Underwater Image Enhancement Based on IMSRCR and CLAHE-WGIF

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Abstract: Aiming at the scattering and absorption of light in the water body, which causes the problems of color shift, uneven brightness, poor sharpness and missing details in the acquired underwater images, an underwater image enhancement algorithm based on IMSRCR and CLAHE-WGIF is proposed. Firstly, the IMSRCR algorithm proposed in this paper is used to process the original underwater image with adaptive color shift correction; secondly, the image is converted to HSV color space, and the segmentation exponential algorithm is used to process the S component to enhance the image saturation; finally, multi-scale Retinex is used to decompose the V component image into detail layer and base layer, and adaptive two-dimensional gamma correction is made to the base layer to adjust the brightness unevenness, while the detail layer is processed by CLAHE-WGIF algorithm to enhance the image contrast and detail information. The experimental results show that our algorithm has some advantages over existing algorithms in both subjective and objective evaluations, and the information entropy of the image is improved by 6.3% on average, and the UIQM and UCIQE indexes are improved by 12.9% and 20.3% on average.

Keywords: Underwater Image Enhancement, HSV Color Space, MSRCR, CLAHE, WGIF

1 Introduction

The ocean is rich in mineral resources and fossil energy[1], and underwater applications such as offshore oil drilling, submarine tunnels, underwater pipeline construction, underwater archaeology, and lifesaving invariably require underwater images to be collected for their analysis. However, unlike atmospheric imaging mechanisms, water bodies have different attenuation rates for red, green, and blue colored light, with red light being most severely attenuated in water and underwater images showing a blue-green bias. Suspended particles in the water absorb light energy and alter the light path, which results in low contrast, low definition, and loss of detail in underwater images. In addition, underwater photography often introduces artificial light sources, and these uneven light sources can make the image appear uneven in brightness.

Currently, underwater image enhancement methods can be divided into the following categories: methods based on spatial domain[2-3], methods based on transform domain[4-6] and methods based on Retinex[7-8]. However, due to the blurred details and color distortion of underwater images[9], it is difficult for a single method to achieve a complete enhancement of all aspects of underwater images, so many comprehensive enhancement algorithms have been proposed in recent years. Zhang et al[10] proposed an enhancement algorithm for color correction and luminance adjustment, using the grayscale world method to correct the color, based on Retinex model and gamma algorithm to correct the luminance unevenness, this algorithm image has the effect of improving the color shift and enhancing the luminance, but the color shift phenomenon still exists and the contrast is not high. Dhanya et al[11] proposed L-CLAHE Enhanced Filter (L-CIF) algorithm, which uses Contrast Limited Adaptive Histogram Equalization (CLAHE) for the L channel of the image LAB color space, and then performs gamma correction, histogram equalization and bilateral filtering algorithm processing, this algorithm improved the contrast and color bias of the image, but the visual effect of local edge details of the image is poor. Zhang and Dong[12] proposed an image enhancement method based on multi-channel convolution and Multi-Scale Retinex with Color Restore (MSRCR). This method combines the MSRCR algorithm with two times multi-scale guided filtering, and this method reduces the noise of the image, but the color bias correction effect still needs to be enhanced. Ancuti et al[13] proposed an algorithm of color balance and multiscale fusion, in which the images after white balance color correction were gamma corrected and sharpened separately, and then fused with multiscale fusion strategy, which was effective in color compensation and contrast enhancement. Gong el al[14] proposed a shallow sea image enhancement method based on underwater imaging system, using Color Channel Compensation and Homomorphic filtering (3C-HF) algorithm to improve color distortion, gamma correction and CLAHE algorithm to enhance contrast, but this method did not enhance the detail information of the image.

For the multifaceted degraded nature of underwater images, existing algorithms often can only partially improve the degradation problem. In this paper, an algorithm based on improved MSRCR (IMSRCR) and CLAHE-Weighted Guided Filtering (CLAHE-WGIF) is proposed to comprehensively enhance underwater images. The IMSRCR algorithm is proposed to deal with the color distortion problem of underwater images, the CLAHE-WGIF algorithm is proposed to enhance the problem of low contrast and missing details of underwater images, and the adaptive 2-D gamma algorithm is used to correct the uneven brightness of underwater images. Finally, it is experimentally verified that the algorithms in this paper have better subjective visual effects and objective evaluation results when applied to different types of underwater images.

