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Underwater Image Enhancement in Epicontinental Sea Based on the Improved Algorithm of Dark Channel

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Abstract: Enhancing underwater images in epicontinental sea is a challenging problem owing to the influence of ocean currents, the refraction, absorption and scattering of light by suspended particles, and the weak illumination intensity. Recently, different methods have relied on the underwater image formation model and deep learning techniques to restore the underwater image, but they tend to degrade underwater image, interference of background clutter and miss boundary details of blue regions. Improved image fusion and enhancement algorithm based on a priori dark channel is proposed in this paper. Image edge features sharpening and dark detail enhancement by homomorphism filtering in CIELab color space is realized. In RGB color space, the multi-scale retinal with color restoration (MSRCR) algorithm is used to improve color deviation and enhance color saturation, and the contrast-limited adaptive histogram equalization (CLAHE) algorithm is used to de fog and enhance image contrast. Finally, according to the dark channel images of the three processing results, the final enhanced image is obtained by linear fusion of multiple images and multiple channels. Experimental results demonstrate the effectiveness and practicality of the proposed method on various datasets.

Keywords: underwater image enhancement; dark channel; improved algorithm; RGB color space

1. Introduction

The ocean is rich in biology, minerals and energy, and is an important source of resources for human survival and future development. In order to better understand the underwater world and develop marine products and minerals, it is often necessary to image and identify underwater objects with the help of photoelectric systems [1]. However, due to the influence of ocean current, and strong scattering and attenuation effect of water on light, especially for epicontinenal sea (which the water depth is 0-200m), the distribution of underwater suspended particles is uneven, resulting in blurred image details with forward scattering of light, and foggy blur with backward scattering. In addition, due to the selective absorption of light by underwater objects, the longer wavelength red light attenuates the fastest, while the shorter wavelength blue propagates the farthest [2]. Therefore, underwater images tend to appear blue. These characteristics of underwater object image limit its image recognition and target detection. It is of great significance to improve underwater object image recognition by using image enhancement technology [3, 4].

Different from the deep sea, restoration and enhancement underwater images is a challenging problem owing to the ocean current disturbance in the epicontinental sea and the light propagation, absorption and scattering by micro suspended particles in epicontinental sea [5]. Special environment under epicontinental sea water provokes several combined degradation in images including color attenuation, blurring, low contrast, and their interaction (e.g., color distortion and haze effects) , these are important problems for underwater image enhancement [6-10]. In order to conquer the color imbalance, blurring, low contrast, etc., a deep retinal decomposition network for underwater image enhancement was proposed and convolutional neural network was designed to estimate the illumination and get reflectance, and color balance and illumination correction was performed on the decomposed reflectance and illumination in [11]. Xue et al. [12] proposed a Joint Luminance and Chrominance Learning Network (JLCL-Net), the disentanglement in degrading factors was realized to avoid introducing interference by separating the luminance and chrominance of the underwater images. By using the red channel to compensate the original image and white balance, an underwater image enhancement method based on local contrast correction (LCC) and multi-scale fusion was proposed by Gao et al. [13] to solve the problem of low contrast and color distortion of underwater image. Aiming at the serious color distortion caused by light scattering and absorption in water, the encoder neural network (an underwater image color restoration network (UICRN)) was used to extract the features of the input underwater image, estimate the light scattering and absorption transmission diagram, calculate the loss function and training strategy in [14], and feature mapping was used to restore image sharpness [15]. Furthermore, two-branch network combining deep learning and traditional image enhancement technology [16], convolutional neural network with deep learning [17], Illumination feature and color information adaptive learning module [18], penalty and generation of countermeasure network (GCN) based on preprocessed image [19], were proposed to solve the serious color distortion and contrast reduction of underwater images.

