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Underwater Image Enhancement Based on the Improved Algorithm of Dark Channel

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Abstract: Enhancing underwater images presents 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 underwater images. However, they tend to degrade the underwater images, interfere with background clutter and miss the boundary details of blue regions. An improved image fusion and enhancement algorithm based on a prior dark channel is proposed in this paper based on graph theory. Image edge feature sharpening, and dark detail enhancement by homomorphism filtering in CIELab colour space are realized. In the RGB colour space, the multi-scale retinal with colour restoration (MSRCR) algorithm is used to improve colour deviation and enhance colour saturation. The contrast-limited adaptive histogram equalization (CLAHE) algorithm defogs and enhances image contrast. Finally, according to the dark channel images of the three processing results, the final enhanced image is obtained by the linear fusion of multiple images and channels. Experimental results demonstrate the effectiveness and practicality of the proposed method on various data sets.

Keywords: image enhancement; feature sharpening; dark detail enhancement; linear fusion

MSC: 68U10

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1. Introduction

The ocean is biologically rich, contains an abundance of minerals and energy, and represents an essential resource for human survival and future development. 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 currents and the strong scattering and attenuation effects of water on light, especially in shallow seas (where the water depth ranges between 0–200 m), there is an uneven distribution of underwater suspended particles, resulting in blurred image details with a forward scattering of light, and foggy blurring with backward scattering. In addition, due to the selective absorption of light by underwater objects, the longer red wavelength light attenuates the fastest. In comparison, the shorter blue wavelength light propagates the farthest [2]. Therefore, underwater images tend to appear blue. These characteristics of the underwater object images limit their image recognition and target detection. It is of great significance to improve underwater object image recognition via image enhancement technology [3,4].

Different from the deep sea, restoration and enhancement of underwater images is a challenging problem owing to ocean current disturbances and light propagation, absorption and scattering by micro-suspended particles in shallow seas [5]. The specific environment present under shallow sea water produces several combined degradation in images, including color attenuation, blurring, low contrast, and their interactions (e.g., color distortion and haze effects). Image degradation caused by the unique conditions of turbid water, and target recognition are the unique influences of turbidity areas during target detection [6]. Due to the optical characteristics of water bodies, underwater video images generally have problems such as color bias and unclear image quality, and image quality degradation is severe. The graph theory has been widely used in underwater image recognition [7], dense underwater 3-D mapping paradigm [8], and graph feature extraction [9]. Underwater visibility can be severely affected by water molecules and suspended particles, which distort light and cause different wavelengths of light to absorb different colors. Using the absorption differences of different color channel wavelengths, the transmission plot through the scene depth was estimated, and the underwater neural network (UWCNN) was enhanced by graph tangent theory [10]. Hu et al. [11] analyzed the imaging principle of underwater images and the reasons for their decline in quality and briefly classified various existing methods, and the underwater video enhancement technologies were mentioned. Underwater imagery suffers from strong absorption, scattering, color distortion, and noise from the artificial light sources, causing image blur, haziness, and a bluish or greenish tone, two methods of underwater image dehazing and color restoration were proposed in [12].

Due to refraction, absorption, and scattering of light by suspended particles in water, underwater images are characterized by low contrast, blurry details, and color distortion. A fusion algorithm to restore and enhance underwater images was proposed in [13], and a color balance algorithm based on CIE Lab color model was proposed to alleviate the effect of color deviation in underwater images in [14]. In order to concurrently address imbalance, blurring, low contrast, etc., a deep retinal decomposition network for untethered image enhancement was proposed. Convolution neural network was designed to estimate the illumination and obtain reflectance, and color balance and illumination correction were performed on the decomposed reflectance and illumination in [15]. Xue et al. [16] proposed a Joint Luminance and Chrominance Learning Network (JLCL-Net), and the disentanglement in critical factors was realized to avoid introducing interference by separating the luminaries and chroming of the underwater images. By using the red channel to compensate for 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. [17] to solve issues concerning low contrast and color distortion of the underwater image. Aiming at the severe color distortion caused by light scattering and absorption in water, the encoder color 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 [18], and feature mapping was used to restore image sharpness [19]. Furthermore, a two-branch network combining deep learning, a color additional image enhancement technology [20], convolution neural network with deep learning [21], Illumination feature and colour information adaptive learning module [22], penalty and generation of countermeasure network (GCN) based on pre-processed image [23], were proposed to solve the severe color distortion and reduced contrast of underwater images.

