TWO-STEP APPROACH FOR SINGLE UNDERWATER IMAGE ENHANCEMENT

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ABSTRACT

Underwater images often suffer from color shift and contrast degradation due to the absorption and scattering of light while traveling in water. In order to handle these issues, we present and solve two sub-problems to improve underwater image quality. First, we introduce an effective color correcting s-trategy based on piece-wise linear transformation to address the color distortion. Then we discuss a novel optimal contrast improvement method, which is efficient and can reduce artifacts, to address the low contrast. Since most operations are pixel-wise calculations, the proposed method is straightforward to implement and appropriate for real-time application. In addition, prior knowledge about imaging conditions is not required. Experiments show an improvement in the enhanced image of color, contrast, naturalness and object prominence.

Index Terms— Underwater images, image enhancement, color correction, contrast enhancement.

1. INTRODUCTION

Underwater imaging is becoming more and more relevant as companies search for the abundant mineral and biological resources in oceans, rivers and lakes. Significant progress has been made in underwater exploration, but underwater image and video processing techniques still have much potential for development for computer vision applications [1]. Due to the light absorption and scattering in water, color shift and contrast degradation are two major problems of underwater images. Color distortion is mostly caused by the way different light wavelengths travel in water, making the color of underwater images appear bluish-green. Moreover, since light is randomly attenuated and scattered by particles suspended in water, image contrast tends to be seriously degraded [2, 3].

To address these problems and improve the quality of underwater imaging, various image restoration and enhancement methods have been proposed [4]. In image restoration, the goal is to recover the image by directly modeling the degradation process [5]. For example, several haze removal algorithms have been proposed to deal with contrast distortions [2, 6–12]. Some of these focus on dark channel modeling [6, 10]. To suppress the blurring effect in underwater images, a point spread function is combined with a modulation transfer function [8]. In [13], the visibility of underwater images is recovered by a polarization haze removal method, while [9] combines wavelength compensation with a haze model. Another model-based approach uses a radiation transfer function to restore the visibility of underwater images [14]. A restoration method based on dictionary learning is introduced in [15]. In [11], the authors propose a dehazing algorithm that aims to minimize the information loss and restore degraded image. Then a contrast enhancement algorithm is followed to further enhance details. Recently, based on the analysis of image blurriness and light absorption, a depth estimation algorithm is proposed in [12] to recover and enhance underwater images.

Since image restoration methods are sensitive to modeling assumptions and parameters, these methods may fail in extremely variable underwater environment. Compared to restoration methods, *enhancement* methods are usually simpler and faster [4]. In this family of algorithms, the goal is to use qualitative, subjective criteria to generate a high quality image with no need for a physical model. For example, [16] fuses different images taken through a polarizer at different orientations to improve underwater visibility, but is impractical for real-time application. In [1], a slide stretching algorithm based on an integrated color model is used to enhance underwater images. In [17], a method based on light attenuation inversion is proposed to improve color rendition. Other methods have been proposed based on different heuristics [3, 18].

In this paper, we propose a simple yet effective two-step enhancing strategy that requires only the single underwater image being enhanced. Each step deals with one of the two major issues of color distortion and low contrast. For the color distortion problem, we propose a color correcting strategy based on a piecewise linear transformation. Compared with other color correcting algorithms, the proposed algorithm is more robust to deal with varying degrees of color distortion in the underwater setting. For low contrast we propose a novel optimal contrast method that is efficient and can reduce artifacts. Traditional contrast enhancement algorithms, e.g., histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE) [19], are easy to im-

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plement, but have undesirable artifacts due to their black-box implementation. Other contrast algorithms based on optimal methods can produce better results, but at a computational cost that is not suitable for practical applications [20–22]. Compared with other optimal contrast methods based on histogram distributions [20–22], the proposed optimal contrast model can be solved efficiently. Additionally, the proposed method only requires a single underwater image as input and does not require expensive specialized devices and additional prior knowledge about imaging conditions.

2. THE PROPOSED APPROACH

In this section, we present the two steps of our proposed underwater image enhancement algorithm to produce a color and contrast corrected image.

