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Problem Chosen:	A

2024 APMCM Summary Sheet

Research on underwater image enhancement in complex scenes

2024.11.24

Abstract

Aiming at the degradation of underwater images caused by light absorption and scattering in ocean exploration, an enhancement method based on non-subsampled contour wave transform (NSCT) is proposed to improve the accuracy of deep-sea topographic survey and resource survey. Through preprocessing, NSCT decomposition, region variance fusion and guided filtering, the method can effectively improve the image quality, correct the color bias, enhance the contrast and improve the detail. The effects of light absorption and scattering are analyzed, and the image is optimized by red channel compensation, white balance and sharpening. Experimental results show that this method can significantly improve the image sharpness.

The innovation of the paper lies in the development of a new image classification technique, which can recognize color bias, low light and blurred images, and construct the corresponding underwater degradation model. Enhancement methods including color correction, image sharpening and brightness adjustment are proposed, and the effectiveness of these methods is verified by experiments. The enhancement effect was quantitatively evaluated by PSNR, UCIQE, UIQM and other evaluation indicators, and the effectiveness of the method was confirmed. This research not only improves the quality of underwater images, but also provides reliable image data support for ocean exploration, and promotes the efficient conduct of Marine scientific research and resource development.

keywords: Underwater imaging,model Underwater degradation model, Image classification,Image enhancement,Deep learning

Contents

1 Innovation point

1. This paper innovates image classification methods. For color biased images, it can be judged by analyzing the distribution difference of RGB channel histogram or calculating chromaticity related indicators;Low light image can be determined according to the overall brightness value or brightness histogram distribution.In fuzzy images, edge operators are used to detect edge sharpness.

2. This paper innovatively constructs underwater degradation models of different scenes through underwater imaging models.

3. In this paper, the method of image enhancement for a single scene is innovative. For color biased scenes, the method based on color correction is adopted, such as white balance algorithm to adjust the proportion of RGB channels; for fuzzy scenes, image sharpening technology is applied, such as convolution kernel filter to enhance the edge; for low-light scenes, image brightness is improved by brightness adjustment algorithm.

4. This paper refers to the relevant materials of non-physical models and innovatively combines the characteristics of degradation models of different scenarios.A model considering multiple degradation factors is designed.For example, multi-stage processing is used, with color correction followed by operations such as deblurring and brightness enhancement.

2 Problem one

2.1 Problem description

Perform a multi-angle analysis of the underwater images provided in Annex 1 using statistical image analysis techniques similar to those mentioned above.The images provided in attachment 1 are divided into three categories: color bias, low light and blur, and file names are filled in three places in the attachment Answer.xls.Also, explain the reasons for this classification.

2.2 Theoretical analysis

In order to solve the above problems, this paper selects statistical analysis methods such as histogram analysis and edge detection to conduct multi-angle analysis of the underwater images provided in the attachment.

