded from the internet. One of the experimental results is shown in Fig.3. All algorithms are implemented with MATLAB R2012b and run on a PC with 3.20GHz Intel Pentium Quad Core Processor. The parameter ρ is usually set to be an empirical value of 2.2. The value K varies in the range of [1,200].The experimental results with different value of K are shown in Fig.4.The value N varies in the range of [1,50]. By adjusting these two parameters, more satisfactory results can be obtained.

In addition, our method is compared with four other up-to-date approaches. The original underwater images with color distortion are shown in Fig.5(a)and Fig.5(a). In Fig.5(b) and Fig.6(b), the results of the standard Grey-World approach are presented. It is obvious that the GW method fails to estimate the illumination accurately for underwater images. Therefore, for the underwater images with a greenish or bluish tone, it results in a reddish appearance in the miss-balanced parts of the image. The results by Histogram Equalization, as shown in Fig.5(c)and Fig.6(c), are over enhancement because it does not take the different distributions of the three color channels into consideration and stretches the histograms of three color channels to the same level, which makes the processed images show a reddish tone. Fig.5(d) and Fig.6(d) show the results by our proposed method. This comparison demonstrates that our method is able to avoid over enhancement and at the same time makes the color of the improved images look more natural.

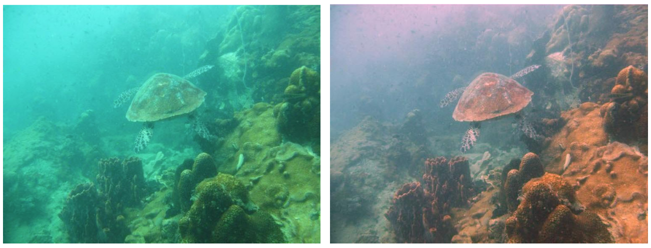
V. Conclusion

In this paper, we present a new color correction scheme based on local surface reflectance statistics for underwater images. In our work, we decompose the original color distorted image into several non-overlapped blocks. For each block, we estimate its illumination based on the aforementioned statistics. Then by applying the theory of Retinex, the true

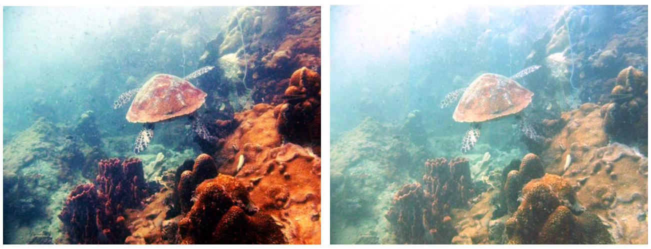


(a) (b) (c) (d)

Fig. 4. processed by setting (a) K=10 (b) K=50 (c) K=100 (d) K=200



(a) (b)



(c) (d)

Fig. 5. (a) raw image (b) the enhanced image by the Grey-World approach.(c) the enhanced image by Histogram Equalization.(d) the enhanced image by our method

(a) (b)

(c) (d)

Fig. 6. (a) raw image (b) the enhanced image by the Grey-World approach.(c) the enhanced image by Histogram Equalization.(d) the enhanced image by our method

reflectance for each image block can be obtained. Our experimental results show that our method can achieve better results than some up-to-date color correction approaches.

ACKNOWLEDGMENT

This work is supported by the Singapore Maritime Institute under SMI Deepwater Technology R&D Programme.

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