Underwater fish image enhancement method based on color correction

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Abstract. Due to the absorption and scattering of light propagation underwater, the captured underwater images often have problems such as color bias, low contrast and poor clarity, resulting in low accuracy of underwater fish identification. To address this problem, this paper proposes an underwater fish image enhancement method based on color correction to enhance the acquired fish images and improve the accuracy of fish target recognition. Firstly, color correction is achieved by stretching the L component and changing the a and b components of the CIE-Lab color space to improve image sharpness. Then the colors of the R-G-B channels of the image are equalized to reduce the color bias. Finally, the histograms of the three R-G-B channels are redistributed. Comparison experiments were conducted with existing methods on a self-built fish image dataset, and the enhanced images were analyzed from both subjective and objective evaluations. The results showed that the enhancement effect of the method in this paper is better than other methods. Finally, the comparison experiments of target recognition before and after image enhancement were conducted on YOLOv5, and the results showed that the enhanced image target recognition accuracy was 99.8%, which was 1.2 percentage points higher than that before enhancement; the average accuracy mAP was 94.5%, which was 5.6 percentage points higher than that before image enhancement. The method in this paper can effectively improve the problems of underwater images and provide technical support for underwater target recognition.

Keywords: Image enhancement, color correction, CIE-Lab, target recognition, YOLOv5.

1. Introduction

The available land resources have been decreasing in recent years, so there is an increasing emphasis on the marine environment to exploit underwater resources. However, the absorption and scattering of light during its propagation underwater make the imaging of the underwater environment complex and the obtained underwater images severely degraded. The degraded images are difficult to satisfy the demands of real-world situations. How to acquire high quality underwater images is a popular topic in these last few years. The research of this problem is beneficial to the research of underwater target identification [1], underwater monitoring of the environment [2], and environmental protection of marine [3].

Currently, methods to improve the quality of underwater images can be broadly classified into two categories, non-physical model image enhancement methods and physical model-based image restoration methods [4]. The non-physical model of image enhancement methods focuses on improving image quality by adjusting image pixels without considering the physical process of image degradation. A few examples, Kashif et al. [5] proposed a sliding stretching method for underwater image perception; Ghani et al. [6] proposed a dual-intensity image synthesis and Rayleigh stretching method; Huang et al. [7] proposed a global histogram stretching method with adaptive parameters for shallow water images; Wang et al. [8] proposed a color-corrected and improved two-dimensional gamma function based underwater image intensification method; Zhang et al. [9] proposed a color rectification and adaptive contrast enhancement approach. The physical model-based image recovery method constructs a mathematical model for the underwater image degradation process. The model is used to invert the image degradation process and obtain an undegraded image in an ideal state. For

example, Peng et al. [10] introduced a technique for depth estimation of underwater scenes based on image blurring and light reflection, which can be used for underwater image recovery and enhancement in image formation models. Wei et al. [11] suggested a depth estimation model for underwater image scenes based on underwater light attenuation, which can recover the radiation of real underwater scenes brightness; Wang et al. [12] proposed an adaptive background light estimation with non-local prior for underwater image recovery algorithm, which can be effectively used in the construction practice of single underwater image recovery; Dai et al. [13] presented a method to fuse underwater image reconstruction algorithm and color balance algorithm for the recovery of underwater images; Song et al. [14] suggested an underwater image enhancement method based on background light fusion and underwater dark channel a priori and color balance, which can restoration the brightness and color of the image effectively.. Some of the methods proposed above can solve certain underwater image degradation problems, but some of them are not applicable to underwater fish images. The enhanced output image suffers from dark brightness, low contrast, unclear image and color imbalance.

Therefore, this paper proposes a color correction-based image enhancement method for underwater fish, which can significantly better the brightness, contrast and sharpness of images and output high quality images.

2. Underwater image enhancement methods

2.1 CIE-Lab Spatial Adaptive Stretching

The brightness and sharpness of the image are extremely important if the objects in the image are to be distinguished from the background color. [15] Affected by the complex underwater environment, the brightness and sharpness of the captured underwater images have a serious degradation phenomenon, so this paper adjusts the sharpness of the images on the image CIE-Lab space. On the CIE-Lab space, the L component represents the brightness of the image, L=0 means the darkest image, L=100 means the brightest image; a represents the component from green to red; b represents the component from blue to yellow. Therefore, the color gradient of a and b components are corrected to obtain the accurate color correction value and improve the image clarity; meanwhile, the L component is stretched to adjust the image brightness.