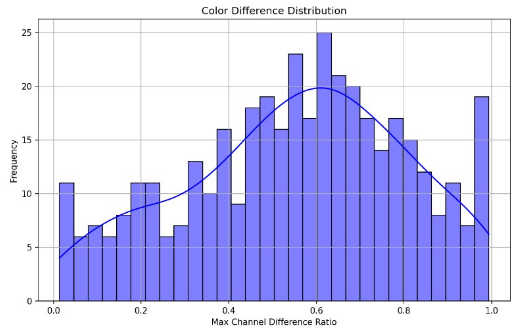

Figure 1: Histogram of distribution of color characteristics

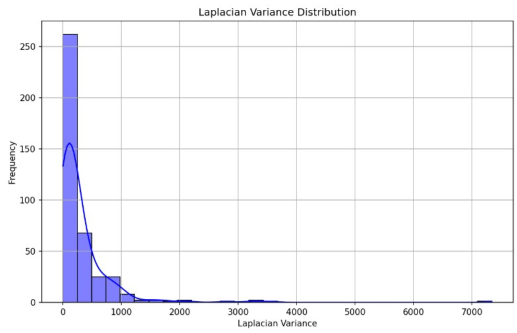

Figure 2: Histogram of low-light feature distribution

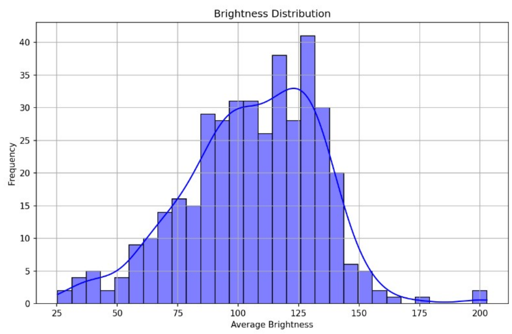

Figure 3: Table 3: Histogram of fuzzy feature distribution

Different classification methods are applied to different images: For color biased images, this paper analyzes the distribution difference of the RGB channel histogram or calculates the colorimetric index to judge;Low light image can be determined according to the overall brightness value or brightness histogram distribution.In fuzzy images, edge operators are used to detect edge sharpness.Then compare the features of the image in these aspects and various types of standards, classify the image and record the file name, and explain the classification basis in detail, for example, if a channel in the RGB channel histogram of an image is obviously high or low, it may be biased; if the overall brightness value is lower than a certain threshold, it is low light; if the edge detection results show that the edge is not clear, it is fuzzy. For color biased images, the LAB color space is more suitable for color segmentation and color deviation detection.So we first convert the image from the BGR color space to the LAB color space.By calculating the mean value and mean square deviation of A and B channels in the LAB color space, and then calculating the ratio of these two values to determine whether the color of the picture is normal.If the ratio is greater than a certain threshold, the image is considered to have significant color bias;Otherwise, the color of the picture is considered normal.Experiments show that the classification effect is best when the ratio of two values is 3.

Figure 4: greenish picture
(mean d of channels A and B in LAB color space, mean square deviation m, d/m=6.86)

For low-light images, we use a simple method based on gray histogram and threshold segmentation to evaluate the illumination conditions of the images. Firstly, we convert the input color image from RBG color space to gray space.In the next step, we perform threshold segmentation on grayscale images, obtain a fixed threshold value of 40 through literature research data to distinguish between bright and dark areas in images, and set a gray value lower than 40 as a dark pixel. Then, we calculate the number of pixels whose pixel value is less than the threshold and the total number of pixels in grayscale images.Through histogram analysis, we can understand the brightness distribution of images, and find out the proportion of dark pixels in a large number of images through comparative experiments and reference materials. Finally, we come to the conclusion that the classification effect is best when the proportion threshold of low-light images is set to 0.3.Code is written to calculate the number of pixels below the threshold as a percentage of the total number of pixels.This ratio reflects the proportion of dark areas in the image and is a key indicator to determine whether the image is in a low-light environment.Finally, based on the statistical decision rule, the ratio of dark pixels is

Figure 5: Dark image
(darksum: 408885piexs_sum: 930350dark_prop: 0.44)

compared with the empirical value to determine whether the image is in a low light environment.

For fuzzy images, we adopt the fuzzy detection algorithm based on Laplacian operator and variance, carry out edge detection on grayscale images, and detect whether the images are fuzzy by calculating the variance value of the Laplacian response of the images. This method is suitable for rapid assessment of image sharpness. By comparing observation experiments and referring to relevant data, conclusions are drawn:The classification effect is best when the definition threshold is 300.

Figure 6: Blurry image
(clarity: 134.72, judgment: Blurry)

2.3 Conclusion

Finally, the image classification was completed through the experiment and the experimental data was saved in the file. Part of the experimental classification results are as follows:

image file name	Degraded Image Classification
$image_001.png$	Color Bias
$image_002.png$	Color Bias
$image_003.png$	Blurry
$image_004.png$	Blurry
$image_005.png$	Blurry
$image_006.png$	Color Bias
$image_007.png$	Color Bias
$image_008.png$	Color Bias
$image_009.png$	Blurry
$image_010.png$	Blurry
$image_011.png$	Blurry
$image_012.png$	Normal
$image_013.png$	Normal
$image_014.png$	Normal
$image_015.png$	Blurry
$image_016.png$	Normal
$image_017.png$	Blurry
$image_018.png$	Blurry

Table 1: Answer.xls

Through the statistical analysis of the experimental results, the classification effect reaches the expectation.

