Research on Underwater Image Enhancement Techniques in Complex Scenarios

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Abstract
This study utilizes algorithms such as the Laplacian operator and Dark Channel Prior (DCP) to enhance marine images. A model is established to represent common degradations in marine images, including low light, color cast, and blurriness. The image enhancement process involves grayscale conversion followed by linear enhancement of dark pixels. The proportion of dark pixels in each image is calculated, and an image is defined as having low-light conditions if this proportion exceeds 15%.For color cast assessment, the study employs the LAB color space. After converting the images, the values for the L, A, and B channels are computed. The variance of each image in this color space is calculated, and a threshold of -20 is defined. Images with a variance greater than -20 are identified as having a color cast. To evaluate blurriness, the Laplacian operator is applied to calculate the variance of each image. Based on a predetermined threshold, a determination is made regarding the presence of blur.Based on the above model, the specific degradation type of an image can be identified. According to the principles of underwater imaging, light is categorized into three components: the direct component, the forward-scattering component, and the backscattering component. Considering transmission and the distance light travels to the camera, a transmission function for light in water is established. This function is combined with the light attenuation coefficient to compute the scattering component of the ambient underwater light, ultimately yielding a degradation model for the underwater scene.
Keywords: Laplacian operator, Underwater Image Degradation Model, Dark Channel Prior (DCP)

1. Introduction

With the advancement of technology, marine exploration has become a critically important research field. It not only delves into the mysteries of the ocean and its seabed but also focuses on gathering key information about the marine environment, the distribution of seabed resources, and biodiversity. Marine exploration has progressed from a peripheral activity to a national strategic priority, holding immeasurable value for ensuring resource security, strengthening environmental protection, and deepening research on global climate change. Its complexity is reflected in the comprehensive, multi-level, and three-dimensional investigation and research that spans from coastal waters to the deep sea, and from the water column to sediments and even the rock layers. Many researchers are dedicated to developing deepwater exploration technologies, constantly pushing the boundaries of existing techniques to address the various challenges present in the deep-sea environment (Wang et al., 2021).

Due to the absorption and scattering of light by water, underwater images often exhibit problems such as color distortion, reduced contrast, and loss of detail. Consequently, underwater image enhancement technology has been developed as a specific image processing technique to address

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these issues of image quality degradation in underwater environments. These problems severely impact the observation effectiveness and data collection in fields such as underwater detection, marine scientific research, underwater archaeology, and environmental monitoring (Ji et al., 2024). Some scholars approach the enhancement of underwater images from both hardware and software perspectives to effectively restore the images, while others research algorithms aimed at improving the quality of underwater pictures (Yang, 2023).

This study aims to algorithmically categorize the provided underwater images into the following three types: color cast, low-light, and blur. For each category of images (color cast, low-light, and blur), degradation models will be established to conduct degradation analysis, and the similarities and differences between these image degradation models will be explored. Based on the degradation models for underwater scene images, enhancement methods will be proposed specifically for the individual scenarios of color cast, blur, and low-light conditions. These methods will be validated using images, ultimately providing image processing solutions for pictures used in marine underwater exploration.

2. Method

2.1 Classification of Marine Images

For different types of ocean images, this paper establishes a model that can classify images into three categories: low-light, color cast, and blur, to facilitate more effective model processing.

2.1.1 Establishment of the Ocean Image Classification Model

To address the low-light issue, this paper employs grayscale processing. Typically, underwater images are in RGB color format, where each pixel is composed of three color channels, and brightness is derived from these three channels, which is not convenient for grayscale calculation in this study. By converting the images to grayscale, they are transformed into grayscale images, where each pixel has only one brightness value.

After grayscale processing, the grayscale value I of each pixel is counted, and a dark pixel threshold is defined as 40. Each pixel is judged according to the following formula:

$$P_{dark} = \begin{cases} 0, I > 40 \\ 1, I < 40 \end{cases} \tag{1}$$

Among them, P_{dark} indicates whether it is a dark pixel.