2 Related Work

2.1 Underwater Imaging System

The underwater environment is an area submerged in water, in a natural or artificial body of water such as an ocean, reservoir, river or aquifer. Understanding the properties of underwater imaging systems is important for conducting research in various fields. The formation of underwater images is the result of a complex interaction between light, medium and scene, as shown in Fig.1. In general, light scattering and absorption are the main reasons for the degradation of underwater image quality. Due to the absorption of light by the water body, the overall image color shows a blue-green distortion. The scattering of light by the water body is divided into forward scattering and backward scattering, the former leading to blurred image details and textures, and the latter leading to reduced image contrast, which looks like a layer of "water mist" covering the upper surface of the image. These degradations in underwater images result in poor visibility, low contrast, color distortion, blurring and uneven illumination.

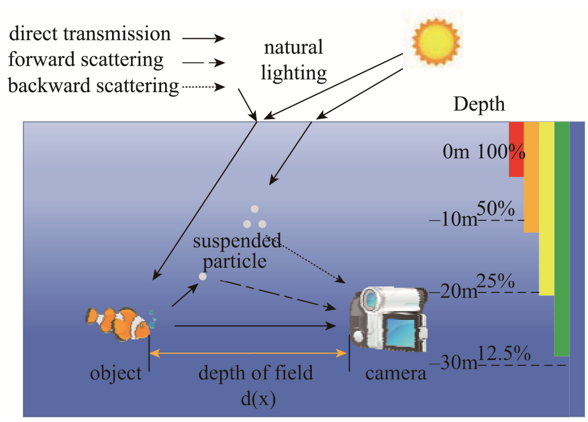


Fig.1 Underwater Imaging System Model

Based on the above-mentioned process of light propagation in the underwater medium, the Jaffe-McGlamery imaging model, which is consistent with its process, was proposed in 1980. The model is based on linear superposition and modeling of the aqueous medium. The irradiance entering the camera consists of a linear combination of three different components: direct transmission E_d, forward scattering E_f, and backward scattering E_b. The total irradiance E_T is shown in equation (1).

$$E_T = E_d + E_f + E_b \tag{1}$$

In equation (1), the direct transmission E_d is the portion of the reflected light from the object that is directly received by the camera. The forward scattering component can be neglected because the underwater ring is poorly lit and usually requires the camera to look at the target object at close range.

2.2 Retinex Theory

Retinex theory is a model that studies how the human visual system modulates the color and luminance of objects as they are perceived. It is based on color constancy and considers that an image can be represented as the product of the illumination component and the reflection component of an object. Let the acquired blurred image be $I(x, y)$, the illumination component be $L(x, y)$, and the reflection component be $R(x, y)$, then according to the Retinex algorithm we have the equation (2).

$$I(x, y) = L(x, y) \times R(x, y) \tag{2}$$

According to the theory of color constancy, the true color of an object is determined by its reflective properties, independent of the irradiated light on the surface of the object. In practical applications, images are often transformed to the logarithmic domain for easy processing. The Single-Scale Retinex (SSR) expression is as follows.

$$\ln[R_i(x, y)] = \ln[I_i(x, y)] - \ln[G(x, y) * I_i(x, y)] \tag{3}$$

In equation (3) $R_i(x, y)$ denotes the output of the ith channel SSR, there are three channels represented by R, G and B, and $G(x, y)$ is a Gaussian function. However, since the SSR cannot satisfy both the detail enhancement and color fidelity properties, the Multi-Scale Retinex (MSR) algorithm is proposed, and MSR achieves the enhancement effect by linearly weighting the fusion of multiple fixed-scale color channels on the basis of SSR. the expression of MSR is shown in equation (4).

$$\begin{aligned} &\ln[R_i(x, y)] = \\ &\sum_{n=1}^{k} W_n \left\{ \ln[I_i(x, y)] - \ln[G_n(x, y) * I_i(x, y)] \right\} \end{aligned} \tag{4}$$

In formula (4), W_n denotes the weight coefficient of the nth scale, and usually W_n is taken as 1/3, n=1, 2, 3. k is the scale parameter, and when k=1, it is the SSR algorithm.

2.3 Guided Filtering

The traditional guided filtering[15] local linear model expression is shown in equation (5).

$$q_b = m_k I_b + n_k \quad \forall b \in h_k \tag{5}$$

As shown in equation (5), q is the output image; I is the guide image; k and b are pixel indices; h_k denotes a square window of radius d; m_k and n_k are the coefficients of this linear function when the center of the window is at position k.