2.1. Color correction

Since the colors of underwater images are difficult to restore due to light absorption, conventional color correction algorithms may fail to recover colors [23–25]. Meanwhile, scenes of underwater images appear dim due to the poor lighting condition. Inspired by the gray-world hypothesis [23], we use a color correcting strategy based on a linear transformation. The gray-world hypothesis assumes that the average color in a scene is achromatic [23]. In other words, the mean value of the image is equal to 128 in an 8-bit image.

Based on this gray-world hypothesis, the proposed color correcting approach adopts a piecewise linear transformation to stretch the image's mean value toward 128. Defining S to be the input image, the operations are as follows: First, the mean, maximum and minimum are calculated in the RGB channels of S. The basic form of the gray-world approach to color correction is

$$S^c_{CR} = \begin{cases} (S^c - S^c_{\text{mean}})\frac{S^c_{\text{min}}-128}{S^c_{\text{min}}-S^c_{\text{mean}}} + 128, \ S^c_{\text{mean}} \leq 128, \\ (S^c - S^c_{\text{mean}})\frac{S^c_{\text{max}}-128}{S^c_{\text{max}}-S^c_{\text{mean}}} + 128, \ S^c_{\text{mean}} > 128, \end{cases} \tag{1}$$

where $c \in \{R, G, B\}$. S^c_{mean}, S^c_{max} and S^c_{min} are the mean, maximum and minimum in the c channel, respectively, and S_{CR} is the color corrected image. The mean is used as a criterion to decide which direction to stretch. However, in special situations such as an underwater image in which the intensity of the red channel is very small because of the quick absorption of red wavelength, adopting the scaling above may lead to an over-correction by excessive stretching. We show this in Fig. 1(b). We therefore propose the following simple improvement instead:

(a) input image (b) output of Eq. (1) (c) output of Eq. (2)

Fig. 1. Example of the proposed color correcting method.

$$S^c_{CR} = \begin{cases} S^c - \lambda(S^c_{\text{mean}} - 128), \ P^c > 0.7, \\ (S^c - S^c_{\text{mean}})\frac{S^c_{\text{min}}-128}{S^c_{\text{min}}-S^c_{\text{mean}}} + 128, \ S^c_{\text{mean}} \leq 128, \\ (S^c - S^c_{\text{mean}})\frac{S^c_{\text{max}}-128}{S^c_{\text{max}}-S^c_{\text{mean}}} + 128, \ S^c_{\text{mean}} > 128, \end{cases} \tag{2}$$

where λ is a positive parameter to control the shifting range and P is the probability of pixel values that are less than or equal to 40. As shown in Fig. 1(c), this can effectively handle the over-correction. The post-processing step, $S_{CR} = \min(\max(S_{CR}, 0), 255)$, is used to avoid exceeding the pixel range. We note that all operations are component-wise.

2.2. Optimal contrast

After color correcting, underwater images will still look hazy since the underwater condition is similar to a haze environment [2, 7, 9, 13]. Contrast should therefore be enhanced to highlight objects and details. The basic idea of our contrast method is to find a modified image between the original image and a reference image. Since both original image S_o and reference image S_r contain different useful information, the goal is to obtain a desired trade-off between S_o and S_r.

We propose the following optimal contrast objective to explain the desired balance:

$$F(E) = \alpha \left\| E - S_o \right\|^2_{W^{1,2}} + (1 - \alpha) \left\| E - S_r \right\|^2_{W^{1,2}}, \tag{3}$$

where $\|u\|_{W^{1,2}} = \sqrt{\|u\|^2_2 + \|Du\|^2_2}$ is the $W^{1,2}$ norm in Sobolev space, E is the enhanced image, $\alpha \in [0, 1]$ is a positive parameter, D denotes the difference operators.