2. Related Work

The 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 [24]. However, 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. [25] presented an image-processing technology based on secondary migration learning and retinal algorithm to solve the problems of small underwater data sets and unclear underwater images. A comprehensive perception of underwater image enhancement using real large-scale images was proposed by Li et al. [26], and an underwater image enhancement benchmark was constructed. This was used to train the generalization of convolution neural network. Due to the need for sufficient training data and effective network structure, the perception and processing of underwater information are significantly affected. Yang et al. [27] presented a conditional generative adversarial network (cGAN), where a multi-scale generation can achieve clear underwater images. 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. [28]. However, the effect of the original images taken from the turbid underwater environment in the shallow sea could be improved, and the complex and diverse degradation enhancement mapping is difficult to model. By learning the 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 [29]. Guo et al. [30] proposed adding the multi-scale, dense concatenation. 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. [31]. To improve the quality of acquired underwater images, numerous methods have been proposed, such as underwater image feature enhancement and fusion technology [32], underwater image cooperative enhancement network based on encoder-decoder integrated structure (UICoE-Net) [33], hybrid underwater image training model based on physical prior and data-driven [34], semi-supervised depth convolution neural network [35].

In order to restore underwater images with precise texture details and vivid color, issues regarding color distortion and low contrast of the enhanced image should be solved.Lin et al. [36] proposed a global and local guidance model in which the global path target was used to estimate the basic structure and color information. In contrast, the local path target was used to remove nasty artefacts, such as noise, overexposed areas and blurred edges. Due to insufficient consideration of the 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 distortion in underwater image reconstruction in [37]. Cheng et al. [38] presented an underwater image enhancement method based on the 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 prior dark channel is proposed in this paper. The main contributions of the current paper are summarized as follows.

(1) Due to the influence of ocean currents, and the strong scattering and attenuation effects of water on light, especially in shallow seas, an improved underwater image fusion and enhancement algorithm is proposed by fusion of homomorphism filtering, MSRCR and CLAHE algorithms. By comparing with four other methods, the proposed approach can effectively and simultaneously compensate for deficiencies in brightness, color, and contrast.

(2) In the RGB color space, the color deviation and enhanced color saturation are improved, and image contrast and clarity are achieved 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 detailed in Section 3. The experiments are shown in Section 4. Finally, conclusions are drawn in Section 5.

3. Description of Dark Channel

3.1. Color Cast

White balance improves image appearance by compensating for the color loss caused by the selective absorption of light under water. Underwater images usually have a blue tone, and the grey world method is the best way to eliminate the blue tone. However, the direct use of the grey world method will cause serious red artefacts, resulting in overcompensation of the red position. Compensate the red channel I_{rc} at each pixel position x, we obtain

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

where I_r and I_g denote the red 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 $\bar{I}_r$ 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

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

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

After compensating for attenuation of red and blue channels, the assumption of the grey world method can be used to estimate and compensate for 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.

3.2. Homomorphic Filtering

Due to the absorption and scattering of light as it propagates through water, the underwater image exhibits uneven illumination, resulting in blurred image details. Homomorphic filtering algorithms can compress the image brightness range and enhance image contrast. Image $f(x,y)$ can be represented by the product of its illuminates function $i(x,y)$ and reflection function $r(x,y)$, yields to

$$f(x,y) = i(x,y) \cdot r(x,y) \tag{3}$$

where $i(x,y)$ describes the illumination of the image, which has nothing to do with the image, $0 < i(x,y) < \infty$. $r(x,y)$ contains the details of the image, which has nothing to do with lighting, $0 < r(x,y) < 1$. Since the relative variation of illuminates is slight, it can be regarded as the low-frequency component of the image, while the reflectivity is the high-frequency component. By dealing with the influence of illuminates and reflectance on the image's grey value, the shadow region's detailed features can be obtained. Taking the logarithm of both sides of (3), we obtain