To make dark pixels clearer, this paper performs linear enhancement on dark pixels. Let the enhanced gray value be I', and the linear enhancement coefficient be K (K>1). The enhancement formula for dark pixels is:

$$I' = \begin{cases} K \times I, P_{DARK} = 1 \\ I, P_{DARK} = 0 \end{cases} \tag{2}$$

Since the pixel value range is 0-255, to prevent dark pixel overflow, this paper sets the maximum pixel value for enhanced grayscale images to 255. If the enhanced pixel value exceeds 255, it is set to 255, which can be expressed by the following formula:

$$I' = \min(I', 255) \tag{3}$$

2.1.2 Establishment of the Ocean Image Color Cast Model

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For the color cast images in Appendix 1, this paper uses the LAB color space. Through a two-step conversion from RGB to XYZ and from XYZ to LAB, the values of the L, A, and B channels are obtained. In the first step of converting from RGB to XYZ, the red, green, and blue values are R, G, and B, ranging from 0 to 255, and are transformed into XYZ through the following matrix multiplication:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

Expand the above expression to get:

$$\begin{aligned} X &= 0.4124R + 0.3576G + 0.1805B \\ Y &= 0.2126R + 0.7152G + 0.722B \\ Z &= 0.0193R + 0.1192G + 0.9505B \end{aligned} \tag{5}$$

After converting RGB to XYZ, proceed with the second step of the conversion. Consider each pixel channel in the LAB color space, referring to the white point values (usually taken under standard illumination conditions). The conversion formula is as follows:

$$L^* = \begin{cases} 116 \times \left(\dfrac{Y}{Y_n}\right)^{\frac{1}{3}} - 16, & \dfrac{Y}{Y_n} > 0.008856 \\ 903.3 \times \dfrac{Y}{Y_n}, & \dfrac{Y}{Y_n} \le 0.008856 \end{cases} \tag{6}$$

$$\begin{aligned} a^* &= 500 \times \left[\left(\frac{X}{X_n}\right)^{\frac{1}{3}} - \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} \right] \\ b^* &= 200 \times \left[\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - \left(\frac{Z}{Z_n}\right)^{\frac{1}{3}} \right] \end{aligned} \tag{7}$$

By calculation, the offsets of A and B are obtained, and the image is processed in the LAB color space.

2.1.3 Establishment of an Ocean Image Blur Model

To assess the blurriness of images, this paper employs the Laplacian operator after grayscale processing. Specifically, an 8-neighborhood Laplacian operator is established, and its corresponding mathematical matrix is as follows:

$$K = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \tag{8}$$

The matrix measures the grayscale variation around a pixel through weighted summation. For instance, when there is significant grayscale variation around the central pixel (such as when an image edge passes through the neighborhood of the pixel, resulting in substantial grayscale changes), the value of this weighted summation becomes larger, thereby enabling edge detection (Lv et al., 2023).

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2.2 Establishment of an Underwater Scene Image Degradation Model

According to the principle of underwater imaging, light consists of three components: direct component, forward-scattering component, and backscattering component. Denote the embedded imaging model and analyze the scattering components, as shown in the analysis figure:

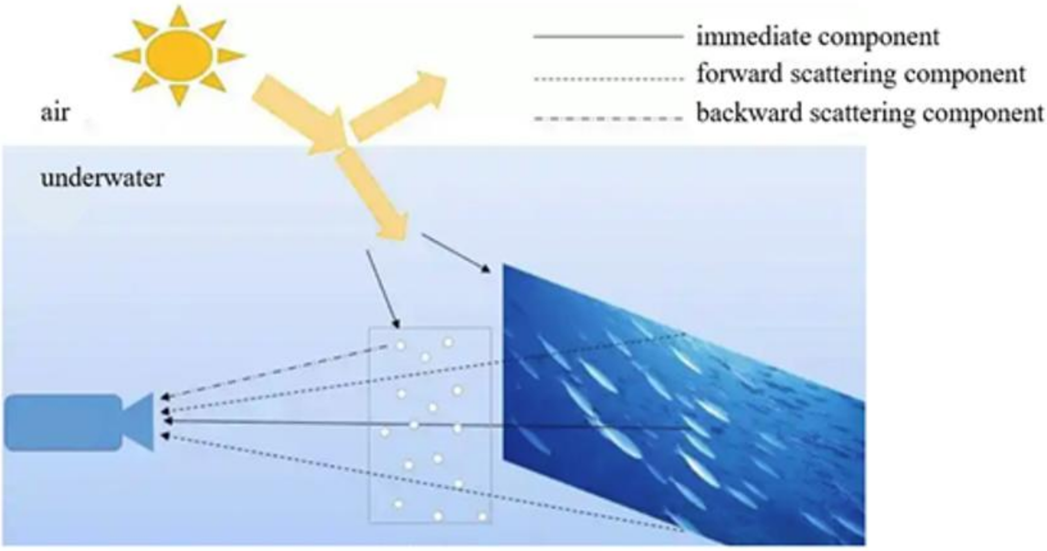

Figure 1 Schematic Diagram of Underwater Light Scattering.