For simplicity, we define the following set:

$$\Lambda = \{E \,|\, E \in W^{1,2}(\Omega), \ 0 \leq E \leq 255\}, \tag{4}$$

where Ω is a connected bounded open subset of $\mathbb{R}^2$ with compact Lipschitz boundary. The minimization problem in (3) is rewritten as:

$$\min_{E \in \Lambda} F(E) = \min_{E \in \Lambda} \alpha \left\| E - S_o \right\|^2_2 + (1 - \alpha) \left\| E - S_r \right\|^2_2 + \alpha \left\| DE - DS_o \right\|^2_2 + (1 - \alpha) \left\| DE - DS_r \right\|^2_2. \tag{5}$$

The first two penalty terms demonstrate that the modified image E is a weighted average of S_o and S_r. Additionally, in order to avoid unnatural images, a weighted gradient constraint can be added to the objective function. This can prevent over-enhanced results by smoothing the enhanced image to avoid abrupt changes without compromising the contrast enhancement. To this end, we introduce a smoothing penalty term on the image gradient in the second line of Eq. (5).

Eq. (5) is an optimal trade-off between S_o and S_r by taking both pixel values and gradients into consideration. Since all terms in Eq. (5) are quadratic, it is a least squares problem, which has a close-form solution that can be directly obtained. The Fast Fourier Transformation (FFT) is used to speedup this process. We solve E by first calculating its Fourier coefficients and then performing an inverse transform,

$$E = \mathcal{F}^{-1}\left(\frac{\alpha\mathcal{F}(S_o)+(1-\alpha)\mathcal{F}(S_r)+\alpha(\Psi\cdot\mathcal{F}(S_o))+(1-\alpha)(\Psi\cdot\mathcal{F}(S_r))}{2\mathcal{F}(\mathbf{1})+\Psi}\right), \tag{6}$$

where $\Psi = \mathcal{F}^*(D_x)\mathcal{F}(D_x) + \mathcal{F}^*(D_y)\mathcal{F}(D_y)$, $\mathbf{1}$ is the identity matrix, $\mathcal{F}$ is the FFT operation, $\mathcal{F}^{-1}$ is the inverse FFT operation, $\mathcal{F}^*$ is the conjugate transpose, x and y are the horizontal and vertical directions. All calculations prior to the inverse Fourier transform in Eq. (6) are performed pixel-wise.

For underwater images, the S_{CR} is converted into the Lab space and S_o is the luminance component. The user can choose different mature algorithms to produce reference images. In this paper, CLAHE is applied on S_o to obtain the reference image S_r, since CLAHE can effectively enhance local contrast [19]. The final result is obtained by converting the enhanced Lab color space into the RGB color space.

3. EXPERIMENTAL RESULTS

In this section we present experimental results to demonstrate the effectiveness of our approach. The simulation tool is Matlab R2012a on a PC with a 4GB RAM. In this paper, $\lambda = 0.4$ to obtain colorful results, we set $\alpha = 0.5$ to give S_o and S_r the same weighting. More enhanced results and the Matlab testing code can be found on our website: ***http://smartdsp.xmu.edu.cn/UnderwaterAppendix.html***.

3.1. Qualitative evaluation

In our qualitative evaluation, we compare our algorithm with four approaches [2, 3, 7, 10]. We tested many images in our experiments, but only show three test images from the PKU-EAQA dataset [26] in this paper. Results on these three images are consistent with what we observed on the larger data set. These images contain different color distortion, such as greenish color in Figs. 2(a) and 3(a) and blue in Figs. 4(a) and 5(a). The test images also contain close shot and long shot to show various distance from objects to camera.

As shown in these figures, details are enhanced by method [2] while color cannot be corrected effectively, e.g., Figs. 2(b) to 5(b). The enhanced result in Fig. 5(b) has a decent subjective visual effect, some red dots are shown on the fish's surface due to the over-correction of color. Since in unclear water and the deep sea, serious color distortion leads to the failure of the dark channel model, the transmission cannot be estimated correctly and color enhancement algorithm cannot work. There exists similar drawbacks in methods [7] and [10].

Method [3] is based on an image enhancement method that uses a fusion strategy. In Figs. 2(e) and 3(e), we see that color is corrected, and contrast and details are improved by this fusion method. However, in Figs. 4(e) and 5(e), colors are over-corrected because the color correcting method is not robust to deal with various underwater environments. Meanwhile, some regions are over-enhanced by method [3], such as the diver's oxygen tank in Fig. 4(e) and the fish's surface in Fig. 5(e). As can be seen in Figs. 2(f) to 5(f), the proposed approach achieves a good performance on color correction, contrast improvement, naturalness preservation and detail enhancement. Due to the proposed robust color correcting algorithm and optimal contrast method, the proposed approach outperforms other methods in overall appearance.