Another key problem of underwater image enhancement is the acquisition and feature extraction of the original image, and underwater images are often blurred and distorted in color [20]. However, the traditional image enhancement algorithms generally only pay attention to a few features of the image environment, and the enhancement effect depends on the features of the original image. Yuan et al. [21] presented an image processing technology based on secondary migration learning and retinal algorithm to solve the problems of little underwater data sets and unclear underwater images. A comprehensive perception on underwater image enhancement using large-scale real images was proposed by Li et al. [22], and an underwater image enhancement benchmark was constructed which used to train the generalization of convolutional neural network. Due to the lack of sufficient training data and effective network structure, the perception and processing of underwater information are seriously affected. Yang et al. [23] presented a conditional generative adversarial network (cGAN), where the clear underwater image can be achieved by a multi-scale generator. Considering the high-frequency and low-frequency parts of the original underwater image, an underwater image enhancement algorithm based on the structural decomposition two-stage underwater image convolution neural network was proposed by Wu et al. [24]. However, the effect of the original images taken from the turbid underwater environment in epicontinental sea is not ideal, and the complex and diverse degradation enhancement mapping is difficult to model. By learning potential consistency between the template and the original underwater image to select the appropriate color transfer template, the problem caused by the incomplete color correction model was alleviated in [25]. Guo et al. [26] proposed adding the multiscale, dense concatenation, and residual learning to the generator to extract the features of the original underwater image, and an end-to-end multi-scale underwater image enhancement network based on attention mechanism was proposed by Fang et al [27]. To improve the quality of acquired underwater images, numerous methods have been proposed, such as underwater image feature enhancement and fusion technology [28], underwater image cooperative enhancement network based on encoder decoder integrated structure (UICoE-Net) [29], hybrid underwater image training model based on physical prior and data driven [30], semi-supervised depth convolution neural netwrok [31], etc.

In order to restore the underwater image with clear texture details and vivid color, color distortion and low contrast of the enhanced image should be fully dealt with. Lin et al. [32] proposed a global and local guidance model, in which the global path target was used to estimate the basic structure and color information, while the local path target was used to remove bad artifacts, such as noise, overexposed areas and blurred edges. Due to insufficient consideration of underwater physical deformation process, underwater light absorption and scattering lead to poor underwater image restoration effect. A two-stage underwater image restoration network (UIR) was proposed to solve the problem of vertical distoration in underwater image reconstruction in [33]. Cheng et al. [34] presented an underwater image enhancement method based on Mueller matrix image neural network to obtain Mueller matrix images of different objects under different water turbidity and realize underwater image enhancement of different materials and textures. An improved image fusion and enhancement algorithm based on a priori dark channel is proposed in this paper. The main contributions of the current paper are summarized as following.

1) Due to the influence of ocean current, and strong scattering and attenuation effect of water on light, especially for epicontinenal sea, an improved underwater image fusion and enhancement algorithm is proposed by fusion of homomorphism filtering, MSRCR and CLAHE algorithms.

2) In RGB color space, the color deviation and enhance color saturation are improved, and the de fog and image contrast are realized with the dark channel.

The rest of this paper is structured as follows: In section 2, the dark channel is described. The proposed improved image fusion and enhancement algorithm based on a prior dark channel is proposed in detail in Section 3. The experiments are shown in Section 4. Finally conclusions are drawn in Section 5.

2. Description of Dark Channel

2.1. Color Cast

White balance is to improve the image appearance by compensating the color loss caused by the selective absorption of light in the depth of water. Underwater images usually have blue tone, and the best way to eliminate the blue tone is the gray world method. However, the direct use of gray world method will cause serious red artifacts, resulting in over compensation of red position.

Compensate the red channel I_{rc} at each pixel position x, we obtain

$$I_{rc}(x)=I_r(x)+\alpha\cdot\left(\bar{I}_g(x)-\bar{I}_r(x)\right)\cdot\left(1-\bar{I}_r(x)\right)\cdot I_g(x), \tag{1}$$

where I_r and I_g denote the red channel and green channel of the pixel positionof image I, respectively. According to the upper limit of its dynamic range and normalized between $[0,1]$, $\bar{I}_g$ and $\bar{I}_r$ are the average of I_g and I_r, respectively. α is a constant parameter.