I(x) represents the degraded underwater image in this paper, J(x) represents the clear image, and t(x) is the transmission function of the underwater scene. In this paper, J(x) experiences attenuation in light intensity, and for the transmission function considered here, assuming the medium in seawater is uniform, t(x) can be expressed as

$$t(\mathrm{x}) = \mathrm{e}^{-\beta d(\mathrm{x})}, 0 < t(x) < 1 \tag{9}$$

Where η represents the attenuation coefficient, and d(x) represents the distance from the object to the camera.

Therefore, the sum of the direct component incident on the camera and the scattering component, E(x), can be represented as:

$$E(x) = J(x) \bullet t(x) = J(x) \bullet \mathrm{e}^{-\beta d(\mathrm{x})} \tag{10}$$

The background scattering component is the part of the ambient light that, after being scattered by suspended particles, enters the imaging device. It is related to the light source and the medium. Compared with the forward-scattering component, the background scattering component has a greater impact on object imaging. According to the figure, as the depth of seawater increases, the projection capability of different colors changes, which leads to color cast in underwater images. The formula for underwater images is as follows:

$$E(x)' = B\left(1 - t(x)\right) \tag{11}$$

Therefore, based on the above analysis, we obtain the underwater scene degradation model in this study.

$$I(x) = J(x) \bullet \mathrm{e}^{-\beta d(\mathrm{x})} + B\left(1 - \mathrm{e}^{-\beta d(\mathrm{x})}\right) \tag{12}$$

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2.3 Establishing Underwater Enhancement Models for Single Scenarios

Based on the three types of image degradation identified in Section 2.1, three corresponding models are proposed for enhancement. The flowchart is as follows:

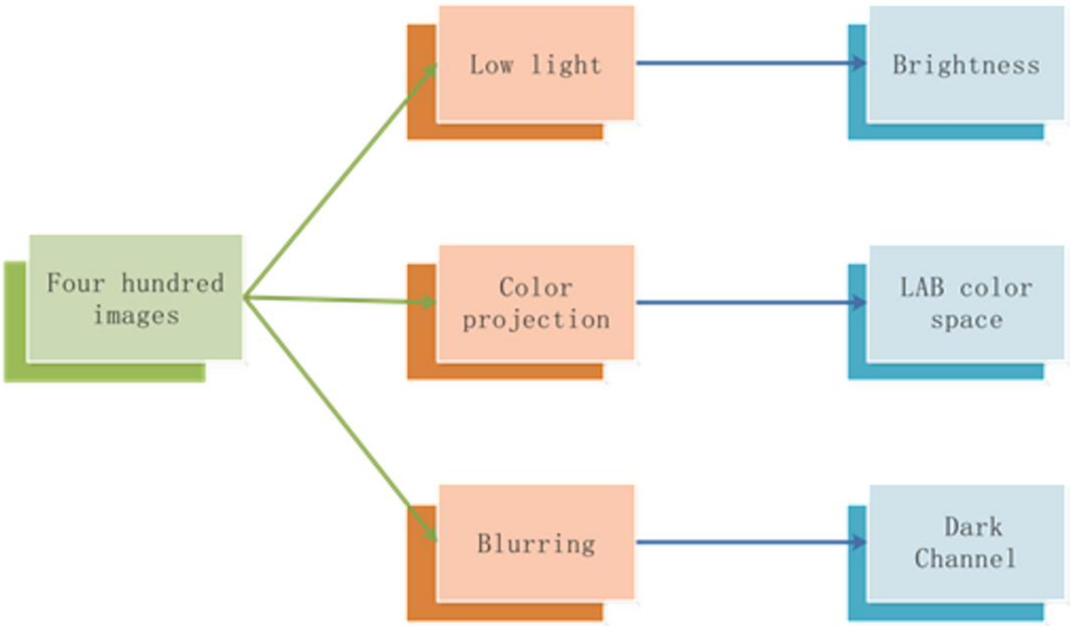

Figure 2 Flowchart.

2.3.1 Enhancement Model for Low-Light Scenarios

For the low-light images in Appendix 1, this paper establishes a low-light enhancement model to enhance images with a high proportion of dark pixels. The images are converted to grayscale, transforming the RGB color images provided in the appendix, and the gray images are obtained using the following formula:

$$Gray = 0.2989R + 0.5870G + 0.1140B \tag{13}$$

After obtaining the gray images, the gray level of each pixel is evaluated. Based on this evaluation, pixels below a certain threshold are enhanced, and enhancements are applied to each RGB pixel.

