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A Preprocessing Algorithm based on Wavelength Adaptive White Balance and Enhanced Dark Channel Prior to Processing Underwater Images

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Abstract: In order to overcome the problems of the bluish-green tone of color, bad contrast, and bad texture of underwater pictures, we introduced a two-step lightweight enhancement algorithm called WAWB-IDCP. The algorithm uses the wavelength-based white balance and an enhanced dark channel post-module, which contribute to the correct color correction and optimization of image quality, respectively. It solves the problem of color distortion and artifacts in blocks seen in traditional DCP algorithms. Experiments with multi-dimensional references were performed on three classic algorithms (Gray-world, CLAHE, DCP). The experimental results on the UIEB dataset prove that our algorithm has the highest subjective visual performance and also performs well on other quantitative measures, like the standard deviation of the algorithm of 44.71 and color cast control of 11.07. Furthermore, the SIFT feature experiment proves that it has a great capacity for recovering details and is also noise-resilient. The algorithm is highly performing and can be used in preprocessing underwater images.

Keywords: Underwater image enhancement; Wavelength adaptive white balance; Improved dark channel prior; Detail preservation; SIFT feature matching

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1. Introduction

With respect to the exploration of marine resources, underwater robot detection, or undersea target classification, which are engineering concepts, the characteristics of underwater images will affect the accuracy of the subsequent stages of feature extraction and target recognition, and it is a critical factor in underwater visual processes [1,2]. As a result of particular optical features of water, the visible light selectively absorbs at different wavelengths, with red light absorbed most strongly, then green light, and finally blue light being the most penetrating [3]. This effect frequently produces extremely strong blue-green color tints in real underwater pictures. Simultaneously, there are some suspended substances in water, like silt and plankton, that disperse the light in all directions, both up and down, thus reducing the image contrast, hiding the texture information of the target object, and ultimately causing imaging quality problems such as color distortion, image blur, and lack of detail [4].

The existing underwater image preprocessing systems do not lend themselves to scenes, and thus, it is difficult to obtain a balance of color correction and detail enhancement. The empirical approach used to perform color correction on the Gray-world white balance algorithm is averaging the mean values of the RGB channels and does not take into consideration the fact that underwater optical attenuation is often the cause of color overcorrection and detail loss [5]. CLAHE adaptive histogram equalization algorithm can only increase contrast of the image by extending the range of grayscale, but it cannot bring back the original blueish-green coloration of underwater images [6]. The old DCP algorithm that was originally developed to suppress atmospheric haze is prone to bias when applied directly to underwater images [7]. Experimental results show that the filtered images with the original DCP bias color by 45.28, causing color distortion and other image quality problems, like the collapse of dark regions and blocky artifacts.

To overcome the multiple deficiencies of the current algorithms, we suggest a two-stage preprocessing enhancement algorithm that is based on both wavelength-adaptive white balance and improved dark channel prior. The algorithm uses a staged optimization approach and can restore colors properly using the RGB attenuation patterns of water bodies. And at the same time, it allows the original dark channel algorithm to work underwater to improve the contrast of the image and the information in the image, as color cast correction, detail enhancement, and artifact reduction are all happening at the same time in underwater images.

2. Physical model of underwater image degradation

As the underwater image degradation can also be explained on the basis of the classical atmospheric scattering imaging model given below:

$$I\left(x\right)=J\left(x\right)t\left(x\right)+A\left(1-t\left(x\right)\right) \tag{1}$$

Here, $I(x)$ refers to the underwater image that is corrupted by the camera, $J(x)$ refers to the clean image to be recovered, $t(x)$ means the water transmission map, or the amount of light transmitted through the water, and A Is all of the ambient light, or the equivalent of the stray light at the back, due to the scattering of the water? The suggested algorithm will restore underwater images through iterative color correction and optimization of the transmission map to recover the clean scene image.

3. Algorithm principle

WAWB-IDCP algorithm is a cascade of two modules, namely the wavelength adaptive white balance mechanism and the enhanced dark channel prior mechanism. The general optimization process is to take the low-quality input underwater image and first restore it to repair the color distortion using the WAWB module, which will then be passed to the IDCP module to maximize the contrast and detail, and ultimately return an output of the high-quality preprocessed underwater image with its original natural colors and textures.

3.1. WAWB module

The proposed wavelength-adaptive white balance does not treat the RGB channels equally, as the traditional gray-world algorithm did empirically by assuming equal averaging of these channels, but rather takes into account the physical property of red-light attenuation selectively in water [5]. Using the blue channel, which is the least attenuated, as a reference standard, adaptive gain compensation occurs with respect to extremely attenuated red and green channels. The detailed steps of implementation are given here:

(1) Split three RGB channels of an input image into three individual channels by dividing it such that the average of all pixels in each channel is computed, denoted as $mean_R$, $mean_G$, and $mean_B$.