In turbid or high plankton concentration water, the blue channel may attenuate significantly, so it is also necessary to compensate for the attenuation of the blue channel. The compensated blue channel can be expressed as

$$I_{bc}(x)=I_b(x)+\beta\cdot\left(\bar{I}_g(x)-\bar{I}_b(x)\right)\cdot\left(1-\bar{I}_b(x)\right)\cdot I_g(x), \tag{2}$$

where I_b and I_g denote the blue channel and green channel of the pixel position x of image I, respectively. According to the upper limit of its dynamic range and normalized between $[0,1]$, $\bar{I}_g$ and $\bar{I}_b$ are the average of I_g and I_b, respectively. β is a constant parameter.

After compensating the attenuation of red and blue channels, the assumption of gray world method can be used to estimate and compensate the color deviation of the image. However, the image after color deviation correction still has the problems of blurred details and low contrast, so it needs to be further processed.

2.2. Homomorphic Filtering

Due to the absorption and scattering of light when it propagates underwater, the underwater image has uneven illumination, resulting in blurred image details.

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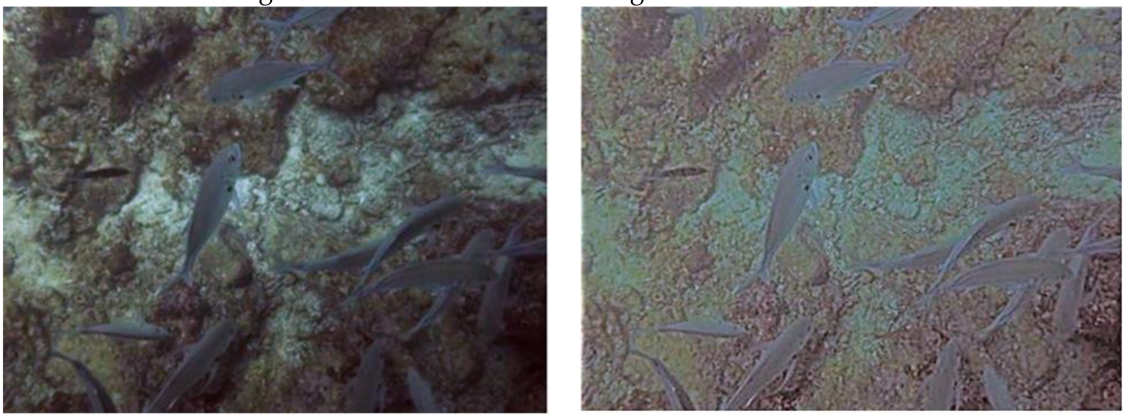
Homomorphic filtering algorithm can compress the image brightness range and enhance the image contrast.

In order to ensure that the color of the corrected image does not change, the image is converted to LAB color space for processing. In this space, the color components A and B are kept unchanged, and only the brightness component L is homomorphically filtered to obtain an image with stronger contrast. The brightness component L after homomorphic filtering is combined with color components A and B to convert to RGB color space. The problem that the dark features are not obvious due to uneven brightness of underwater images is solved and is shown in Fig.1.



(**a**) (**b**)

Figure 1. Comparison of algorithms. (**a**) Color coast; (**b**) Homomorphic filtering in LAB color space.

2.3. Multiscale Retinex Algorithm with Color Restoration

By using Retinex enhancement algorithm, the inherent reflection characteristics of the target object can be obtained by eliminating the interference of light illumination.

Assumed that the initial image is $I(x,y)$, there has

$$I(x,y)=L(x,y)R(x,y), \tag{3}$$

where $L(x,y)$ is the incident component, and $R(x,y)$ is the reflection component.