The minimization cost constraint function is constructed to find the optimal solution of the coefficients m_k and n_k such that the input and output differences are minimized, and the expression is given in equation (6).

$$E(m_k, n_k) = \sum_{b \in h_k} \left[\left(m_k I_b + n_k - p_b \right)^2 + \varepsilon m_k^{\ 2} \right] \tag{6}$$

In equation (6), p_b is the value of the bth pixel point in the image to be filtered. In this paper, both the guide image and the image to be filtered are set to the same image, at this time, the guide filter can smooth the flat area of the image while keeping the edges of the image better, and the linear regression algorithm was used to find the linear coefficient as equation (7).

$$\begin{cases} m_k = \dfrac{\sigma_k^2}{\sigma_k^2 + \varepsilon} \\ n_k = \mu_k \left(1 - m_k \right) \end{cases} \tag{7}$$

The σ_k^2 and μ_k in the formula denote the variance and mean of the bootstrap image I within the window h_k, respectively. ε is the regularization parameter, which determines the degree of image smoothing and has a large impact on the filtering effect.

3 Proposed Underwater Image Enhancement Method

Our proposed method is an underwater image enhancement algorithm based on IMSRCR and CLAHE-WGIF. For the color shift of underwater images, the IMSRCR algorithm used in this paper improves the color factor of traditional MSRCR by improving its fixed gain coefficients into adaptive gain parameters, which makes the images more balanced in color on the basis of improved color shift. Since the HSV (Hue, Saturation, Value) color model is not only more consistent with the visual characteristics of human eyes, but also the H, S and V components are independent of each other, and the changes of the Value component and Saturation component are independent of the Hue component. Therefore, in order not to affect the already corrected color information during the subsequent algorithm, the algorithm in this paper first converts the color space of the image from RGB to HSV, and then transforms the color space back to RGB after enhancing the S and V components respectively. For the S component, the segmented exponential algorithm is used for enhancement. For the V component, the multi-scale Retinex layering process is used to decompose it into detail layer and base layer. The CLAHE-WGIF algorithm is applied to the detail layer to enhance contrast and edge detail information, and the adaptive gamma is applied to the base layer to correct luminance unevenness. The framework of the proposed method in this paper is shown in Fig.2.

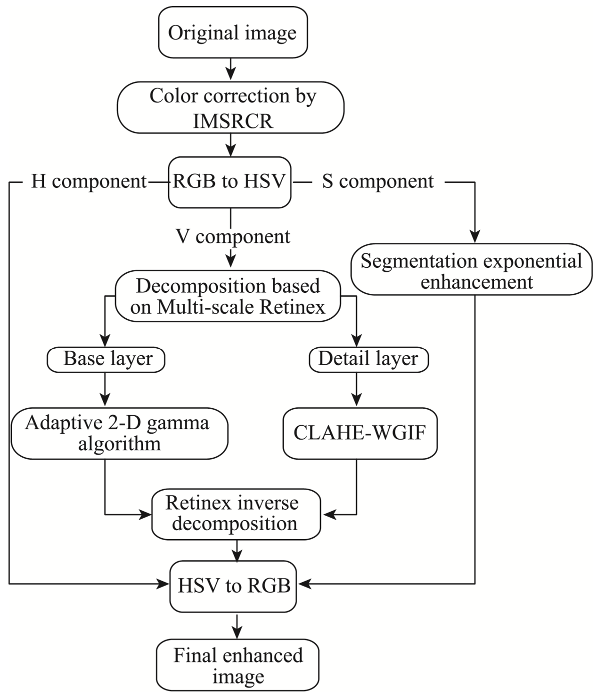


Fig.2 Framework for the Proposed Method

3.1 IMSRCR Algorithm

Jobson et al[16] introduced a color recovery factor in the MSR algorithm and proposed the MSRCR algorithm to compensate the color distortion caused by local contrast enhancement of the image. The MSRCR algorithm expression is shown in equation (8).

$$R_{msrcr_i}(x,\ y) = C_i(x,\ y) R_{msr_i}(x,\ y) \tag{8}$$

In, equation (8), $C_i(x,\ y)$ indicates the color correction factor of the *ith* channel, which is used to control the ratio of the color channels of the composite image. By adjusting the ratio between the three RGB color channels to achieve the effect of correcting the image color shift, the expression is equation (9).

$$C_i = \alpha[\log(\theta I_i) - \log(I_R + I_G + I_B)] \tag{9}$$

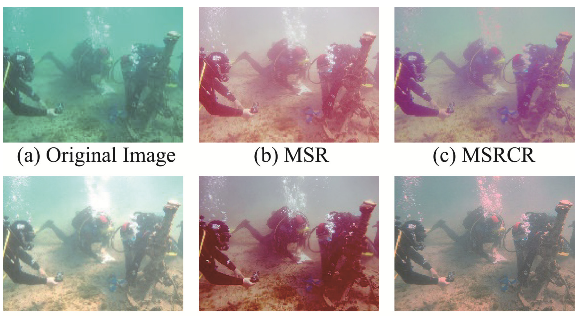
In equation (9), α is the gain constant; θ is the controlled nonlinear intensity, and θ is taken as 125 in this paper.