(2) Find the compensation gain of the red and green channels with a small constant added into them to prevent division by zero;

$$k_R = \frac{mean_B}{mean_R + \varepsilon}, k_G = \frac{mean_B}{mean_G + \varepsilon} \tag{2}$$

(3) Apply the computed gain of the red and green channels, but do not use it on the blue channel;

$$R_{new} = R \times k_R, G_{new} = G \times k_G \tag{3}$$

(4) The color correction is made by truncating the corrected pixel values to an interval of 0 and 255.

The suggested corrective measure based on the physically driven method will not lead to the artificial distortion and detail loss due to empirical equalization, as in the conventional white balance techniques.

3.2. IDCP module

The DCP (Dark Channel Prior) algorithm was initially developed to remove atmospheric haze, and it has critical adaptation problems when used underwater [7]. The approximation of the global ambient light is determined by the pixel with the largest value of the uppermost 0.1 percentile pixels in the dark channel, which is prone to underwater highlight interference, including water surface reflection and bubbles, leading to an overestimated ambient light. Also, the initial algorithm does not have a mechanism for concealing highlights, and the bright pixels persistently corrupt the dark channel extraction and transmission map computation. The initial transmission coefficient is also not smoothed, and it would cause the emergence of block artifacts in improved underwater images. We have suggested that there are three improvements to the problem mentioned above, whereby the parameters used are as per the original paper specification of $t_0 = 0.1$ and $\omega = 0.65$.

(1) Optimization of ambient lighting

The maximum value selector is substituted by the arithmetic mean of the brightest 0.1 percent dark channel pixels, which eliminates the effect of non-normal highlight pixels and provides a better estimate of the ambient light, which can be used in underwater scenes.

(2) Masking the brightness of the highlight area

To remove any bright highlight in the eroded dark channel that is likely to distort invalid highlights produced by the reflection of light on the water surface and white bubbles, all regions with a brightness value greater than 0.9 are set to 0.1, as they cannot interfere with the transmission map calculation.

(3) The initial transmission map is smoothed with the help of the 5x5 Gaussian filter, which leads to the decrease of harsh block mutations and removal of edge block artifacts in enhanced images.

The final image restoration formula is defined as:

$$J(x) = \frac{I_{wb}(x) - A}{max(t(x), t_0)} + A \tag{4}$$

where I_{wb} denotes the white balance corrected image, and t_0=0.1 is the lower bound of the transmission rate that does not lead to pixel overflow produced by near-zero denominator values.

4. Experimental results and analysis

4.1. Experimental setup

To verify the effectiveness of the proposed algorithm, it is done in detail through the selection of three classic image-enhancing algorithms, namely, Gray-world white balance, CLAHE adaptive histogram equalization, and the original DCP, to compare them with the baselines. The experiment is divided into six groups of test samples, which include original underwater images, images processed by the Gray-world, CLAHE, original DCP, single WAWB module, and full WAWB-IDCP cascaded algorithm. The experimental design could allow comparing its performance with the traditional designs and also to check the ablation of each module of the proposed algorithm.

The development of a multi-dimensional assessment system depends on subjective visual perception, objective quantitative measurements, and the ability to identify the SIFT features. The performance of various algorithms in color recovery and detail recovery is assessed by human observation of actual underwater corals to intuitively measure the performance of each algorithm. To assess the results objectively, it is necessary to test 20 multi-scene underwater images of different levels of color deviation and turbidity, which are included in the publicly available UIEB dataset in batches, and average metric scores are computed to allow the reliability and generalization of the experiment [8]. The SIFT feature-matching has been extended to quantitatively compare the detail retention and texture restoration capabilities of the different algorithms based on the feature viewpoint that supports each algorithm.