The RGB image is first converted to CIE-Lab space, and then a linear sliding stretch is applied to the L component. To minimize the influence of extremity brightness values on globally stretched, the upper and lower scales of luminance values are divided. The minimum $L_{\min}$ and maximum $L_{\max}$ values of L components are calculated, as in (1). The stretching of L components is performed to the range [0,100], as in (2). Then the S-curve model is stretched for the a and b components, and the stretching range is [-128,127], where 0 is the median value, as in (3).

$$\begin{cases} L_{\min} = R.sort[R.length * 0.1\%] \\ L_{\max} = R.sort[-R.length * 0.1\%] \end{cases} \tag{1}$$

Where $R.sort$ denotes the dataset sorted in ascending order according to image brightness; $R.length$ denotes the length of the dataset; and $R.sort[x]$ denotes the value in the positive sort index x.

$$\begin{cases} 0 & L < L_{\min} \\ (L - L_{\min}) \times \dfrac{100}{L_{\max} - L_{\min}} & \mathrm{L}_{\min} \le L \le L_{\max} \\ 100 & L > L_{\max} \end{cases} \tag{2}$$

Where L denotes the brightness value of the image.

$$O_{\lambda} = I_{\lambda} \times (\varphi^{1-\left|\frac{I_{\lambda}}{128}\right|}), \qquad \lambda \in \{a,b\} \tag{3}$$

Where I_λ and O_λ denote the input and output pixels, respectively; $\lambda \in \{a,b\}$ denote the "a" and "b" components; and φ is a constant, which is set according to the actual experiment.

After the L, a, and b components of the image are stretched, the channels are combined and converted into an RGB spatial image. At this time, the sharpness and brightness of the image are improved.

2.2 Color equalization

Some existing underwater image enhancement methods do not equalize the image color, resulting in the enhanced image retaining too many blue-green tones and serious image color bias. Therefore, after adjusting the clarity of the image, the color of the image should be balanced. Because light propagates exponentially in water and different light waves have different attenuation rates, the longer the light wave, the stronger the degree of attenuation, and this results in rapid attenuation of red light, the captured underwater images often show blue-green tones and unbalanced colors [16]. However, for high quality images, the image R-G-B channels have equal colors. Therefore, inspired by Iqbal et al. [17], two gain factors a and b are calculated to equalize the R and G channels with the B channel to achieve the effect of color equalization. First calculate the average values of channels R, G, and B R_{avg}, G_{avg}, and B_{avg}. The calculation formula is presented in (4).

$$\begin{cases} R_{avg} = \dfrac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I_R(i,j) \\ G_{avg} = \dfrac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I_G(i,j) \\ B_{avg} = \dfrac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I_B(i,j) \end{cases} \tag{4}$$

Where $I_R(i,j)$, $I_G(i,j)$ and $I_B(i,j)$ are R, G, B components of the RGB image of M × N pixels, respectively; $i = 1,2,\cdots,M$, $j = 1,2,\cdots,N$.

The average value of each color channel is used to compute the gain factor a, b. The calculation formula is shown as (5).

$$\begin{cases} a = B_{avg} / R_{avg} \\ b = B_{avg} / G_{avg} \end{cases} \tag{5}$$

The main color channel is set to the target average and the pixel values of the other two-color channels are adjusted with the von Kries assumption [18] to reduce the color projection of the affected image and achieve color equalization. The calculation formula is as (6).

$$\begin{cases} R^{'} = a \times R \\ G^{'} = b \times G \end{cases} \tag{6}$$

Where R, G, $R^{'}$, $G^{'}$ denote the pixel values of the original image R and G channels and the pixels of the image R and G channels after adjustment, respectively.

2.3 Contrast stretching

The low contrast image makes it difficult to identify the target underwater, so it is essential to increase the contrast of the image after the color equalization process. The degree of stretching of the R, G and B channels is different owing to the different attenuation of the light waves. The stretching range is [0,255]. Since the extreme gray value has a significant effect on the stretching outcomes, this paper takes 0.5% above and below the gray value of each channel as the dividing point, the top 0.5% of the gray value as the minimum threshold, and the bottom 0.5% of the gray value as the maximum threshold. The grayscale values of each channel are divided into three parts according to the minimum and maximum thresholds [19], and each part is adjusted separately.