However, the choice of the gain constant α is very important for the effect of color correction, too large or too small will lead to chromatic aberration in the image. Therefore, our IMSRCR algorithm proposed introduces a standard deviation $std(\cdot)$ in the gain coefficient so that α becomes equation (10) to better correct the color shift, and the improved color correction factor expression of this algorithm is shown in equation (11).

$$\alpha = \frac{\max[std(I_i)]}{std(I_i)} \tag{10}$$

$$C_i = \frac{\max[std(I_i)]}{std(I_i)}[\log(\theta I_i) - \log(I_R + I_G + I_B)] \tag{11}$$

This color correction factor enables adaptive adjustment of the relationship between weak color channels and other color channels, making each color channel more reasonably compensated. In this paper, several typical color correction algorithms are selected for comparison with our IMSRCR algorithm, and the color correction results are compared as shown in Fig.3. From Fig.3, we can see that the MSR algorithm improves the color shift to some extent, but the effect is not good, and the overall image is reddish; the MSRCR algorithm improves the image color shift well, but the overall color is monotonous and the contrast is not enough; the image processed by the Perfect Reflector (PR) algorithm has a general effect of removing color shift and the overall brightness of the image is high, and the noise in the local area increases; the correction result of HF algorithm does not meet the human visual effect, the contrast is too strong and the overall image is dark; but our proposed IMSRCR method can effectively remove color bias while maintaining color balance and obtaining natural colors that match human visual effects.



(a) Original Image (b) MSR (c) MSRCR

(d) PR (e) HF (f) IMSRCR

Fig.3 Color Correction of Various Methods.

3.2 Segmentation Exponential Algorithm to Enhance Saturation

Since the saturation of images taken in underwater environment has different degrees of stretching, the segmentation exponential algorithm is used to non-linearly enhance the saturation of different regions in order to make the saturation of underwater images more evenly distributed and achieve better visual effects. According to the magnitude of saturation, the saturation of the image is divided into 3 regions: high, medium and low. The low saturation region is stretched by exponential transformation to moderately increase the saturation; the medium saturation is appropriately adjusted; the high saturation region is compressed by exponential transformation to moderately decrease the saturation. The expression of this algorithm is shown in equation (12).

$$S'(x,y)=\begin{cases} a(e^{S(x,y)}-1) & S(x,y)\leqslant 0.3 \\ e^{S(x,y)}-1 & 0.3\leqslant S(x,y)\leqslant 0.7 \\ b(e^{S(x,y)}-1) & else \end{cases} \quad (12)$$

In equation (12), S is the saturation value of the image to be enhanced; S' is the saturation of the image after nonlinear stretching; a and b are the adjustment transformation scale parameters. It is known that the enhancement effect is best when a is taken from 1.2 to 1.5 and b is taken from 0.6 to 0.9. In this paper, the value of a is taken as 1.3 and the value of b is 0.7.

3.3 Image Decomposition of Multi-scale Retinex

Unlike the thinking of many image algorithms based on Retinex in the literature, we consider the lighting component to be very important, due to the fact that the lighting component contains not only the lighting component, but also the larger structural information in the scene. If the illumination component is directly removed and only the reflection component is enhanced, problems such as loss of detail and unevenness of light and dark will inevitably occur. Therefore, both the illuminated image and the reflected image need to be enhanced and then combined to obtain an underwater enhanced image with complete features and excellent results.

Given that the multiscale Gaussian function can effectively compress the dynamic range and accurately estimate the illumination component of the scene. We define the illumination component as the base layer of the image and the reflection component as the detail layer of the image. Therefore, using the multi-scale Gaussian function and the original image to do convolution, the base layer of the image can be obtained. The base layer is described below.

$$G(x,y)=\lambda e^{-\frac{x^2+y^2}{c^2}} \quad (13)$$

$$L(x,y)=\sum_{n=1}^{k}W_n[F(x,y)*G(x,y)] \quad (14)$$

In equation (13) and (14), $F(x,y)$ denotes the color correction result image; $L(x,y)$ denotes the base layer; c denotes the scale factor; λ is the normalization factor to ensure that the Gaussian function meets the condition: $\iint G(x, y)dxdy=1$; W_n is the weight coefficient of the base layer, and k is the number of scales used, considering the balance between the accuracy of the base layer extraction and the amount of operations, this paper takes k=3, and the three scales chosen are 15, 80 and 250, and the weight coefficient of the base layer extracted by each scale is set to 1/3.