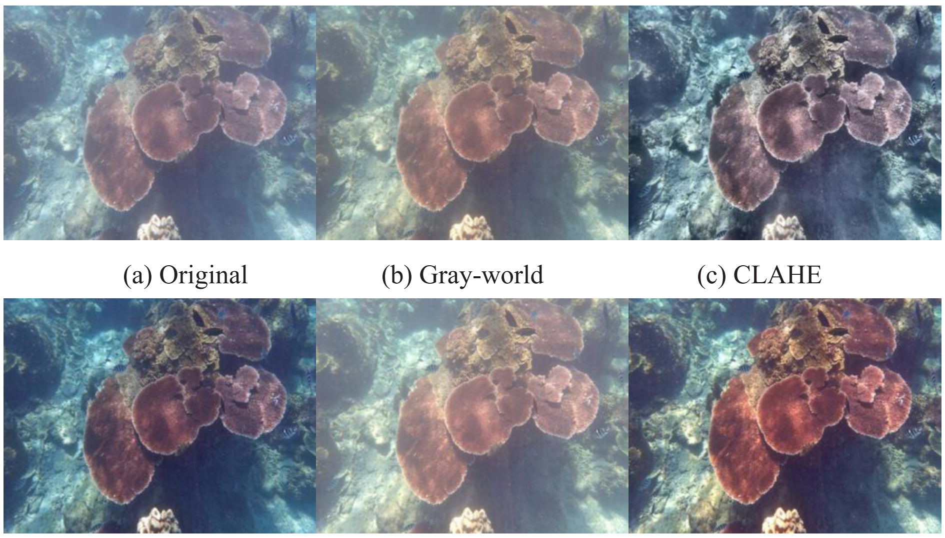
4.2. Evaluation metrics

In the assessment of performance, six quantitative measures of no-reference image quality assessment are used. The evaluation criteria have been designed in such a manner that:

The lower Color Cast implies that the RGB channels are more uniformly distributed and the color deviation is lower; larger values of Information Entropy (IE), Average Gradient (AG), Standard Deviation (Std), UIQM, and UCIQE indicate more detail richness, edge sharpness, overall contrast, and total quality of underwater imaging [9,10]. The most notable amongst them are UIQM and UCIQE, which are the official standard comprehensive measurement tools that focus on the values of chrominance, saturation, and sharpness in underwater images and have been extensively applied to the study of underwater image enhancement. The rest of these four metrics are all employed to obtain the fine numerical indicators of information abundance, edge definition, brightness contrast, and color deviation, and hence they can be applied to perform the multi-dimensional and multi-angle quality assessment.

4.3. Subjective visual comparison

Subgraphs (a)-(f) in Figure 1 show how the subjective performance of various algorithms is illustrated, where the subgraph depicts the original image, Gray-world, CLAHE, original DCP, one WAWB, and proposed WAWB-IDCP in turn.



(a) Original (b) Gray-world (c) CLAHE

(d) DCP (e) WAWB (f) WAWB-IDCP

Figure 1. Subjective visual comparison of underwater coral image enhancement results with different algorithms.

Because of the fact that water has a selective ability to absorb light, the initial underwater image is clearly cyan-green in color, has low-quality coral and benthic textures, and low hierarchy perception. In the Gray-world model, the color prejudice is eliminated, but the overall picture becomes over-whitened, and the texture becomes over-blurred as the RGB channels are forcefully equalized, and therefore the loss of detail is huge. The CLAHE algorithm is an algorithm to boost the brightness of the image and local contrast by histogram stretching, and it does not fix the intrinsic underwater color distortion, so it gives an apparent cyan-green offset in enhanced images. The original DCP algorithm, as it should have been used in atmospheric deshazing, also does not work well under the water conditions and leads to blue color deviation and dark area failure artifacts. One WAWB block can provide accurate color correction using underwater wavelength attenuation rules, eliminate cyan-green distortion, and restore the natural scene color, but the end photo remains dark since the contrast is not optimized.

As compared to the aforementioned proposal, the suggested WAWB-IDCP algorithm will bring together both the positive aspects of WAWB color correction and enhanced DCP information. It can be used to naturally regain colors without distorting them and is extremely effective in enhancing the contrast of images with a sharp boundary of coral and subtle details of benthic textures. In the meantime, it does not contain any overexposure, dark collapse, or block artifact, which is why its visual quality is the best among all.

4.4. Objective quantitative analysis

Table 1 contains the mean values of 20 underwater images in the UIEB dataset that represent the statistical behavior of each algorithm under multi-scene and complex underwater conditions.

Table 1. Average quantitative metrics of different algorithms on 20 UIEB dataset images

Algorithm	IE	AG	Std	ColorCast	UIQM	UCIQE
Original	6.81	29.78	30.18	36.36	0.51	10.93
GrayWorld	6.85	30.56	30.80	0.26	0.32	11.18
CLAHE	7.31	62.95	43.61	35.71	0.66	23.01
DCP	6.93	40.90	34.99	45.28	0.92	15.00
WAWB	6.98	33.65	33.97	0.85	0.33	12.32
WAWB-IDCP	7.23	56.33	44.71	11.07	0.77	19.78

High IE, AG, and Std are linked to enhanced picture detail recovery and picture quality with finer textures and sharper boundaries. The CLAHE algorithm has the largest IE (7.31) and AG (62.95) due to the fact that the algorithm maximally spreads the gray levels, yet ColorCast is 35.71, which is the same as the original image, and this means that it is unable to correct the colors of the underwater scenery in any way. The suggested WAWB-IDCP algorithm has a marginally smaller IE and AG compared to CLAHE, yet a higher Std (44.71) and ColorCast (11.07) performance, which can effectively recover the texture information that was obscured by water scattering and will not change the underwater colors.