For the R channel, the contrast stretching formula as in (7). When the pixel value of the original image is less than the minimum threshold, the pixel value after stretching takes the value of the minimum threshold. When the pixel value of the original image is between the minimum threshold and the maximum threshold, the stretched pixel value is calculated using Eq. When the pixel value of the original image is greater than the maximum threshold, the stretched pixel value is taken as 255.

$$P_{out}=\begin{cases} I_{\min} & I<I_{\min} \\ (I-I_{\min})\times\dfrac{255-I_{\min}}{I_{\max}-I_{\min}} & I_{\min}<I<I_{\max} \\ 255 & I>I_{\max} \end{cases} \tag{7}$$

Where P_{out} denotes the output pixel value after stretching, and I denotes the pixel value of the original image. The latter equation indicates the same meaning.

For the G channel, the contrast stretching formula as in (8). When the pixel value of the original image is less than the minimum threshold, the stretched pixel value is taken as 0. When the pixel value of the original image is between the minimum threshold and the maximum threshold, the stretched pixel value is calculated using Eq. When the pixel value of the original image is greater than the maximum threshold, the stretched pixel value is taken as 255.

$$P_{out}=\begin{cases} 0 & I<I_{\min} \\ (I-I_{\min})\times\dfrac{255}{I_{\max}-I_{\min}} & I_{\min}<I<I_{\max} \\ 255 & I>I_{\max} \end{cases} \tag{8}$$

For the B channel, the contrast stretching formula as in (9). When the pixel value of the original image is less than the minimum threshold, the stretched pixel value is taken as 0. When the pixel value of the original image is between the minimum threshold and the maximum threshold, the stretched pixel value is calculated using Eq. When the pixel value of the original image is greater than the maximum threshold, the stretched pixel value is taken as the value of the maximum threshold.

$$P_{out}=\begin{cases} 0 & I<I_{\min} \\ (I-I_{\min})\times\dfrac{I_{\max}}{I_{\max}-I_{\min}} & I_{\min}<I<I_{\max} \\ I_{\max} & I>I_{\max} \end{cases} \tag{9}$$

Stretching the image contrast using the above formula yields a high-quality image with high contrast.

A comparison of the image histogram before and after contrast stretching is shown in Figure 1. As can be seen from the figure, the histogram after contrast stretching increases the dynamic range of the pixel gray value from [0,155] to [0,255], which enhances the overall contrast of the image. From the histogram of the final enhanced image, we can see that the brightness of the original darker areas in the image has been effectively improved, and the brightness and sharpness of the image has been improved.

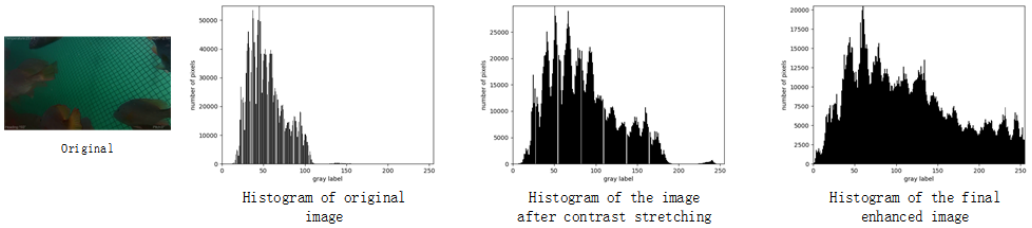


Figure 1. Histogram comparison of before and after image enhancement

3. Experimental dataset

The underwater fish dataset used for the experiment was the underwater robotic whale GLADIUS MINI (Figure 2) developed by Shenzhen Submerged Innovation Technology Co., Ltd. and the fish videos taken by the project team on a sunny day of November 11, 2020, at a temperature of about 25 degrees Celsius, in the seawater net tank culture area of Nan'ao District, Shenzhen, Guangdong Province. And the videos were extracted into images in chronological order by manual method. The size of each net box was 6 m long, 4 m wide and 5 m deep. 1000 images were randomly extracted as the experimental data set. The images to be enhanced are shown in Figure 3.



Figure 2. The whale GLADIUS MINI.