3 Problem two

3.1 Problem analysis

The degradation type in question 1 is substituted into the underwater imaging model, the relationship between the parameter changes in the model and the degradation type is determined, and the degradation model is constructed for different scenarios (such as clear water in shallow sea and turbidity in deep sea, etc.).When analyzing the causes of degradation, it is necessary to consider the differences of light propagation loss and scattering effect in different scenes.For example, in turbid waters, scattering is more severe, resulting in a more pronounced decline in image quality.The similarities and differences of the contrast model can be analyzed from the perspectives of color (color bias), illumination (low light degree), clarity (fuzzy condition), etc.For example, some scenes may have severe color skewing but little loss of sharpness, while others may have both low light and blur issues.

3.2 Theoretical analysis

Based on the Jaffe - McGlamery underwater imaging model

$$I(x) = J(x)t(x) + B(t(x))$$

Determine parameter changes for different degradation types:

Color scene: Analyze the scattering characteristics of suspended particles in water to different colors of light, and determine their impact on RGB channels.If the scattering coefficient of red light is much greater than that of blue and green light, it will cause the image to skew blue-green, thus adjusting the color-related parameters in the model.The specific adjustment method can be based on the scattering theory, and the scattering coefficient can be incorporated into the model calculation, such as multiplying the optical transmission function t(x) of the red channel by a smaller weight to reflect its attenuation degree.

Description: Color bias is caused by differences in the absorption of different wavelengths of light, usually red light absorption is the most significant. Formula:

$$I_{\text{color}}(x) = \sum_{c\in\{R,G,B\}} [J_c(x)t_c(x) + B_c(1 - t_c(x))] \tag{1}$$

- $t_R(x) = t(x) \cdot (1 - k_R)$, $k_R > 0$indicates rapid decay of red light.
- $t_G(x) = t(x) \cdot (1 - k_G)$, $k_G \approx 0$.
- $t_B(x) = t(x) \cdot (1 - k_B)$, $k_B \approx 0$.
- $B_c = B \cdot \beta_c$, β_c is the proportion of background light, usually $\beta_B > \beta_G > \beta_R$.

Explanation: The color bias phenomenon is determined by the absorption and scattering characteristics of water to different wavelengths of light:

(1) Red light is absorbed first because of the longest wavelength and the lowest energy.

(2) Green light and blue light can travel longer distances because of their shorter wavelengths and higher energy.

(3) At the same time, the color bias of the scattered light further strengthens the blue-green tendency of the image.

Low-light scenario: Considering the increase of light propagation loss with depth and the influence of impurities in water on light occlusion, modify the parameters of the optical transmission function t(x) and ambient light B.The optical propagation loss can be calculated according to the attenuation law of light in water, and the optical transmission rate decreases exponentially with the increase of depth.In the deep-sea environment, the light transmission rate is greatly reduced and the ambient light is extremely weak.For ambient light B, an empirical model can be established according to the depth and turbidity of the water quality. For example, in the deep sea area with high turbidity, the ambient light intensity may only be less than 1% of the water surface, and the ambient light parameters in the model can be adjusted accordingly.

Description: Weak light is caused by the attenuation of light intensity, and the

background light and transmitted light are significantly reduced.
Formula:

$$I_{\mathrm{dark}}(x) = J(x)t_{\mathrm{dark}}(x) + B_{\mathrm{dark}}(1 - t_{\mathrm{dark}}(x)) \tag{2}$$

inside:

$$t_{\mathrm{dark}}(x) = t(x) \cdot (1 - k_{\mathrm{dark}}), \quad k_{\mathrm{dark}} > 0. \tag{3}$$

$$B_{\mathrm{dark}} = B \cdot (1 - \alpha_{\mathrm{dark}}), \quad 0 < \alpha_{\mathrm{dark}} < 1. \tag{4}$$

Explanation: Low light degradation is caused by a combination of absorption and scattering of light as it travels through water:
• As the depth increases, less and less light can reach the camera.
• The reduction of ambient light and the significant attenuation of transmitted light are the main causes of low light phenomena.