The expression of the detail layer of the image is obtained according to the Retinex theory decomposition as equation (15).

$$R(x, y) = \exp\{\ln[F(x, y)] - \ln[L(x, y)]\} \quad (15)$$

3.4 Adaptive 2-D Gamma Algorithm to Enhance the Base Layer

For the problem of uneven luminance of underwater images, the idea of our method is to reduce the luminance value of the regions whose luminance is too high and increase the luminance value of the regions whose luminance is too low, so as to achieve the effect of luminance equalization. The adaptive two-dimensional gamma function[17] is constructed to adjust the luminance unevenness based on the base layer image extracted from equation (13). The algorithm is described as follows.

$$L'(x, y) = 255 \times \left(\frac{L(x, y)}{255}\right)^{\gamma} \quad (16)$$

$$\gamma = \omega^{\frac{m - L(x, y)}{m}} \quad (17)$$

$$m = \overline{L(x, y)} = mean[L(x, y)] \quad (18)$$

In the above equation, $L'(x, y)$ denotes the corrected base layer image, γ denotes the luminance enhancement index value of local dynamic features, m is the luminance average of $L(x, y)$, and ω denotes the illumination coefficient[18] with the expression $\omega=L(x, y)/255$.

Since $L(x, y)\in[0, 255]$, $\omega\in[0, 1]$. However, given that artificial illumination sources can be used for supplementary illumination, there is rarely a case where $L(x, y)$=0 or $L(x, y)$=1, so in general $\omega\in[0, 1]$. The mean value of the illumination component extracted from most images is fluctuating up and down from 128, so we set ω to 1/2. γ adaptively varies with $L(x, y)$ to achieve correction of image brightness unevenness. The algorithm can not only increase the pixel values of dark regions with too low luminance in the base layer, but also moderately decrease the pixel values of bright regions with too high luminance, which can well solve the problem of uneven luminance of underwater images.

3.5 CLAHE-WGIF Algorithm to Enhance the Detail Layer

According to Retinex theory, the detail layer contains not only the structural information of the scene, but also the texture and detail information of the object, but due to the special characteristics of underwater imaging, especially in the more turbid water or deep water areas, the detail layer of the image has the problems of missing details and blurred images, in addition to low contrast. Therefore, the processing of the detail layer should not only improve its contrast, but also enhance the texture and details of the image. We propose the CLAHE-WGIF algorithm to achieve the desired effect.

Histogram Equalization (HE) is often used to enhance the brightness and contrast of images, but the algorithm has the problem of introducing noise and weakening image details. To solve this problem, CLAHE algorithm is proposed by related scholars. As shown in Fig.4, the algorithm trims the histogram at the specified threshold before calculating the cumulative distribution function of the neighborhood, and distributes the cropped portion evenly to other parts of the histogram to achieve the effect of limiting the contrast amplification, which suppresses the noise amplification to a certain extent. Although there are still some gray-level pixels beyond the threshold after redistribution, such as the part marked as green in Fig.4, the area beyond is small and has limited impact on the magnification.

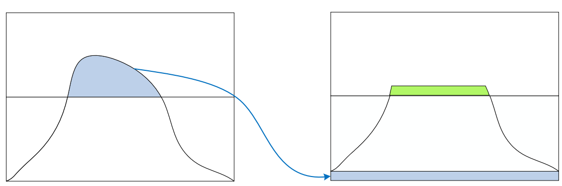


Fig.4 CLAHE Algorithm Histogram Transform Process

The CLAHE algorithm can make the gray level distribution of the overall image area more uniform and provide better brightness enhancement and contrast enhancement, but it does not enhance the image edge detail information and cannot achieve complete suppression of noise amplification. Therefore, we propose to combine the CLAHE algorithm and WGIF algorithm to process the detail layer to smooth the image noise and enhance the edge detail information.

Since the conventional guided filtering takes the same ε value for all pixel points, this results in a certain degree of halo phenomenon for regions with drastic texture changes and rich edge information, resulting in edge details not being very well represented. Therefore, an edge weighting factor is introduced to adjust ε adaptively considering the difference information of different regions, so as to improve the edge-preserving smoothing performance of the algorithm. Both the guide image and the image to be filtered in equation (6) are set as the result of CLAHE processing of the detail layer image, that is, $P=I=R_C$, and the expression of the edge weight factor $G(b)$ is equation (19).

$$G(b)=\frac{1}{M}\sum_{b=1}^{M}\frac{\sigma^2(b')+\alpha}{\sigma^2(b)+\alpha} \tag{19}$$