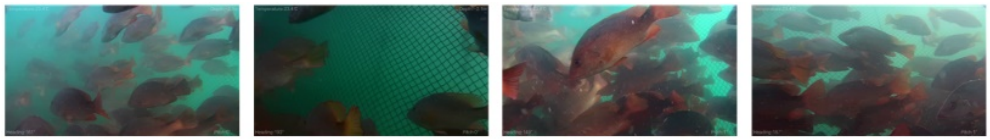


Figure 3. Images to be enhanced.

4. Experimental results and analysis

Firstly, we analyze the value of φ when the CIE-Lab space adaptive stretching is modified for the a, b components. Then the method of this paper is compared and analyzed with other existing methods in terms of subjective evaluation and objective evaluation, which shows that the enhancement effect of this paper method is better and the performance is superior. Then the target recognition accuracy is analyzed on the target recognition method using the image before enhancement and the image after enhancement using the method of this paper, which shows that the enhanced image using the proposed method can effectively improve the accuracy of target recognition.

4.1 Analysis of the value of φ

The value of φ affects the modification of the a, b components on the CIE-Lab space of the image. It directly affects the color and sharpness of the final image after enhancement. Therefore, the value of φ is particularly important. If the value of φ is low, the color of the enhanced image will not be sharp enough and the true color of the image will not be restored. If the value of φ is high, the enhanced image will have color bias and deviate from the true color of the image. The enhanced images with varied φ values are shown in Figure 4. From the figure, it can be noticed that as the value of φ increases, the sharpness of the image becomes clearer and clearer. However, if the value of φ is high, the green light in the image will be heavy, and the fish target in the image will be too bright. Therefore, for a more ideal experimental effect, the optimal value of φ is 1.3 in this experiment.

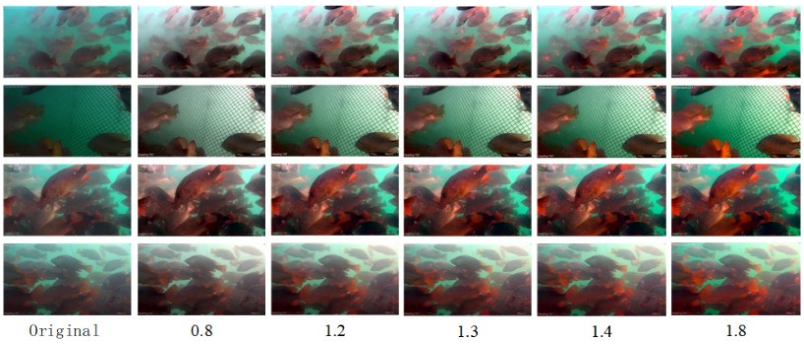


Figure 4. Enhancement effect under varied values of φ.

4.2 Subjective evaluation

The fish images were enhanced using the methods of Ghani et al. [6], Huang et al. [7], Peng et al. [10], Wei et al. [11], Iqbal et al. [17] and this paper in turn. The comparison of the results after image enhancement using the above method is shown in Figure 5. The method of Ghani et al. overly enhances the brightness and contrast of the image, resulting in an extremely bright image. Huang et al.'s method improves the brightness of the image well, but the contrast of the image is not nicely improved, and it cannot distinguish the target from the background clearly. The method of Peng et al. overly enhances the red light of the image, and there is too much red light around the fish. The method of Wei et al. does not enhance the brightness and contrast well for low light images. The method of Iqbal et al. enhances the image too much with green light. Compared with the above methods, the method in this paper improves the above problems. The enhanced image in this paper does not excessively enhance the brightness of the image, which causes image distortion, nor does it excessively enhance or preserve the brightness of a certain color, and the image color is balanced. The brightness, contrast and sharpness of the enhanced image are greatly improved by the method in this paper.

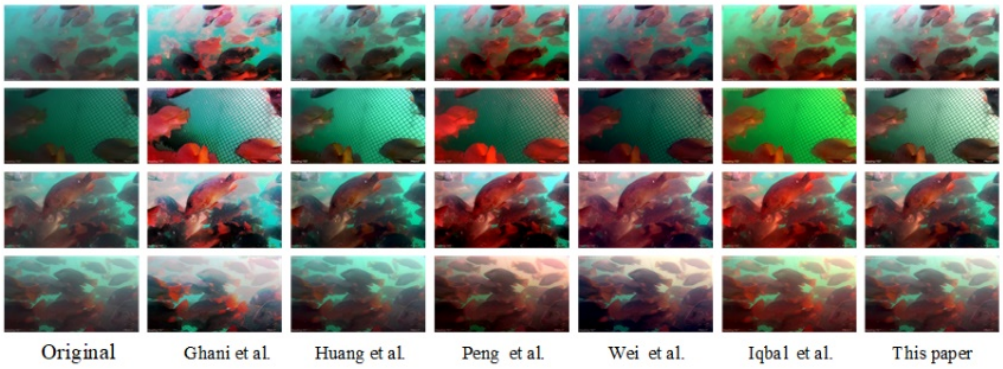


Figure 5. Comparison of enhancement effects of different methods.