2.3.2 Enhancement Model for Color Cast Scenarios

This paper addresses images with color casts by performing color space conversion and adjusting contrast and saturation. The RGB color space images are converted to HSV color space to facilitate subsequent adjustments to image attributes such as brightness and saturation. The conversion for the three channels is done using the following formula:

$$\begin{aligned}
&\mathrm{V} = \max(\mathrm{R,G,B}) \\
&\mathrm{S} = \begin{cases} 0, & \text{if } \mathrm{V} = 0 \\ \dfrac{\mathrm{V}-\min(\mathrm{R,G,B})}{V}, & \text{otherwise} \end{cases} \\
&H = \begin{cases} 0, & \text{if } \mathrm{S} = 0 \\ 60 \times \left(\dfrac{G-B}{\mathrm{V}-\min(\mathrm{R,G,B})} + \begin{cases} 0, \text{if } \mathrm{V} = \mathrm{R} \\ 2, \text{if } \mathrm{V} = \mathrm{G} \\ 4, \text{if } \mathrm{V} = \mathrm{B} \end{cases} \right) \bmod 360, & \text{otherwise} \end{cases}
\end{aligned} \tag{14}$$

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In the HSV color space, adjust the brightness and saturation, and convert the HSV color space to the RGB color space using the following formula:

$$
\begin{aligned}
&\mathrm{C}=\mathrm{V}\times S\\
&X=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)\\
&Y=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)\\
&Z=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)\\
&R=\begin{cases}V-C, & \textit{if}\ \mathrm{H<60\ or\ H\geq 300}\\ X, & \textit{if}\ \mathrm{H\geq 60\ andH<120}\\ V-C, & \textit{if}\ \mathrm{H\geq 120andH<180}\\ Y, & \textit{if}\ \mathrm{H\geq 180andH<240}\\ V-C, & \textit{if}\ \mathrm{H\geq 240andH<300}\end{cases}\\
&G=\begin{cases}V-C, & \textit{if}\ \mathrm{H<60\ or\ H\geq 300}\\ X, & \textit{if}\ \mathrm{H\geq 60\ andH<120}\\ V-C, & \textit{if}\ \mathrm{H\geq 120andH<180}\\ Y, & \textit{if}\ \mathrm{H\geq 180andH<240}\\ V-C, & \textit{if}\ \mathrm{H\geq 240andH<300}\end{cases}\\
&B=\begin{cases}V-C, & \textit{if}\ \mathrm{H<60\ or\ H\geq 300}\\ X, & \textit{if}\ \mathrm{H\geq 60\ andH<120}\\ V-C, & \textit{if}\ \mathrm{H\geq 120andH<180}\\ Y, & \textit{if}\ \mathrm{H\geq 180andH<240}\\ V-C, & \textit{if}\ \mathrm{H\geq 240andH<300}\end{cases}
\end{aligned}
\tag{15}
$$

2.3.3 Enhancement Model for Blurry Underwater Scenes

This paper addresses underwater blurry scenes by employing an underwater image processing method based on the dark channel prior (Liu, 2021). The dark channel prior is grounded in the haze imaging model, and underwater imaging shares similarities with haze imaging, differing primarily in the red wavelength range. This paper first calculates the red dark channel, which serves as the basis for estimating the atmospheric light and transmission rate, thereby restoring the underwater image. The degradation and blurring of underwater images mainly result from the absorption and scattering of light by water, leading to issues such as color cast and reduced contrast. By estimating and compensating for these influencing factors, image restoration is achieved (Hu, 2017).

First, the RGB dark channel is calculated, splitting the imaging model into three channels, and then the red channel is inverted.

$$
\begin{aligned}
&1-I^{R}=t\left(1-J^{R}\right)+\left(1-t^{R}\right)\left(1-A^{R}\right)\\
&I^{G}=t^{G}J^{G}+\left(1-t^{G}\right)A^{G}\\
&I^{B}=t^{B}J^{B}+\left(1-t^{B}\right)A^{B}
\end{aligned}
\tag{16}
$$

Here, $I=\left(I^{R},I^{G},I^{B}\right)$ and $J=\left(J^{R},J^{G},J^{B}\right)$ are the original image (the input color-degraded

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image) and the restored image, respectively. By calculating the RGB channels, the characteristics of dark areas in the image or areas heavily affected by water scattering are reflected.