$$\ln f(x,y) = \ln i(x,y) + \ln r(x,y) \tag{4}$$

By using the Fourier transform of (4), we obtain

$$F[\ln f(x,y)] = F[\ln i(x,y)] + F[\ln r(x,y)] \tag{5}$$

Equation (5) can be rewritten as

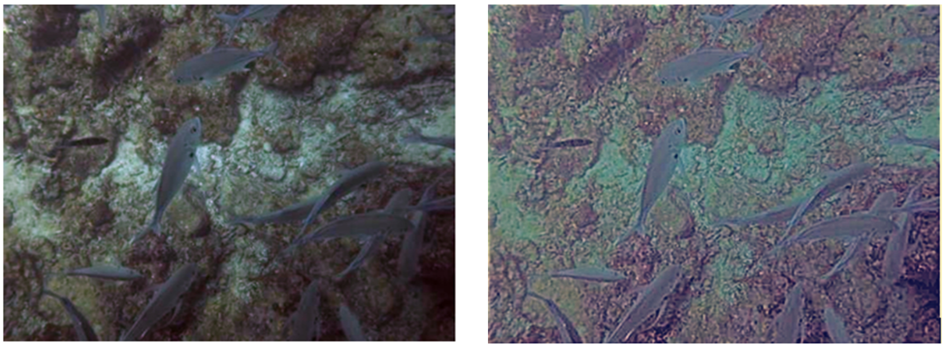
$$s(x,y) = F^{-1}[S(x,y)] = F^{-1}[H(x,y)F(x,y)] = F^{-1}[H(x,y)i(x,y)] + F^{-1}[H(x,y)r(x,y)] \tag{6}$$

where $H(x,y)$ is the homomorphic filter function, which can be applied to the illuminates component and the reflection component, respectively, satisfied with

$$H(x,y) = (\gamma_H - \gamma_L)\left[1 - e^{-cD^2(x,y)/D_0^2}\right] + \gamma_L \tag{7}$$

where $D^2(x,y) = \left(x^2 + y^2\right)$, the constant c is used to control the sharpness of the slope, transitioning between γ_L and γ_H. γ_L and γ_H are the parameters for adjusting, $\gamma_L < 1$ and $\gamma_H > 1$.

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. After homomorphic filtering, the brightness component L combines color components A and B to convert to RGB color space. The problem where the dark features are not evident due to the uneven brightness of underwater images is solved, as shown in Figure 1.



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

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

3.3. Multi-Scale Retinex Algorithm with Color Restoration

By using the Retinex enhancement algorithm, the inherent reflection characteristics of the target object can be obtained by eliminating the interference of light illumination. Assume that the initial image is $I(x,y)$, there has

$$I(x,y) = L(x,y)R(x,y) \tag{8}$$

where $L(x,y)$ is the incident component, and $R(x,y)$ is the reflection component. The multi-scale Retinex algorithm with color restoration can be given by

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

where $R_{MSR}(x,y)$ is the high-frequency detail image obtained after multi-scale filtering, $G_n(x,y)$ is the 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, $R_{MSRCRi}(x,y)$ is the multi-scale filtered high-frequency detail image of the ith channel combined with the color restoration factor. The parameters η and λ are the nonlinear intensity control factor and the information, respectively. This paper adopts the restricted contrast adaptive histogram equalization algorithm to obtain more image edge information. 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 to limit the amplitude of the histogram. The limit threshold C is given by

$$C = \frac{N}{L} + \sigma\left(N - \frac{N}{L}\right) \tag{9}$$

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

3.4. Dark Channel Prior Image Enhancement Algorithm

In the dark channel prior theory, it is proposed that in most non-sky local regions, some pixels will always have at least one color channel (RGB) with low values. This non-sky local region shows that the intensity value of the prior dark channel 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 atmosphere is similar to the fog image underwater, and the atmosphere scattering model can be used for modelling. Therefore, the dark channel prior image intensity characteristics of foggy underwater 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

$$I_{\text{dark}}(x) = \min_{x\in\Omega(x)}\left(\min_{c\in\{RGB\}} I_c(x)\right), \quad I_{\text{dark}}(x) \to 0 \tag{10}$$

where $I_{\text{dark}}(x)$ is a prior 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.