4.3 Objective evaluation

This paper uses four commonly used underwater image evaluation metrics to compare and analyze various underwater image enhancement methods from a quantitative perspective. Two reference evaluation metrics, Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measurement (SSIM) [20], and two non-reference evaluation metrics, Underwater Image Color Metric (UICM) and Underwater Image sharpness Metric (UISM) [21], were chosen for the four-evaluation metrics. Larger PSNR and SSIM values indicate less distortion and higher quality images; larger UICM and UISM values indicate more desirable color and contrast images. The quality of the images in Figure 3 was evaluated using these four-evaluation metrics, and the first to fourth rows in the figure were named img1, img2, img3, and img4. The evaluation results can be analyzed from Table 1. The average values of the four evaluation indexes for the four images are shown in Table 2.

From Table 1, we can see that the UICM of this paper's method is not the maximum in the evaluation of img1 and img3. The img1 has the maximum value of UICM for Wei et al., and the img3 has the maximum value of UICM for the original image. Although the value is high, it does not have a better visual effect. In contrast, the visual effect of the method in this paper is better. Thus, the large UICM value alone does not represent the high quality of the image. The image quality also depends on the comprehensive evaluation metrics. So the UICM value is too large, it may cause the image color bias problem. From the UISM, the UISM values of the methods in this paper are all higher than those of other methods, indicating that the enhanced images of this paper have the best clarity. The PSNR and SSIM of the method in this paper are superior to other methods, except for the enhancement results of img2 by the method of Wei et al. However, it can be seen from Table 2 that the average values of each metric of the images under the enhancement of this paper's method are optimal. Therefore, on the comprehensive view, the enhancement of underwater fish images by the method in this paper is more satisfactory and the enhanced underwater fish images are of higher quality. The brightness, contrast and sharpness of the images are effectively improved.

Table 1. Evaluation and comparison of underwater image enhancement by different methods.

images	**img1**				**img2**			
Evaluation Indicators	***PSNR***	***SSIM***	***UICM***	***UISM***	***PSNR***	***SSIM***	***UICM***	***UISM***
Original	\	\	16.5433	0.2284	\	\	14.2532	1.0505
Ghani et al.	27.9753	0.7649	16.0347	0.8779	27.8224	0.6116	11.0119	1.3802
Huang et al.	27.2747	0.9006	15.2279	0.5760	27.9041	0.7882	12.3324	1.2872
Peng et al.	28.0257	0.8215	14.4947	0.8836	28.7199	0.8632	13.3524	1.4932
Wei et al.	28.3852	0.8982	**17.0316**	0.6541	28.3491	**0.8868**	15.7769	1.5325
Iqbal et al.	28.2448	0.9278	13.5779	0.6089	21.4158	0.6972	6.9864	1.494
This paper	**28.9584**	**0.9321**	16.8371	**0.9052**	**28.0068**	0.8176	**16.6497**	**1.6851**
images	**img3**				**img4**			
Evaluation Indicators	***PSNR***	***SSIM***	***UICM***	***UISM***	***PSNR***	***SSIM***	***UICM***	***UISM***
Original	\	\	**18.8529**	0.2669	\	\	19.5775	0.2964
Ghani et al.	28.0541	0.8113	16.4895	**0.8811**	28.0984	0.8745	19.887	0.7754
Huang et al.	28.0382	0.9043	17.8666	0.6699	**30.1635**	0.9677	18.2174	0.4488
Peng et al.	28.0971	0.7918	12.2611	0.0165	27.8534	0.8614	3.9774	0.5476
Wei et al.	28.2342	0.9129	7.7108	0.4963	28.2508	0.8172	14.1265	0.2930
Iqbal et al.	28.5307	0.9166	8.2482	0.5813	29.5789	0.9604	13.1753	0.468
This paper	**28.5688**	**0.9201**	18.3134	0.8435	29.8899	**0.9679**	**20.6068**	**0.8531**

Table 2. Average value of each metric of four images by different methods.