The multiscale Retinex algorithm with color restoration is expressed as

$$\begin{cases} R_{MSRCRi}(x,y)=C_i(x,y)R_{MSRi}(x,y) \\ C_i(x,y)=\eta\left(\log\left(\lambda\cdot I_i(x,y)\right)-\log\left(\sum_{i=1}^{N}I_i(x,y)\right)\right) \\ R_{MSR}(x,y)=\sum_{n=1}^{n_z}\mu_n\left(\log I(x,y)-\log\left(I(x,y)\cdot G_n(x,y)\right)\right) \end{cases}, \tag{4}$$

where $R_{MSR}(x,y)$ is the high-frequency detail image obtained after multi-scale filtering, $G_n(x,y)$ is single scale Gaussian filtering, and n denotes a certain scale parameter. μ_n is the weight and its value can be adopted as $\mu_n = {}^1\!/_3$. n_s is the number of scales used, where three scales are used. $R_{MSRCRi}(x,y)$ is the multi-scale filtered high-frequency detail image of the $i^{\#}$ channel combined with the color restoration factor. The parameters η and λ are the nonlinear intensity control factor and the gain constant, respectively.

In order to obtain more image edge information, the restricted contrast adaptive histogram equalization algorithm is adopted in this paper. The contrast limiting amplitude is to cut the pixels higher than a certain threshold in the histogram of the block region, and evenly distribute the intercepted parts to the histogram, so as to limit the amplitude of the histogram. The limit threshold C is given by

$$C = \frac{N}{L} + \sigma\left(N - \frac{N}{L}\right), \tag{5}$$

where N is the total pixels in a block area, L is the maximum gray leavel series in the block area, and σ is the truncation coefficient between $[0,1]$.

2.4. Dark Channel Prior Image Enhancement Algorithm

In the dark channel prior theory, it is proposed that in most non sky local regions, some pixels always have at least on color channel (RGB) with low values. This shows that the intensity value of the dark channel prior image of the fog free image is lower than that of the dark channel prior image of the fog image. Because the fog image in the atmosphere is similar to the fog image underwater, the atomosphere is similar to the fog image underwater, the atomospheric scattering model can be used for modeling. Therefore, the dark channel prior image intensity characteristics of underwater foggy images should also be similar to those of atmospheric foggy images. The dark channel prior theory is applied to the underwater image to generate the dark channel prior image of the underwater image, and the algorithm is given by

$$I_{dark}(x) = \min_{x \in \Omega(x)}\left(\min_{c \in \{RGB\}} I_c(x)\right), \quad I_{dark}(x) \to 0, \tag{6}$$

where $I_{dark}(x)$ is a priori image of dark channel, c is a channel of RGB, $I_c(x)$ is a channel of underwater image, $\Omega(x)$ is a local window centered on x, and the window size is 15×15.

3. Prior Improved Algorithm of Dark Channel

According to the processing results of homomorphic filtering algorithm, MSRCR and CLAHE algorithms on the underwater image enhancement, it can be concluded that homomorphic filtering algrithm can alleviate the uneven brightness of the image to a certain extent and improve the characteristics of the dark part of the image, and MSRCR algorithm can effectively improve the brightness and color saturation of the image, and CLAHE algorithm has a certain de fogging effect. These algorithms have their own best application scenarios. In view of the complex and changeable underwater environment of epicontinental sea, it is not enough to rely on only one image enhancement algorithm to solve the degradation problem of all underwater image enhancement. Therefore, the robustness of underwater image enhancement algorithm can be further enhanced by weighted image fusion of the results of these algorithms according to certain rules.

The prior weight coefficient w_{DCP} of the dark channel is calculated from the exp function of the prior image mean of the dark channel, which is defined as

$$w_{DCP} = \exp\left(-\frac{I_{mdark}}{\upsilon^2}\right), \tag{7}$$

where I_{mdark} is the mean value of the prior image of the dark channel, and υ is a constant. Through the calculation of the mean value of the prior image of the dark channel of the underwater image, $\upsilon = 10$ can effectively ensure that the prior weight coefficient of the dark channel will not be too small, and the calculation efficiency is higher.