4. Prior Improved Algorithm of Dark Channel

According to the processing results of the homomorphic filtering algorithm, MSRCR and CLAHE algorithms on underwater image enhancement, it can be concluded that the homomorphic filtering algorithm can alleviate the uneven brightness of the image to a certain extent and improve the characteristics of the dark part of the image. MSRCR algorithm can effectively improve the brightness and color saturation of the image, and CLAHE algorithm has a particular de fogging effect. These algorithms have their own best application scenarios. Because of the shallow sea's complex and changeable underwater environment, more is needed to rely on more than one image enhancement algorithm to solve the degradation problem of all underwater image enhancement. Therefore, the robustness of the underwater image enhancement algorithm can be further enhanced by weighted image fusion of the results of these algorithms according to specific 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, yields to

$$w_{DCP} = \exp\left(-\frac{I_{mdark}}{v^2}\right) \tag{11}$$

where I_{mdark} is the mean value of the prior image of the dark channel, and v is a constant parameter. By calculating the mean value of the prior image of the dark channel of the underwater image, $v = 10$ 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 according to the dark channel prior weight coefficient, we obtain

$$W_i = 1 - \frac{w_{DCPi}}{w_{DCPother} + w_{DCP\text{ another}}} \tag{12}$$

where w_{DCPi} is the dark channel prior weight coefficient of the current image, $w_{DCPother}$ and $w_{\text{DCP another}}$ are the dark channel prior weight coefficients of other images. The underwater image enhancement fusion algorithm with the improved dark channel can be expressed as follows:

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

Step 2. Calculate the dark channel prior weight coefficient w_{DCP} of the fused image according to (11), and then use (12) 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 fusion channels are merged to obtain a complete fusion image. The structure of underwater image enhancement fusion algorithm is shown in Figure 2.

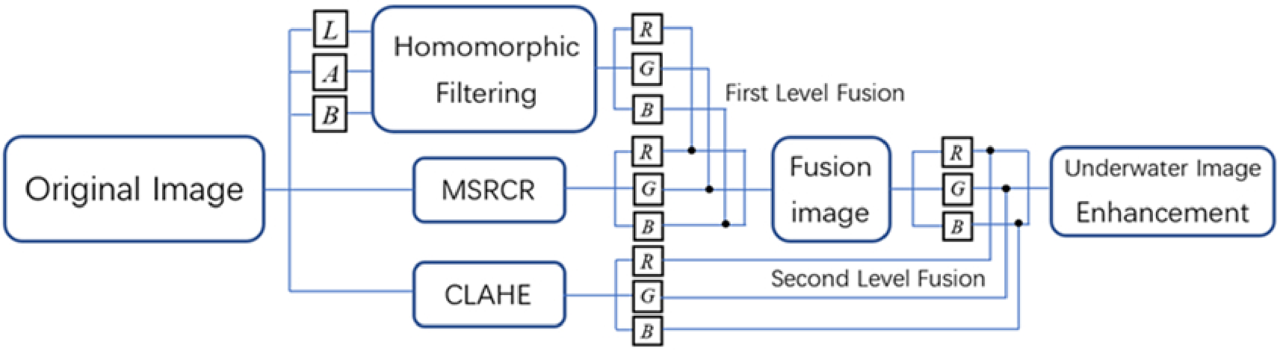


Figure 2. Structure of underwater image enhancement fusion algorithm.

5. Experiments and Analysis

5.1. Experiments

The validity of this method is verified by establishing the underwater image data set. The images in the experiment come from the underwater image data set searched by the network. The experiments are carried out on the Underwater Image Enhancement Benchmark (UIEB) [26] dataset, which includes 950 real-world underwater images in all. 890 of them have corresponding reference images which are considered to be the best restoration results selected by 50 volunteers, while the rest 60 underwater images cannot obtain satisfactory references and are treated as challenging data. 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 the literature [39,40].