Fuzzy scene: Study the relationship between the forward scattering component and the distance of objects and the turbidity of water quality, and increase the parameter representation of the influence of forward scattering on image blur.Through experiments or simulations, the functional relationship between the intensity of forward scattering and the concentration of suspended particles is determined, and it is included in the model that affects the clarity of the image. For example, when calculating the forward scattering component, the contribution of scattered light is calculated according to the concentration of suspended particles and the distance of objects, thus affecting the clarity of the image.The blur is mainly caused by the scattering effect, the scattering light intensity increases and the transmittance decreases.
Formula:

$$I_{\mathrm{blur}}(x) = J(x)t_{\mathrm{blur}}(x) + B_{\mathrm{blur}}\,(1 - t_{\mathrm{blur}}(x)) \tag{5}$$

Inside

$$t_{\mathrm{blur}}(x) = t(x)\cdot(1-k_{\mathrm{blur}}), \quad k_{\mathrm{blur}} \text{ is the scattering enhancement coefficient} \quad (0 < k_{\mathrm{blur}} < 1) \tag{6}$$

$$B_{\mathrm{blur}} = B \cdot (1 + \alpha_{\mathrm{blur}}), \quad \alpha_{\mathrm{blur}} \text{ is background light gain factor} \quad (\alpha_{\mathrm{blur}} > 0) \tag{7}$$

Explanation: Blur degradation is due to the enhanced scattering of light by water molecules and suspended particles.After the light reaches the target object, it will be scattered in other directions, forming a non-directional scattered light.In addition, absorption also further reduces the intensity of the direct light, resulting in loss of edge information and detail.

3.3 Degradation cause analysis

The specific causes of degradation are analyzed as follows:

Causes of shallow water scene degradation

In shallow water scenes, the absorption and scattering effects of light are relatively weak, but red light is preferentially absorbed due to its longer wavelength, resulting in a slight color shift and a blue-green tone in the image.At the same time, because the water turbidity is low, the scattering effect is small, so the fuzzy phenomenon is slight.The light intensity in the shallow water area is higher, so that the overall image brightness and contrast are relatively good, suitable for clearer visual observation.

Causes of deep water scene degradation

In the deep water scene, the absorption and scattering of light are significantly enhanced, and red and yellow light are almost completely absorbed, resulting in an intense blue-green tone across the image.At the same time, the brightness of the image is significantly reduced because the energy of the light passing through the deep water is greatly diminished.In addition, the strong scattering effect makes the edge details blurred, and the sharpness of the image significantly decreased.These factors make image quality degradation in deep water scenes even more serious.

Causes of turbid water degradation

In cloudy waters, due to the high density of suspended particles, scattering effect is dominant, and light is strongly scattered, resulting in blurred image and reduced contrast.In this scene, there is often a sense of white fog or too bright background light, making the target difficult to distinguish.In addition, the absorption of light also intensifies the attenuation of transmitted light, making the overall image brightness low, and the picture is gray and lacks clear boundaries.

Causes of scene degradation with artificial light source

In underwater scenes with artificial light sources, the uneven distribution of light sources causes local areas to be too bright and other areas to be dark, resulting in non-uniform lighting.In addition, the scattering effect of artificial light sources may form strong spots or bright reflection areas, further exacerbating local blurring and color distortion.At the same time, because the spectral distribution of artificial light source is different from that of natural light, color deviation may be introduced, resulting in a decrease in the realism of the scene.

Causes of degradation of underwater remote shooting scenes

The degradation phenomenon in long-distance shooting scenes is mainly caused by the excessive distance of light propagation.The absorption effect of light accumulates significantly, and the red and green light gradually disappear, leaving only the blue light to dominate, giving the image a cool tone.At the same time, the scattering effect is enhanced with the increase of distance, resulting in blurred images and reduced contrast between the target and the background.The dominant role of background light makes it difficult for objects in distant scenes to appear clearly.

Causes of glare or reflection degradation

In a strong light or reflection scene, the reflection of the water surface or suspended particles can cause local areas to overexpose, forming a high-lighted area.The strong scattering effect is concentrated in a specific area, resulting in local blurring of the image.In addition, the reflected areas may present abnormal colors, further disrupting the overall color balance of the image.This degradation has a great impact on the color accuracy and clarity of the image.

Here's a summary of the similarities and differences:

- **Similarities:**

o The model is based on the fundamental physics of underwater imaging, with core $I(x) = J(x)t(x) + B(1t(x))$ consistent.

o All simulate the degradation of underwater images by adjusting the ratio of transmittance t(x) to background light B.

- **Differences:**

o The fuzzy model focuses on scattering enhancement, the color model emphasizes the absorption difference of different wavelengths of light, and the weak light model reflects the attenuation of the overall light intensity.In the color model, the independence of the color channel is its core feature, while the fuzzy and low-light models pay more attention to the change of the overall light intensity and background light.