3. Result Analysis

3.1 Solution of Underwater Image Model Classification

Based on the models established in Section 2.1, various underwater image models are classified into three types: low-light, color cast, and blur. Corresponding to each classification model, this paper processes different types of underwater images, yielding the following three categories of results.

3.1.1 Solution to the Low-Light Model for Marine Images

The image was processed to obtain the following figure:

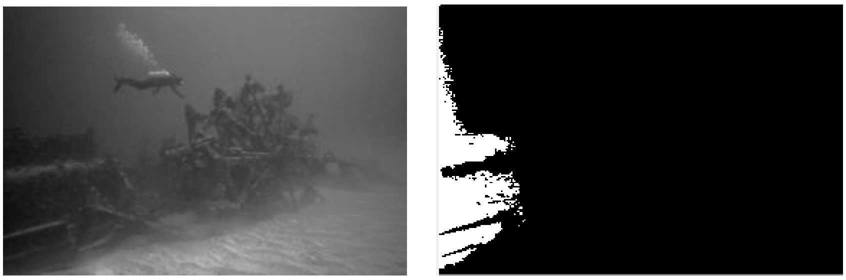

Figure 3. Dark Pixel Processing Diagram: (a) Gray level image (b) Dark pixels mark.

Using MATLAB, the number of all dark pixels in the image was counted and the results were summarized in the following table:

Table 1. Dark Pixel Ratio Table

Figure	Number of dark pixels	Dark pixel ratio
image_003	124528	29.544
image_004	118783	51.5551
image_011	263911	24.1712
image_018	364418	39.5419
image_019	781549	84.8035
image_020	739706	80.2632
image_021	579046	62.8305
image_023	583618	63.3266

3.1.2 Solution of the Ocean Image Color Cast Model

Images are processed in the LAB color space. An underwater image is imported into MATLAB to obtain its LAB color space results. Taking the provided image as an example, the following four images are derived:

Through calculation, the L, A, and B values of each image can be obtained. By outputting the L, A, and B channels of the image separately, the following figure is generated:

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Figure 4. Processed Image in LAB Color Space: (a) Original Image (b) L Channel (c) a, b Offsets (d) Color Cast.

To compare the overall color cast of the images, this paper calculates the variance and mean for each image, obtaining the evaluation indicators for each image. According to the research by scholars on the image segmentation algorithm with threshold (Yang, 2023), this paper defines the judgment threshold as -20, and arranges the data to obtain the following table:

Table 2. Mean Values of a and b Channels

Image	Mean of a Channel	Mean of b Channel
image_002	-27.58683008	17.80856752
image_004	-11.403461	3.348889966
image_006	-46.98660093	29.21604341
image_014	0.410758938	1.882950065
image_015	-1.544051454	-7.600884019
image_017	-3.078591489	-12.66368607
image_018	-6.944083597	-4.736707433
image_019	-1.749305022	-7.342883955

3.1.3 Solution of the Ocean Image Blurring Model

When there is a significant change in grayscale around the central pixel (for example, the grayscale variation is large in the neighborhood of the pixel at the edge of the image), the value of the weighted summation will be relatively large, thereby enabling the detection of the edge. Taking image_009 in Appendix 1 as an example, the following image is obtained after processing:

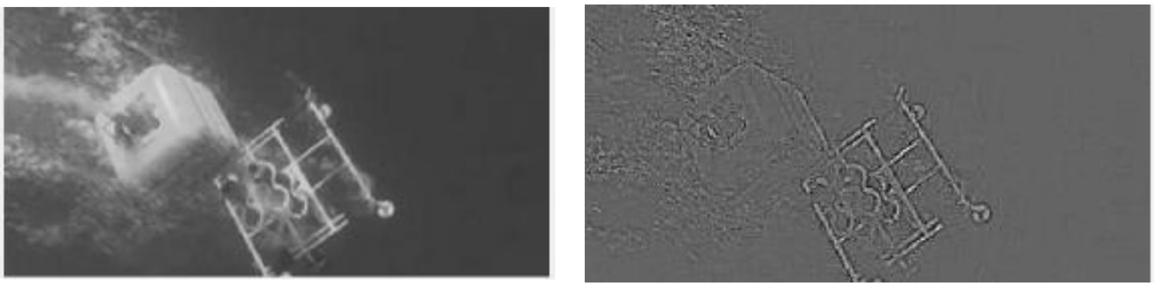

Figure 5. Laplacian Edge Detection Image: (a) Original gray image (b) Image after edge detection.