Figure 3 shows that the literature [39] and the CLAHE algorithm have improved image clarity and contrast. However, the color deviation has not been eliminated, and the image is dark after the [39] 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 excellent visual effect while improving the contrast and clarity and adjusting the color deviation.

5.2. Analysis

In total, three quality indexes, including UIQM, information entropy and EAV point sharpness, are adapted to evaluate the processing results of the different algorithms.

UIQM is the effective evaluation index method for underwater color image quality, which is evaluated by the linear combination of chromatically, saturation and contrast. However, there is uncertainty for the value of the UIQM index [41]. The larger the index value, the better the image effect. The calculation formula is given by

$$\text{UIQM} = c_1 \cdot \text{UICM} + c_2 \cdot \text{USIM} + c_3 \cdot \text{UIConM} \tag{13}$$

where c_1, c_2 and c_3 are the weight factors of each component in the linear combination, and $c_1 = 0.0282$, $c_2 = 0.2953$, $c_3 = 3.5753$, respectively. UICM is chroming component, USIM is sharpness component, and UIConM is contrast component. Information entropy is mainly an objective evaluation index to measure the amount of information 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

$$E = -\sum_{x=1}^{m}\sum_{y=1}^{n} p(x,y)\log(p(x,y)) \tag{14}$$

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 grey level change of a certain boundary in the image. The greater the grey level change in the image, the clearer the boundary. The calculation formula is given by

$$EVA = \frac{\sum_a^b (df/dx)^2}{|f(b) - f(a)|} \tag{15}$$

where df/dx is the grey change rate in the average direction of the image edge, and $f(b) - f(a)$ is the overall grey change in this direction. The five images in Figure 3 are evaluated using three image quantity indexes, as shown in Table 1.