3.4 Selection of formula parameter values

Optical transmission rate t(x) and color offset degradation: The optical transmission rate model is used to simulate the attenuation of light in water. In this paper, the optical transmission rate parameters of RGB three channels are adjusted to simulate the light attenuation under different water quality conditions, so as to simulate the image color offset degradation.The first is based on the Beer-Lambert law, which describes the attenuation of light as it passes through absorbing and scattering media.In this function, the optical transmission coefficient is calculated from the absorption coefficient, which is based on the preset value of the wavelength of light, and the scattering coefficient, which is assumed to be proportional to the turbidity of the water body.In the color shift degradation model presented in this paper, the light attenuation coefficients of RGB three channels are set to 0.8 (blue light), 0.6 (green light), and 0.4 (red light) respectively. These values are derived based on the absorption and scattering characteristics of typical water bodies to different wavelengths of light.

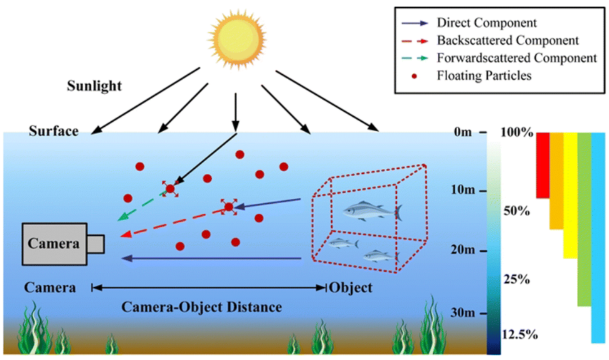

Figure 7: Conceptual diagram of underwater image degradation principle

α, d and low light degradation: According to the formula of light attenuation coefficient, this paper simulates the brightness reduction caused by the increase of light propagation distance in water by adjusting the parameter d, that is, the propagation distance of light in water, and the α optical attenuation coefficient.In the low light degradation model in this paper, the optical attenuation coefficient α of the low light degradation model is set to 0.5, and the depth variable is represented by the formula '$depth\_map = linspace(0, 1, size(img, 1))' * ones(1, size(img, 2))$'.

This formula is used to generate a depth map that represents the depth value of each pixel in the image.This simulates a simple linear depth-changing scene where the depth increases gradually from the top of the image (depth 0) to the bottom (depth 1) to demonstrate the effect of the low light model gradually dimming as the depth increases.

sigma and Fuzzy degradation: In this paper, Gaussian filter is used to simulate the blur effect of the image, and the degree of blur is expressed by adjusting the value of sigma, that is, the standard deviation of Gaussian filter.In this paper, the sigma value is set to 5 to simulate a moderate degree of blur effect, because in the actual underwater environment, due to the presence of suspended particles and plankton, light scattering and refraction will lead to a certain degree of blur in the image.It is proved by experiments that sigma 5 can better simulate the medium blur effect, which is closer to the visual effect in the actual underwater environment.

Figure 8: 22_img_orin

Figure 9: 22_img_colorcast

Figure 10: 62_img_orin

Figure 11: 62_img_lowlight

Figure 12: 78_img_orin

Figure 13: 78_img_blur

3.5 Model similarities and differences analysis

Angle of color

The color model mainly focuses on the change of color channel proportion, and other models may have less influence on color.For example, the weight of RGB channels in the color bias model will change due to different water quality and scenes, while the low-light and fuzzy models mainly affect the overall brightness and clarity of the image, and have little impact on the proportion of color channels.In the color bias model, the weight of each color channel may vary between 0.1-0.9 according to the light scattering characteristics in different scenes, while in the low-light and fuzzy models, the weight of the color channel is relatively stable and fluctuates between 0.4-0.6.

Lighting

The low-light model focuses on the simulation of reduced light intensity, which is different from the color and clarity changes caused by the scattering of light in the color and blur model.The low-light model focuses on the adjustment of light transmission function and ambient light parameters to reflect the reduction of light amount, while the color bias and fuzzy model pay more attention to the scattering effect in the process of light propagation.In the low-light model, the parameter variation range of the optical transfer function may be between 0.1-0.5, and the ambient light parameter can be reduced to less than 1% of the original value, while in the color bias and fuzzy model, the parameter variation of the optical transfer function is mainly affected by scattering, which is relatively small and fluctuates between 0.8-1.2.