Table 1. Quantitative Measurement Results of SRNSS [27].

	input	[2]	[7]	[10]	[3]	proposed
Diver 1	89.3	88.6	74.1	78.4	74.0	**89.9**
Diver 2	75.4	78.5	56.8	79.9	75.4	**82.6**
Diver 3	76.2	59.2	66.8	76.4	48.6	**91.6**
Fish	83.9	69.2	80.8	82.1	55.0	**92.5**
Average	81.2	73.9	69.6	79.2	63.3	**89.2**

Table 2. Quantitative Measurement Results of NIQE [28].

	input	[2]	[7]	[10]	[3]	proposed
Diver 1	4.41	3.36	3.53	3.37	3.88	**3.20**
Diver 2	5.56	**3.30**	4.63	3.76	4.37	3.66
Diver 3	3.30	2.94	2.92	2.97	2.97	**2.89**
Fish	3.45	4.06	3.32	3.97	2.91	**2.35**
Average	4.18	3.48	3.60	3.52	3.53	**3.03**

3.2. Quantitative evaluation

In this test, objective evaluations are shown to demonstrate the quality of enhanced images shown in Figs. 2 to 5. Since ground truths of scenes cannot be obtained, two blind image quality assessments are adopted. One is based on the sparse representation of natural scene statistics (SRNSS) [27]. Table 1 shows the quantitative measurement results and a higher value indicates a higher image's quality. It is clear that our method has the highest values for all tested images, which implies the highest quality of visual perception.

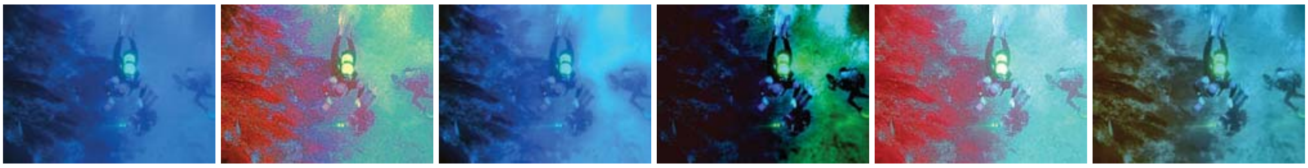
Another objective evaluation is the natural image quality

(a) input image (b) method [2] (c) method [7] (d) method [10] (e) method [3] (f) proposed method

Fig. 2. Results of ***Diver 1*** image.

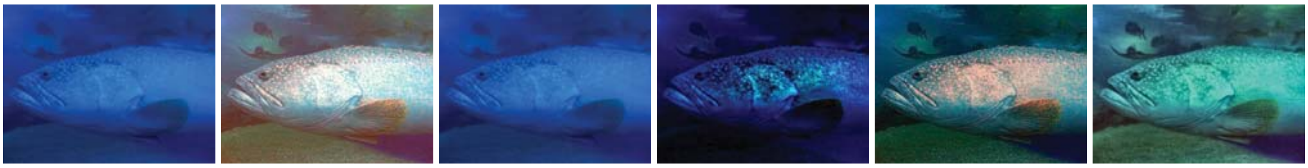
(a) input image (b) method [2] (c) method [7] (d) method [10] (e) method [3] (f) proposed method

Fig. 3. Results of ***Diver 2*** image.



(a) input image (b) method [2] (c) method [7] (d) method [10] (e) method [3] (f) proposed method

Fig. 4. Results of ***Diver 3*** image.



(a) input image (b) method [2] (c) method [7] (d) method [10] (e) method [3] (f) proposed method

Fig. 5. Results of ***Fish*** image.

evaluator (NIQE) [28] which is based on measurable deviations from statistical regularities observed in natural images. As shown in Table 2, our method has the lowest average value, in accordance with the lowest distortion and the highest quality of enhanced results in general. Enhanced results and quantitative measurement results demonstrate the proposed method has the best trade-off between subjective assessment and objective assessment.