In equation (19), b' is all the pixel points in the guide image R_C; $\sigma^2(\cdot)$ is the variance of the pixel points in h_k; α is a fixed regularization factor, usually $\alpha=(0.001\times L)^2$, and L is the dynamic range of the image. $G(b)$ can reflect the proportion of edge pixels in the total pixels to a certain extent, when $G(b)<1$, it is the pixel at the smoothing and has a small weight; when $G(b)>1$, it is the pixel at the edge and has a larger weight. The addition of edge weighting factors allows better edge preservation without increasing the complexity of the operation. The adjusted expressions of the regularization parameter ε' and the linear factor m_k' are as follows.

$$\varepsilon'=\frac{\varepsilon}{G(b)} \tag{20}$$

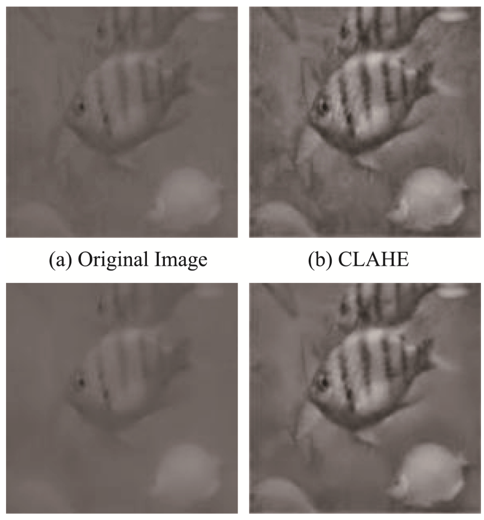
$$m_k=\frac{\sigma_k^2}{\sigma_k^2+\varepsilon'} \tag{21}$$

We set the window radius d of the weighted guided filter to 3, which means that h_k is 3×3 window.

Therefore, the expression of the detail layer processed by the CLAHE-WGIF is equation (22).

$$R'(x,y)=m_k R_C(x,y)+n_k \tag{22}$$

Fig.5 shows the original underwater image with its CLAHE, WGIF, and CLAHE-WGIF processed results. Fig.5 (b) shows that after the CLAHE algorithm, the contrast of the image is effectively enhanced and the sharpness is improved, but the noise in the background region as well as the edge structure increases, making the edge region less clear. Comparing Fig.5 (b) and Fig.5 (d), it can be observed that the noise in the background region is effectively smoothed in the effect image obtained by using the CLAHE-WGIF algorithm, the detail of the edge texture is significantly increased, and the distribution of light and dark regions is more uniform. Therefore, our proposed CLAHE- WGIF algorithm can effectively enhance the image edge structure details and smooth the noise in the background region of the image while improving the image contrast.



(a) Original Image (b) CLAHE

(c) WGIF (d) CLAHE-WGIF

Fig.5 Algorithm Result Image

4 Experimental Results and Analysis

Our algorithm is implemented to test the underwater images in a running environment with Windows 10 64-bit operating system and simulation software MATLAB R2020b. In order to prove the feasibility of the proposed underwater image enhancement algorithm, our method is compared with the relatively mature underwater image enhancement algorithms: MSR, CLAHE and those of Zhang et al[10], Ancuti et al[13] and Gong el al[14], and five different types of underwater environmental images are selected for experiments, and subjective and objective aspects are analyzed separately.

4.1 Subjective Evaluation

The experimental results are shown in Fig.6. A total of five underwater images with blue tones, green tones, and a large degree of fog blur were selected for a comprehensive evaluation of the effectiveness of the algorithm. Among them, Image A and Image B have an overall blue tint, Image C has an overall green tint, and Image D and Image E have a large degree of fog blur.

From Fig.6 (b) to Fig.6 (f), it can be seen that the MSR algorithm improves the color deviation problem of the image, but the edge details of the image are blurred and the overall sharpness decreases. The CLAHE algorithm increases the contrast of the image, but the effect is not significant in correcting the color deviation and enhancing the details of the image. The approach proposed by Zhang et al[10] improves the color deviation and low contrast problem to a certain extent, but the overall image is reddish, the detail information is lost in some areas, and there is overexposure problem in some areas. Ancuti et al[13] method improves the contrast of the image and the blurring degree of the image is improved to some extent but still has the problem of color imbalance; The algorithm of Gong el al[14] solves the problem of blurred edge details and low contrast degree of the image but the problem of color deviation is not well solved. However, as shown in Fig.6 (g), after the original images of different underwater scenes are enhanced by our method, the image color shift problem is effectively corrected, the color is more natural, the problem of foggy blurring of underwater images is solved, the overall contrast and brightness of the image is more balanced, and the local details are clear and obvious, which is more in line with the visual system of human eyes. Therefore, the best underwater image enhancement effect is obtained by our algorithm in terms of subjective evaluation.