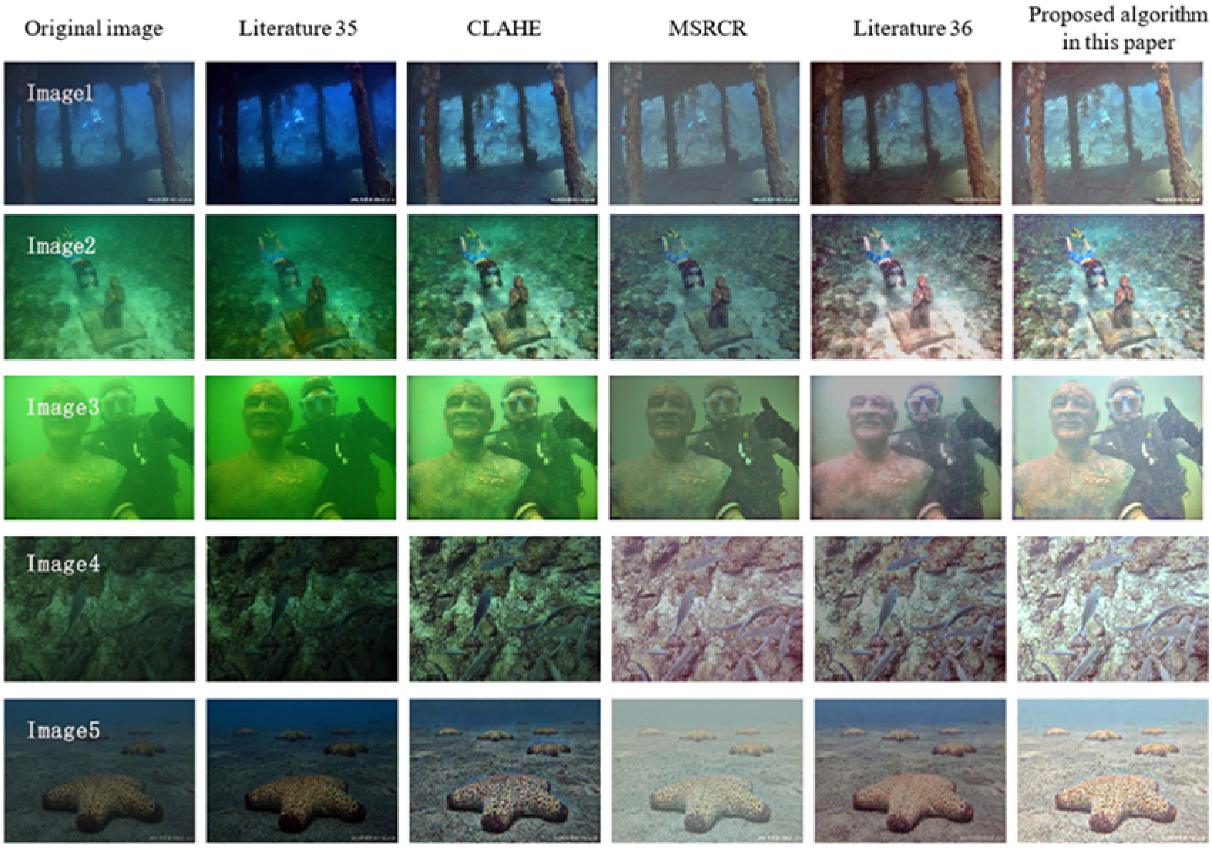


Figure 3. Comparison of experimental results with different algorithms.

The algorithm in [39] does not significantly improve the image in UIQM, information entropy, or even slightly lower than the original image, and the image contrast and sharpness are reduced. CLAHE algorithm, MSRCR algorithm and the literature [40] 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 Figure 3 that there is still a significant color difference in the CLAHE enhanced image, which impacts the UIQM index. Although the MSRCR algorithm improves the brightness and color saturation, the EVA index is still slightly lower and the definition is reduced. Literature [40] corrected image's color deviation and improved the image's contrast, 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 detailed 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 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, effectively improving the image color deviation and enhancing the image definition and contrast.

Table 1. Underwater image quality evaluation.

Image Number	CLAHE	MSRCR	Literature [39]	Literature [40]	Proposed Algorithm in This Paper
			UIQM		
1	1.310	2.099	1.936	4.104	4.363
2	4.352	4.262	4.351	4.396	4.370
3	4.008	3.725	3.852	4.131	4.161
4	5.863	6.013	4.419	5.916	6.191
5	4.256	3.966	4.238	4.314	4.399
			Information Entropy		
1	4.635	4.180	4.330	6.515	4.777
2	4.914	4.430	4.384	5.113	5.028
3	4.941	4.408	4.617	4.682	4.825
4	4.833	4.822	4.682	4.700	5.634
5	4.757	4.060	3.938	4.362	4.655
			EVA		
1	8.741	5.847	3.956	4.669	11.330
2	14.320	11.610	6.399	13.110	18.040
3	21.110	17.090	10.400	8.951	32.480
4	35.380	34.890	8.951	22.350	5.051
5	39.170	20.670	16.610	15.310	42.380

6. Conclusions

Owing to the complex and varying underwater environment of shallow seas, issues arise regarding blurred details, decreased contrast and color distortion of underwater images. Consequently, an underwater image-enhancement algorithm is proposed in this paper based on a prior improved algorithm of the dark channel. By compensating for the loss of red and blue channels, the color distortion caused by the selective absorption of light can be effectively corrected. Homomorphic filtering of the L component in LAB space is carried out by using the corrected images. This allows for the resolution of issues concerning blurred details caused by forward light-scattering and obscure dark details caused by uneven illumination in underwater images. CLAHE algorithm of the image in RGB space is adapted to solve the problem whereby the underwater image is foggy due to the backscattering of light. MSRCR algorithm in RGB space is adapted to solve the problem of underwater image brightness, improve color saturation and enhance the overall contrast of images. The UIQM, information entropy, and EVA indexes of the proposed algorithm in this paper demonstrate superior performance than the four comparison algorithms. The definition index EAV is much higher than all the experimental methods. The UIQM index is also almost higher than all the algorithms, effectively improving the image color deviation and enhancing image definition and contrast.

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