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After obtaining the images, the second-order derivative of the eight-neighborhood Laplacian operator is calculated using MATLAB. By calculating the variance of each image, a larger variance indicates that the pixel points of the image change significantly, making the image relatively blurry. On the other hand, a smaller variance suggests a more gradual change, indicating a relatively clear image. In this paper, a threshold of 780.49 is set. If the variance is greater than this value, it is considered that the image is blurry. The following part of the data in Appendix 1 is as follows:

Table 3. Variance of Laplacian Second-Order Derivative

Image	Variance of Laplacian Second-Order Derivative
image_001.png	3393.699245
image_012.png	3299.280209
image_013.png	1810.106449
image_014.png	2659.23904
image_015.png	1137.280946
image_016.png	2850.316804
image_022.png	808.6690203
image_023.png	787.644406

3.1.4 Image Visualization Processing

In this study, there are three indicators: low light, blurriness, and LAB color space. All of these describe three dimensions of the image. Therefore, this paper establishes a three-dimensional coordinate system, and each image can be represented in the graph. The dark pixel ratio is set as the x-axis, the LAB offset as the y-axis, and the variance value of the Laplacian model as the z-axis. The visualization is as follows:

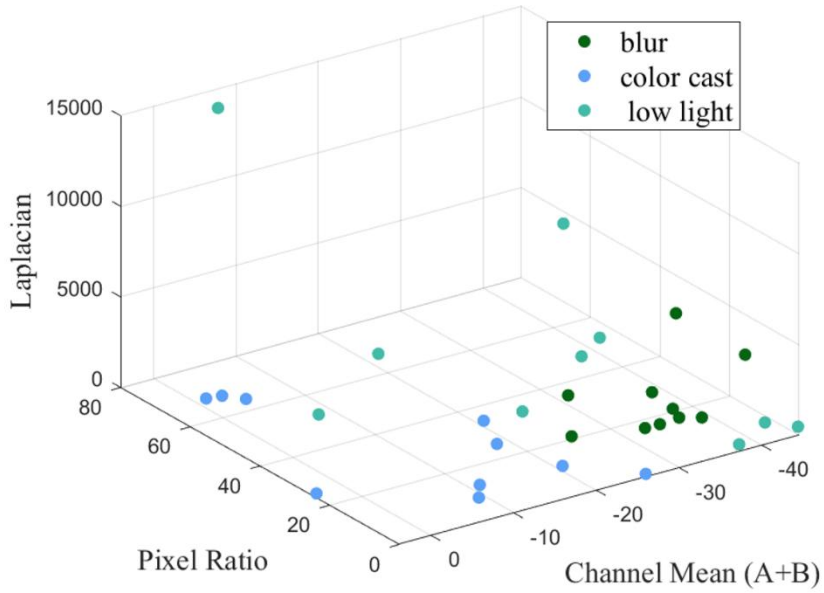

Figure 6. Three-Dimensional Distribution Chart

As shown in the figure, the blue part represents color cast, the green part represents low light, and the dark part represents blurriness. The space can be roughly divided into three parts.

At the same time, in this study, there was a case where the three values of a certain figure did not fall within the range of low light, color cast and blurriness. This paper adopts the Euclidean distance to calculate the distance of each indicator to the threshold. The one with a smaller distance is classified as this indicator. Some data are shown in the following table:

Table 4. The distance from the indicator to the threshold

Image	Dark pixel ratio	Sum of the means of the a and b channels	Variance of the Laplacian second-order derivative
image_005	0.5236	-37.41756168	323.7007294
image_007	6.7435	-43.15320078	141.2449347
image_008	0.34461	-44.46288439	441.1086192
image_009	0	-39.41248808	264.9961826
image_010	0	-23.48119889	237.969131
image_033	2.5047	-34.97721592	575.4221529
image_035	0	-25.48210499	706.4987476
image_039	1.9129	-46.13999954	154.1645529
image_041	9.0331	-28.01683233	754.1771123

3.2 Solution for Enhancement Models Targeting Different Scenarios

After classifying the images, this paper applies algorithms to enhance the three types of images—low-light, color cast, and blur—to make them clearer and more visually appealing.