4.2 Objective Evaluation

Since different evaluators have different sensitivity to images, we also use three objective evaluation metrics to assess underwater image quality, namely, Information Entropy (IE), Underwater Image Quality Measure (UIQM) and Underwater Color Image Quality Evaluation (UCIQE), in order to make the evaluation results of the algorithm more objective and accurate.

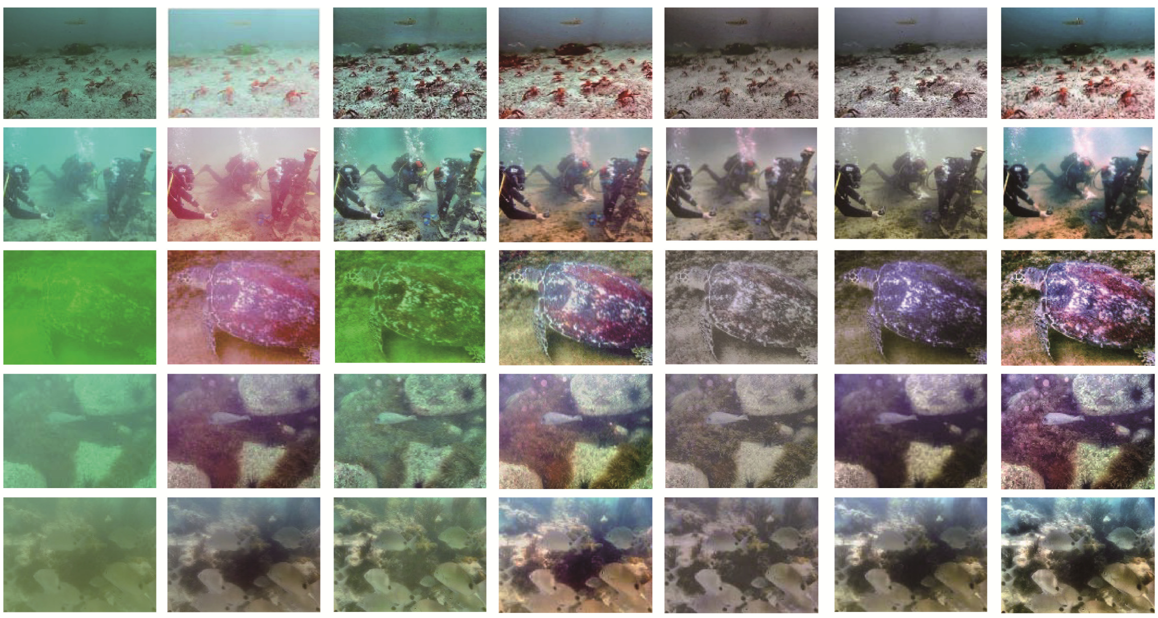


Fig.6 Qualitative Comparison of Our Method with Five Other Methods

IE is a measure of how much information an image contains. Higher information entropy means that the image contains more information and the quality of the image is better. The expression is equation (23).

$$E = -\sum_{x=1}^{m}\sum_{y=1}^{n} p(x,\ y)\log(p(x,\ y)) \tag{23}$$

UIQM is a comprehensive evaluation index, including three attribute metrics of contrast, chromaticity and sharpness. Its calculation formula is equation (24).

$$U_{IQM} = c_1 \times U_{ICM} + c_2 \times U_{ISM} + c_3 \times U_{IConM} \tag{24}$$

In equation (24), U_{ICM} denotes the color metric, U_{ISM} denotes the sharpness metric, U_{IConM} denotes the contrast metric, c_1, c_2 and c_3 are the weight parameters of the linear combination, and the weight parameters of UIQM are set to c_1=0.0282, c_2=0.2953, and c_3=3.5753, respectively, according to the literature of Panetta et al[19].

UCIQE is obtained by linearly weighting the combination of chromaticity, saturation and contrast of underwater images, and is an index specifically used to evaluate the quality of underwater images, it can quantitatively evaluate the non-uniform blurring, color shift and low contrast of underwater images, the higher the value of UCIQE, the better the quality of the image. Its calculation formula is equation (25).

$$UCIQE = c_4 \times \sigma_c + c_5 \times con_l + c_6 \times \mu_s \tag{25}$$

In equation (25), σ_c is the standard deviation of chromaticity, con_l is the contrast of luminance, μ_s is the mean of saturation, c_4, c_5 and c_6 are the weight parameters of linear combination, generally taken as 0.4680, 0.2745 and 0.2576, respectively.