Evaluation Indicators	***PSNR***	***SSIM***	***UICM***	***UISM***
Original	\	\	17.3067	0.4606
Ghani et al.	27.9801	0.7656	16.9161	0.9787
Huang et al.	28.3451	0.8902	15.9111	0.7455
Peng et al.	28.174	0.8345	11.0214	0.7352
Wei et al.	28.3048	0.8788	13.6615	0.7439
Iqbal et al.	26.9426	0.8755	10.4971	0.7882
This paper	**28.8561**	**0.9094**	**18.1018**	**1.0717**

4.4 Ablation experiment

Because three stages were divided for image enhancement in this paper, ablation experiments were conducted to demonstrate that each stage is a mutually reinforcing result. The same four images from the above experiments were selected for results comparison and analysis. The image comparison results are shown in Figure 6. Where columns a, b, c, and d represent the enhancement results of CIE-Lab spatial adaptive stretching only, color equalization only, contrast stretching only, and all three stages, respectively. As displayed in Figure 6, the images after CIE-Lab spatial adaptive stretching

enhancement only are not satisfactory in terms of color balance and contrast. The image sharpness, brightness and contrast after only color equalization enhancement are not satisfactory. The image after only contrast stretching enhancement has serious color bias. Therefore, only with three stages of enhancement, the enhanced image can achieve the desired effect. It shows that these three stages can play a mutually reinforcing effect.

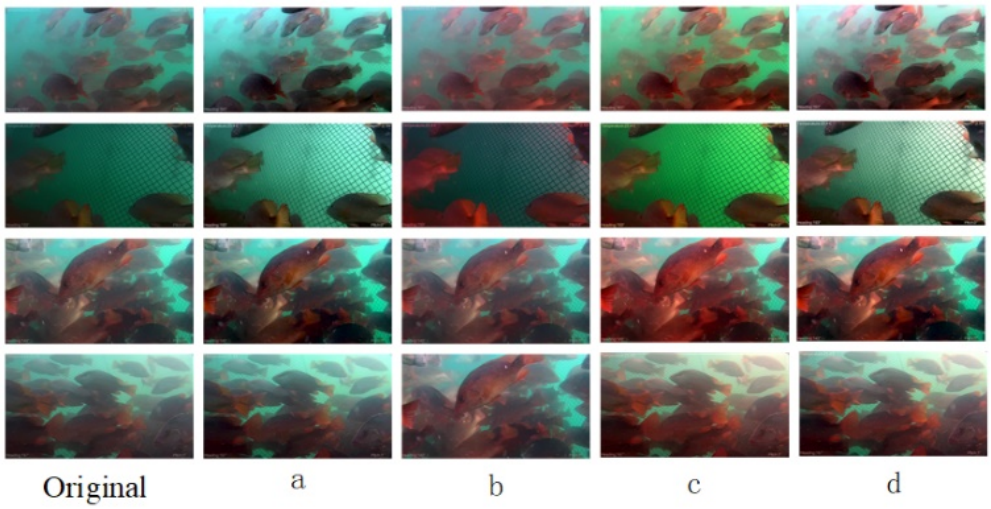


Figure 6. Comparison of ablation results.

4.5 Target Recognition

In this paper, the image enhancement method is applied to underwater target recognition. The image targets were manually labeled with the Labelimg tool (as in Figure 7). 1000 images were divided into training and test sets in the ratio of 7:3. The training was performed on the YOLOv5 [22] on a hardware platform with a CPU model Core i7-9700, 16 GB of RAM and a GPU model GeForce RTX 2070; and a software platform with Window 10 operating system, Python 3.7 programming language and Pytorch 1.4 deep learning framework. The pre-trained model uses yolov5s. The training parameters are set as follows: the image size is set to 640x640, the batch-size is set to 16, the use of Adam optimizer, the number of generations epoch is set to 500, the learning rate is set using the idea of warm-up, the initial learning rate is set to 0.001, in the warm-up phase, the learning rate of each iteration is updated using the one-dimensional linear interpolation method, and after the warm-up phase the learning rate is updated using the cosine annealing algorithm.