3.2.1 Enhancement Model for Low-Light Scenarios

Using MATLAB, the low-light images compiled in Section 2.1.1 were processed. Taking image_019 as an example, the image was input into the model to obtain an enhanced image:

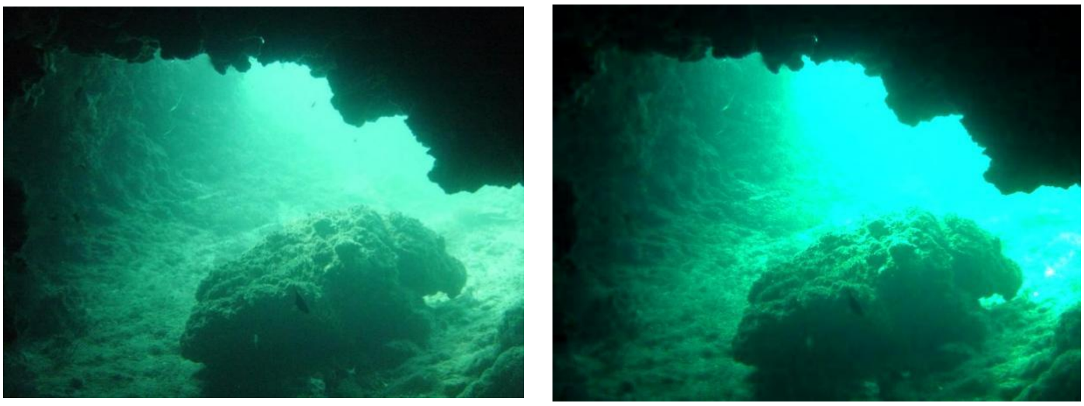

Figure 7. Comparison of images before and after enhancement: (a) Original underwater low-light image (b) Enhanced underwater image.

3.2.2 Enhancement Model for Color Cast Scenarios

This paper conducts color space conversion and contrast, saturation adjustment for color cast images. By converting RGB color space images to HSV color space, it is possible to adjust the attributes of image colors (such as brightness, saturation) in the subsequent steps. The following formulas are used to convert the three channels:

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$$V= \max(R,G,B)$$

$$S=\begin{cases} 0, & \text{if } V=0 \\ \dfrac{V\text{-}\min(R,G,B)}{V}, & \text{otherwise} \end{cases}$$

$$H=\begin{cases} 0, & \text{if } S=0 \\ 60\times\left(\dfrac{G-B}{V\text{-}\min(R,G,B)}+\begin{cases} 0, \text{if } V=R \\ 2, \text{if } V=G \\ 4, \text{if } V=B \end{cases}\right) \bmod 360, & \text{otherwise} \end{cases} \tag{17}$$

In the HSV color space, the brightness and saturation are adjusted. By using the following formula, the HSV color space can be converted to the RGB color space:

$$C=V\times S$$

$$X=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)$$

$$Y=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)$$

$$Z=C\times\left(1-\left|\frac{H}{60}-\left|\frac{H}{60}\right|-\frac{1}{2}\right|\right)$$

$$R=\begin{cases} V-C, & if\ \text{H<60 or H} \geq 300 \\ X, & if\ \text{H} \geq 60 \text{ andH<120} \\ V-C, & if\ \text{H} \geq 120\text{andH<180} \\ Y, & if\ \text{H} \geq 180\text{andH<240} \\ V-C, & if\ \text{H} \geq 240\text{andH<300} \end{cases} \tag{18}$$

$$G=\begin{cases} V-C, & if\ \text{H<60 or H} \geq 300 \\ X, & if\ \text{H} \geq 60 \text{ andH<120} \\ V-C, & if\ \text{H} \geq 120\text{andH<180} \\ Y, & if\ \text{H} \geq 180\text{andH<240} \\ V-C, & if\ \text{H} \geq 240\text{andH<300} \end{cases}$$

$$B=\begin{cases} V-C, & if\ \text{H<60 or H} \geq 300 \\ X, & if\ \text{H} \geq 60 \text{ andH<120} \\ V-C, & if\ \text{H} \geq 120\text{andH<180} \\ Y, & if\ \text{H} \geq 180\text{andH<240} \\ V-C, & if\ \text{H} \geq 240\text{andH<300} \end{cases}$$

By using Matlab to process the original image, the result is as follows:

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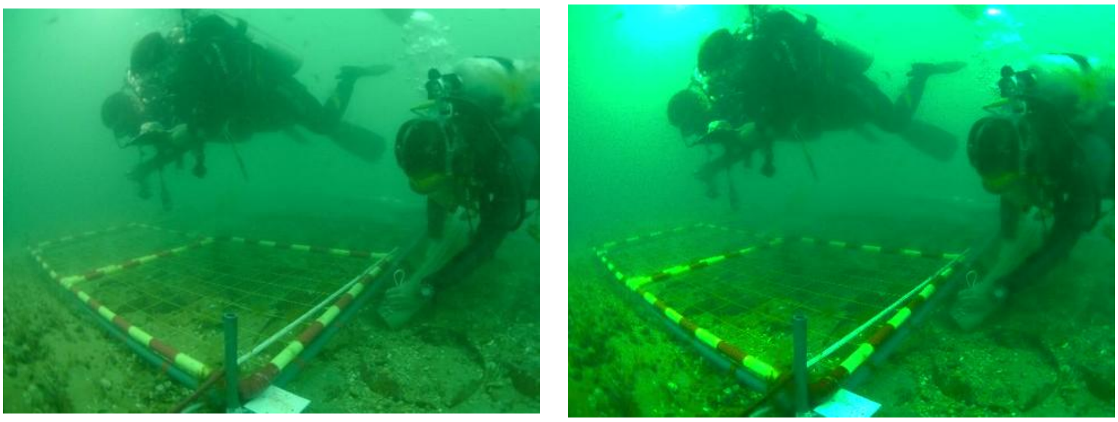

Figure 8. Comparison of images before and after enhancement: (a) Original underwater Color Cast image (b) Enhanced underwater image.

3.2.3 Enhancement Model for Blurry Scenes

This paper addresses underwater blurry scenes by employing an underwater image processing method based on the dark channel prior. As described in Section 2.3.3, the dark channel prior is grounded in the haze imaging model, and underwater imaging shares similarities with haze imaging, differing primarily in the red wavelength range. This paper first calculates the red dark channel, which serves as the basis for estimating the atmospheric light and transmission rate, thereby restoring the underwater image. The degradation and blurring of underwater images mainly result from the absorption and scattering of light by water, leading to issues such as color cast and reduced contrast. By estimating and compensating for these influencing factors, image restoration is achieved.

First, the RGB dark channel is calculated, and the imaging model is split into three channels. Then, the red channel is inverted.

$$\begin{aligned} 1-I^R &= t\left(1-J^R\right)+\left(1-t^R\right)\left(1-A^R\right) \\ I^G &= t^G J^G+\left(1-t^G\right)A^G \\ I^B &= t^B J^B+\left(1-t^B\right)A^B \end{aligned} \tag{19}$$

Here, $I=\left(I^R,I^G,I^B\right)$ and $J=\left(J^R,J^G,J^B\right)$ represent the original image (the degraded color image input) and the restored image respectively. Through the calculation of the RGB channels, the characteristics of the dark areas in the image or the areas significantly affected by water body scattering are reflected.

4. Conclusion

This study focuses on underwater image enhancement techniques in complex scenarios, conducting in-depth research around three core issues. At the background level, the strategic value of marine exploration is increasingly prominent, but underwater light absorption and scattering lead to problems such as color distortion, reduced contrast, and blurred details, which seriously affect the data collection and observation results in related fields, thus making the research and development of underwater image enhancement technology of great practical significance. A single enhancement technique has the advantages of low cost and simple system. However, in specific scenarios, sparse representation methods combined with degradation models can be used to improve the quality of the image (Hu, 2017). The LAB color space, as a derivative of the CIE XYZ color space after nonlinear compression, consists of three dimensions: L, a, and b. The L dimension represents brightness, while the a and b dimensions represent the two opposite attributes of color. These three coordinate values change uniformly visually and can comprehensively cover all colors within the human visual range. The LAB color space also plays an important role in daily life, especially in the matching of skin tones and clothing colors. Underwater images use the L channel (brightness) and a and b channels (color) separated in the LAB color space model, making it possible to adjust colors under different lighting conditions. The underwater lighting conditions change with depth, which is particularly useful for underwater image enhancement. In practical applications, enhancing underwater images can be approached from multiple angles. Using deep learning technology, convolutional neural networks and other models can be explored for underwater image enhancement (Song, 2023). These models can automatically identify targets through algorithmic training, effectively improving image enhancement outcomes (Qin & Gao, 2024). Additionally, integrating multiple techniques can better address issues such as color cast and low contrast. Meanwhile, enhancing the performance of underwater imaging equipment is also a crucial means to improve underwater vision.

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Data Availability
The image data used in this study were provided by the organizing committee of the Asia Pacific Mathematical Contest in Modeling. The data are not publicly available due to competition restrictions. Requests for access may be directed to the corresponding author.

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