Small ColorCast values indicate color recovery accuracy in terms of color correction performance. The original image has a very high ColorCast of 36.36. Both GrayWorld and single WAWB modules can be combined to greatly limit color distortion with ColorCasts of 0.26 and 0.85, respectively. But the UIQM and UCIQE are low, which means that color balance cannot be achieved without compromising on detail loss and overall image quality reduction. The first DCP algorithm produces a ColorCast of 45.28, which is very high and makes color distortion underwater even worse. Conversely, the suggested WAWB-IDCP algorithm has a moderate ColorCast of 11.07, which is the best compromise between good color correction and sufficient detail preservation.

To assess the overall quality of underwater images, the greater UIQM and UCIQE values show that the overall imaging quality is improved. The first DCP results in the largest UIQM (0.92), though it experiences a very high color distortion. CLAHE has the highest UCIQE (23.01) but cannot correct the inherent underwater color bias and creates artificial blue-green artifacts. The suggested WAWB-IDCP algorithm has a UIQM of 0.77 and a UCIQE of 19.78 and ranks second among all the comparison methods. It is the only algorithm that can simultaneously have low color distortion and high overall enhancement performance, high stability, and flexibility in operating under more sophisticated underwater conditions, regardless of the degree of turbidity and color distortion.

4.5. SIFT feature matching evaluation

In order to further evaluate the detail preservation and texture recovery ability of various algorithms quantitatively in terms of features, the SIFT (Scale-Invariant Feature Transform) algorithm is selected to extract the local image features, and the FLANN (Fast Library for Approximate Nearest Neighbor) matcher is utilized to find and filter the feature points. Experiments on feature extraction and matching were conducted on images that were processed in different ways by algorithms using the original image of the corals as a standard. The total number of feature points is an indication of the richness of overall details, whereas the number of successful matches can be used to describe the similarity in structure between enhanced images and the original scene. The statistical results are indicated in **Table 2**.

Table 2. SIFT-FLANN feature detection and effective matching statistics

Algorithm	Total feature points	Effective matching points
Gray-world	1572	1257
CLAHE	3549	1051
DCP	2380	1189
WAWB	1827	1246
WAWB-IDCP	2943	1168

According to the experimental findings, CLAHE has the largest total number of feature points (3549), but the smallest number of effective matching points (1051). Extreme feature points are mostly an artifact of false noise, causing the over-expansion of the gray scale levels, which are not real scene features. The Gray-world algorithm has the maximum effective matching points, but the minimum total feature points, which means it has sacrificed some fine textures to achieve gray-scale uniformity with the original image, with the loss of extreme details. The proposed WAWB-IDCP algorithm generates the largest mass of permissible real scene features after removing noise interference. Even though contrast optimization somewhat destroys the matching consistency, it is still more effective in matching performance compared to CLAHE and DCP. The SIFT test will determine whether the proposed algorithm can recover the hidden underwater texture information and provide better quality of detail preservation without adding any noise or over smoothing compared to the traditional comparison algorithms.

5. Conclusion

The paper applies a cascaded preprocessing algorithm on the basis of wavelength adaptive white balance and enhanced dark channel to address the overall degradation issues of underwater images, such as color distortion, low contrast, and blurry details. The WAWB module rectifies colors in a physics-based fashion, following the differential RGB absorption of water, eliminating the blindness of empirical classical white balance techniques. The optimized DCP module has been found to be useful in improving the ambient light estimates, highlighting masking, and smoothing transmission in underwater conditions, and it is highly effective in eliminating the effects of color decay, block artifacts, and dark collapse error of the DCP algorithm. The subjective visual evaluation, objective quantitative measures, and the SIFT feature validation are all three that indicate that the proposed algorithm may be extremely precise in restoring colors and enhancing the details. It is a light approach and does not use deep learning, and hence, the approach can be used for real-time pre-processing of embedded underwater visual cameras. In future studies, additional turbid datasets will be presented in order to improve the capabilities of enhancement under the worst conditions underwater even more.

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Disclosure statement

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