The target recognition was performed on the fish images before and after enhancement, respectively, and the experimental results are shown in Table 3. The accuracy and recall of target recognition after image enhancement reached 99.9%, improving 1.3 percentage points and 1.8 percentage points, respectively, compared with that before image enhancement. The mAP after image enhancement reached 94.5%, improving 5.6 percentage points over that before image enhancement. The comparison results of target recognition before and after image enhancement are shown in Figure 8. From the figure, it can be seen that the accuracy rate of the recognition of the same target after image enhancement is higher than the accuracy rate before image enhancement. And the missed detection of the target after image enhancement is lower than that before image enhancement.

Table 3. Comparison results of target recognition performance before and after image enhancement.

	precision%	***recall%***	***mAP%***
Image enhancement before	98.6%	98.1%	88.9%
Image enhancement after	99.9%	99.9%	94.5%



Figure 7. Labeling for target labeling.

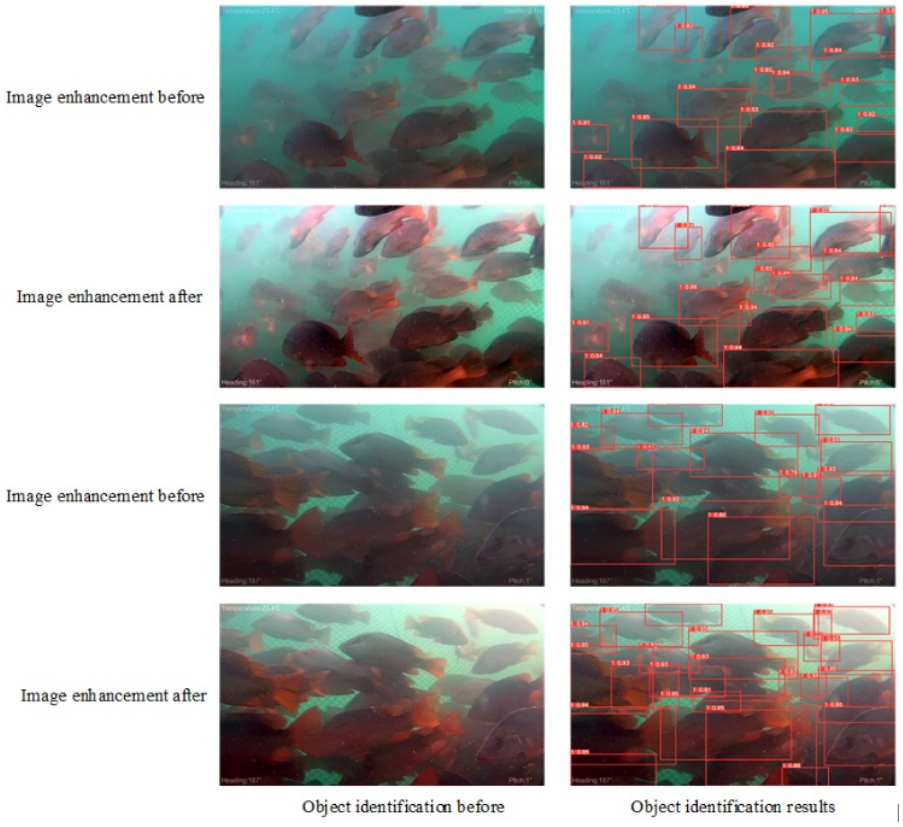


Figure 8. Comparison of target recognition results before and after images enhancement.

5. Conclusion

After To address the problems of low brightness, low contrast, unbalanced color and unclearness of the captured underwater fish images, this paper proposes a color correction based underwater image enhancement method. Firstly, the L component and a, b component of the CIE-Lab space of the image are stretched to improve the sharpness of the image. Then two gain factors are calculated in the RGB space to equalize the image color. Finally, the contrast of the image is stretched to enhance the contrast of the image and better distinguish the target from the background. The methods of this paper are compared with other existing methods. The enhanced images of these methods are analyzed in both subjective and objective ways. Both in terms of subjective observation and objective

evaluation indexes, the enhancement results of this proposed method are better than other methods. Finally, 1000 fish datasets before enhancement and fish datasets after enhancement with the method of this paper were used for target recognition on YOLOv5 network structure. Comparing the accuracy, recall and mAP before and after image enhancement, the enhanced image results are improved by 1.3, 1.8 and 5.6 percentage points, respectively, compared with the pre-enhanced image results.

The method in this paper can provide a good foundation for the image processing phase of underwater target recognition.

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