The final fusion weight coefficient can be calculated accoring to the dark channel prior weight coefficient, we obtain

$$W_i = 1 - \frac{w_{DCPi}}{w_{DCPother} + w_{DCPanother}}, \tag{8}$$

where w_{DCPi} is the dark channel prior weight coefficient of the current image, $w_{DCPother}$ and $w_{DCPanother}$ are the dark channel prior weight coefficients of other images.

Underwater image enhancement fusion algorithm with the improved dark channel is expressed as follows:

Step 1. Homomorphic filtering and MSRCR are fused with RGB channel.

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Step 2. Calculate the dark channel prior weight coefficient w_{DCP} of the fused image according to (8), and then use (9) to calculate the weight coefficient W_i of the second fusion step.

Step 3. The fusion is performed again according to the weight coefficient, and the RGB channel image fusion is performed for the first fusion image and the CLAHE image, respectively.

Step 4. The three RGB channels of the fusion are merged to obtain a complete fusion image.

The structure of underwater image enhancement fusion algorithm is shown in Fig.2.

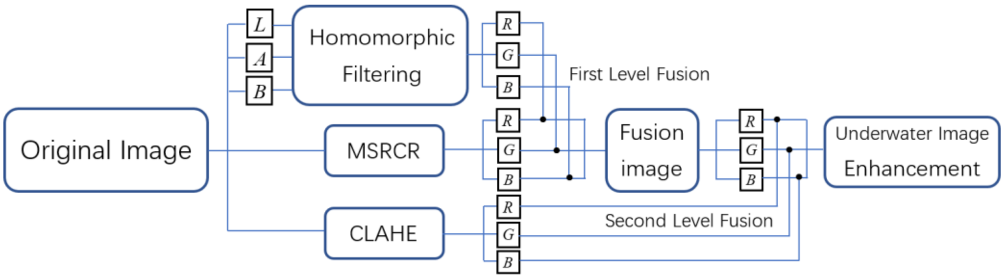

Figure 2. Structure of underwater image enhancement fusion algorithm.

4. Experiments

The validity of this method is verified by establishing the underwaterimage data set. The images in the experiment come from the underwater image data set searched by the network. The computer configuration of the experimental environment is CUP Intel (R) core ™ i5-9400f 2.90GHz, RAM 16GB. The experimental algorithm programming environment is Spyder (Python 3.7).

In order to illustrate the effectiveness of the proposed algorithm, five underwater images with different scenes and hues are selected, and compared with four algorithms in literatures [35, 36].

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Figure 3. Comparison of experimental rusults with different algorithms: (**a**) Original images; (b) Algorithm in literature [35]; (c) CLAHE algorithm; (d) MSRCR algorithm; (e) Algorithm in literature [36]; (f) The proposed algorithm in this paper.

Figure 3 shows that both the literature 35 and the CLAHE algorithm have improved the image clarity and contrast. But the color deviation has not been eliminated, and the image is dark after the [35] processing,. MSRCR algorithm effectively improves the brightness and color saturation of the image, but the color deviation still exists and the image details are fogged. The color deviation is improved effectively, so as the image clarity and contrast, but the image is prone to overexposure, resulting in the loss of details. The proposed algorithm in this paper can enhance the dark details and has a good visual effect while improving the contrast and clarity and adjusting the color deviation.

Three quality indexs, including UIQM, information entropy and EAV point sharpness, are adapted to evaluate the processing results of the different algorithms.

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UIQM is the underwater color image quality evaluation index, which is evaluated by the linear combination of chromaticity, saturation and contrast. The larger the index value, the better the image effect. The calculation formula is given by

$$UIQM = c_1 \cdot UICM + c_2 \cdot USIM + c_3 \cdot UIConM \ , \tag{9}$$

where c_1, c_2 and c_3 are the weight factors of each component in the linear combination, and $c_1 = 0.0282$, $c_2 = 0.2953$, $c_3 = 3.5753$. $UICM$ is chrominance component, $USIM$ is sharpness component, and $UIConM$ is contrast component.