Table 1 IE of Our Method with Five Other Methods

	Original	MSR	CLAHE	Zhang et al	Ancuti et al	Gong el al	Our Method
Image A	7.2063	6.7718	7.6434	7.7368	7.3154	7.6447	7.9404
Image B	7.5577	7.1667	7.6242	7.6142	7.3172	7.6904	7.9799
Image C	6.7040	7.5084	7.5980	7.6844	7.0354	7.4788	7.8854
Image D	7.1570	7.3910	7.1934	7.7086	7.0948	7.6412	7.8336
Image E	6.9151	7.3192	7.4031	7.7187	7.1561	7.6972	7.9131
Average	7.1080	7.2314	7.4924	7.6925	7.1838	7.6305	7.9105

Table 2 UIQM of Our Method with Five Other Methods

	Original	MSR	CLAHE	Zhang et al	Ancuti et al	Gong el al	Our Method
Image A	3.9319	3.5321	5.4261	5.3079	4.7408	4.8084	5.6878
Image B	3.0022	4.0719	4.7362	5.0094	5.3791	4.5493	5.5057
Image C	2.8429	4.8043	4.9021	4.9619	4.9231	5.5024	4.9944
Image D	2.4269	4.6282	4.7092	5.2774	4.6783	4.9952	5.0832
Image E	2.8895	4.1213	4.8817	5.0445	4.8168	4.8683	5.3591
Average	3.0187	4.2316	4.9311	5.1402	4.9076	4.9847	5.4460

Table 3 UCIQE of Our Method with Five Other Methods

	Original	MSR	CLAHE	Zhang et al	Ancuti et al	Gong el al	Our Method
Image A	0.4249	0.4127	0.4874	0.5273	0.4590	0.4678	0.5507
Image B	0.4295	0.4501	0.4324	0.5166	0.4933	0.4629	0.5335
Image C	0.3236	0.4550	0.4065	0.4934	0.4648	0.4874	0.5019
Image D	0.4478	0.4807	0.4072	0.4686	0.4380	0.4785	0.5106
Image E	0.4251	0.4717	0.4891	0.5542	0.5131	0.5165	0.5643
Average	0.4102	0.4540	0.4445	0.5120	0.4736	0.4826	0.5322

As can be seen from Table 1, comparing with other algorithms, the information entropy value of the algorithm proposed in this paper is the highest regardless of the underwater scene, indicating that the image processed by our method contains the richest image information, and the information entropy is increased by 6.3% on average compared with other algorithms. As can be seen from Table 2, Image C and Image D have the highest UIQM values after the algorithms of Gong el al[14] and Ancuti et al[13], respectively, but combined with the analysis of subjective visual effects, the detailed information contained in Image C processed by the algorithm of Gong el al[14] is not as rich as the resultant image of the new algorithm, and the Ancuti et al[13] algorithm processed Image D is richer in color but less sharp than the proposed algorithm. Besides, the mean UIQM of the five groups of images processed by the new algorithm is higher than that of the other comparison algorithms and improved by 12.9% on average, which indicates that the images processed by our algorithm have better overall evaluation in three aspects: chromaticity, sharpness and contrast. As can be seen from Table 3, the proposed algorithm obtained the highest values for all the UCIQE metrics, indicating that our algorithm can obtain underwater images with more balanced colors and higher saturation and contrast, and the UCIQE values of the images were improved by 20.3% compared to the average values of other algorithms. In summary, the values of three evaluation indexes of our method are almost optimal compared to other algorithms. Combining the subjective and objective evaluations, the proposed algorithm can effectively remove color shift, improve contrast, equalize brightness and increase details, and moreover obtain clear underwater images.

5 Conclusion

In this paper, we propose an underwater enhancement algorithm based on IMSRCR and CLAHE-WGIF for the problems of color deviation, low contrast, uneven brightness and blurred detail features caused by the phenomenon of light scattering and absorption in the water body of the image. By adapting the fixed channel gain of the original MSRCR algorithm to improve the color bias, the channels of different colors are more and reasonably compensated, and the image colors are more balanced. The color space is converted to HSV space, the Value component image is decomposed into base layer and detail layer by multi-scale Retinex, the CLAHE-WGIF algorithm is proposed to increase the contrast and edge structure information of the detail layer, and the adaptive gamma correction algorithm is used to improve the luminance unevenness of the base layer. The experimental results show that the proposed algorithm outperforms several other more mature underwater image enhancement algorithms, and improves the color distortion, low contrast, uneven brightness and blurred details of underwater images to different degrees, effectively improving the quality of underwater images.

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