3.3. Runtime

In Fig. 6 we show the computational runtime of our algorithm. As can be seen, the computational time to process different images is closely related to the image size. Note that only 9 seconds are needed to enhance one color image containing nearly 12 million pixels with un-optimized Matlab code. The proposed algorithm can be further accelerated in optimized C and other advanced computing devices, such as Graphic Processing Unit (GPU). This demonstrates that our proposed method has an acceptable computational time and is appropriate for real-time applications.

3.4. Extension: ordinary image enhancement

Additionally, the proposed optimal contrast algorithm in this paper can be applied to ordinary image enhancement. As can be seen in Fig. 7, the output by the proposed method are visual pleasing meanwhile details are well enhanced. The girl's eyes are more vivid than original ones in magnified regions as shown in Figs. 7(c) and 7(d). Due to the decent trade-off between input image and reference image, naturalness preservation and contrast improvement can be obtained in the enhanced result. This test implies that the proposed optimal contrast algorithm can be further embedded into ordinary image/video enhancement, such as consumer camera and mobile phone photography.

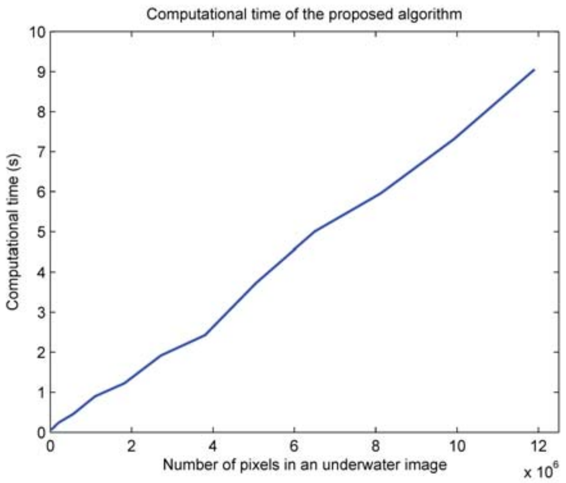


Fig. 6. Computational time of different image sizes.

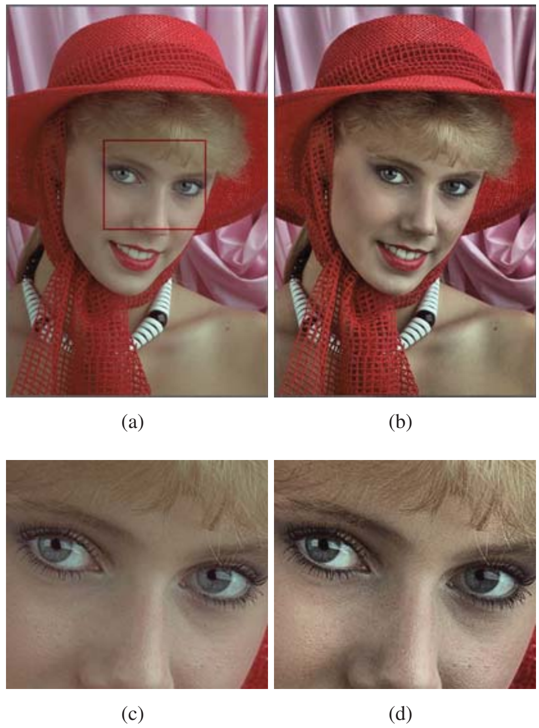


Fig. 7. **Contrast improvement.** (a) input image; (b) the proposed optimal contrast approach; (c)(d): magnified regions from (a) and (b) in red rectangles.

4. CONCLUSIONS

In this paper, we propose an effective and efficient two-step image enhancement procedure for single underwater images. Focusing on the two major problems of underwater images—color shift and low contrast—the proposed method addresses these problems individually. First, an effective color correcting strategy based on linear transformation is introduced to deal with color distortion. Then, a novel optimal contrast method is proposed to improve contrast meanwhile can reduce artifacts. Experimental results show that our method can generate promising results while comparing well with other methods. Additionally, computational times are presented to indicate our method is suitable for real-time applications.

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