Information entropy is mainly an objective evalution index to measure the amount of information contained in an image. The higher the information entropy, the higher the information content of the fused image and the better the quality. It can be expressed as

$$E = -\sum_{x=1}^{m}\sum_{y=1}^{n} p(x,y)\log\left(p(x,y)\right), \tag{10}$$

where $p(x,y)$ represents the gray scale of each pixel, m and n denote the size of the image.

EVA point sharpness is to evaluate the image sharpness by calculating the gray level change of a certain boundary in the image. The greater the gray level change in the image, the clearer the boundary. The calculation formular is given by

$$EVA = \frac{\sum_{a}^{b}\left(\frac{df}{dx}\right)^2}{\left|f(b) - f(a)\right|}, \tag{11}$$

where $\frac{df}{dx}$ is the gray change rate in the normal direction of the image edge, and $f(b) - f(a)$ is the overall gray change in this direction.

By using three image quanlity indexes, the five images in Fig.3 are evaluated, as shown in Table 1.

Table 1. Five images enhancement quanlity evaluated by three indexs with different algorithms.

Image number	CLAHE			MSRCR			Literature [35]			Literature [36]			Proposed algorithm in this paper		
	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c
1	1.310	4.635	8.741	2.099	4.180	5.847	1.936	4.330	3.956	4.104	6.515	4.669	**4.363**	**4.777**	**11.33**
2	4.352	4.914	14.32	4.262	4.430	11.61	4.351	4.384	6.399	**4.396**	**5.113**	13.11	4.370	5.028	**18.04**
3	4.008	**4.941**	21.11	3.725	4.408	17.09	3.852	4.617	10.40	4.131	4.682	8.951	**4.161**	4.825	**32.48**
4	5.863	4.833	35.38	6.013	4.822	34.89	4.419	4.682	8.951	5.916	4.700	22.35	**6.191**	**56.34**	**5.051**
5	4.256	**4.757**	39.17	3.966	4.060	20.67	4.238	3.938	16.61	4.314	4.362	15.31	**4.399**	4.655	**42.38**

Note: *a is UIQM, b is information entropy, and c is EVA.*

The algorithm in [35] does not significantly improve the image in UIQM, information entropy, or enen slightly lower than the original image, and the image contrast and sharpness are reduced. CLAHE algorithm, MSRCR algorithm and literature [36] have significantly improved the image quality. The image information entropy of the part processed by CLAHE is slightly better than that of all experiment algorithms. However, it can be seen from Fig.3 that there is still a large color difference in the CLAHE enhanced image, which has an impact on the UIQM index. Although the MSRCR algorithm improves the

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brightness and color saturation as a whole, the EVA index is still slightly lower and the definition is reduced. Literature [36] corrected the color deviation of the image and improved the contrast of the image, and some UIQM and information entropy indexed are slightly better than all the experimental algorithms. However, the processed image will have the problem of uneven brightness due to overexposure, resulting in the loss of detail information of the image, and the EVA index is only slightly higher than the original image, reducing the overall clarity of the image.

The UIQM, information entropy and EVA indexes of the proposed algorithm in this paper are basically better than the four comparison algorithms. The definition index EAV is much higher than all the experimental methods, and the UIQM index is also almost higher than all the algorithms, which effectively improves the image color deviation and enhances the image definition and contrast.

5. Conclusions

In view of the complex and changeable underwater environment in epicontinental sea, which leads to the problems of blurred details, decreased contrast and color distortion of underwater images, an underwater image enhancement algorithm is proposed in this paper based on a priori improved algorithm of dark channel. By compensating the loss of red and blue channels, the color ditortion caused by the selective absorption of light can be effectively corrected. Homomorphic filtering of L component in LAB space is carried out by using the corrected images, which can solve the problems of blurred details caused by forward light scattering and unclear dark details caused by uneven illumination in underwater images. CLAHE algorithm of the image in RGB space is adapted to solove the problem that the underwater image is foggy due to the backscattering of light. MSRCR algorithm in RGB space is adapted to solve the problem of the brightness of underwater images, and improve the color saturation and enhance the overall contrast of imagesThis section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

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