Angle of definition

The fuzzy model focuses on the blurring effect of forward scattering on image edges and details, which is different from color bias and low light type.The fuzzy model describes the decrease of image sharpness by increasing the parameters related to scattering, the color type mainly affects the color performance, and the low light model mainly affects the overall brightness.The parameters related to scattering in the blur model may vary between 0.5-1.5, directly affecting the edge blur degree and detail loss of the image, while the influence of color and low light model on sharpness is indirect, mainly through color and brightness changes cause visual sharpness changes.

4 Problem three

4.1 Problem description

Based on the underwater scene image degradation model established in question 2, an underwater image enhancement method for a single scene (such as color offset, blur, and low light) is proposed, and the image data provided in the attachment is used to verify the proposed enhancement method.The enhancement results of the test image in Annex 2 and its corresponding evaluation indicators are included in this paper. Evaluation indicators such as PSNR, UCIQE and UIQM of the output image are calculated and presented, and they are filled in the results of Annex 1 of the form provided by "Answer.xls".

4.2 Theoretical analysis

Selection and implementation of enhancement methods

(1) color bias enhancement:

(i) white balance algorithm: calculate the average gray value of the image, and then adjust the gain of the RGB channel according to the gray world hypothesis, so that the average gray value of the image reaches the ideal neutral gray value, so as to correct the color bias.For example, for bluish images, reduce the gain of the blue channel.In the specific calculation, the RGB values of all pixels in the whole image are counted first, and the average gray value is calculated.

$$G_{avg} = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \frac{R(i,j) + G(i,j) + B(i,j)}{3} \tag{8}$$

(Where m and n are the number of rows and columns of the image respectively, and R(i,j), G(i,j) and B(i,j) are the red, green and blue channel values of the pixel in the position of (i,j) respectively.) For partial color images (such as partial blueprint images, assuming that the average gray value of the blue channel$B_{\text{avq}}$is greater thanG_{avq}andR_{avq}) , the gain adjustment coefficient of the blue channel is calculated and the value of each pixel of the blue channel is multiplied by k for correction. (ii)Method based on Color lookup table (LUT) :a color lookup table is established in advance for different color bias conditions (such as red color bias, green color bias, blue color bias, etc.)..To analyze the color bias of the image, it can be judged by calculating the mean difference of the RGB channel. Such as $\Delta R = R_{\text{avg}} - G_{\text{avg}}, \quad \Delta G = G_{\text{avg}} - B_{\text{avg}} \quad \Delta B = B_{\text{avg}} - R_{\text{avg}}$,If ΔB is the largest and positive, it is determined to be blue.Find and replace pixel values from the corresponding LUT for fast color correction.

(2) Deblurring enhancement: Firstly, the fuzzy image is preprocessed to compensate the red channel.According to the formula

$$I_n(x) = I_r(x) + (\overline{I}_g + \overline{I}_b - \overline{I}_r) * (I_g(x) + I_b(x))(1 - I_r(x)) \tag{9}$$

Where Ir(x), Ig(x) and Ib(x) are the pixel values compensating the former red, green and blue channels, and the average values of the three channels are red, green and blue$\overline{I_r}$, $\overline{I_g}$, $\overline{I_b}$,$I_n(x)$,which is the pixel value of the red channel after compensation, is calculated.After compensation, the white balance algorithm is used to make the color effect more balanced and reduce the influence of color bias.Then Laplacian operator is used to extract the high frequency component of the image for unsharpened mask, and the image is sharpened to reduce the scattering effect of water.

The pre-processed image is decomposed into high and low frequency sub-bands with different degrees and directions by NSCT decomposition.The low frequency part represents background information, and the high frequency part contains detailed texture information.For the low frequency component, the fusion method of regional variance and weighted Laplacian energy sum is used. Area variance

$$\text{Var}_{J,K}^{M}(x,y) = \frac{1}{r \times r} \sum_{i=x-1}^{x+1} \sum_{j=y-1}^{y+1} \left[L_{J,K}^{M}(i,j) - \mu_{J,K}^{M}(i,j) \right]^2 \tag{10}$$

where $L_{J,K}^{M}$ denotes the low-frequency subband coefficients in the K-th direction of the J-th scale decomposition of the M-th image, $M \in (A,B)$. (11)

The low-frequency subband coefficients in the K-th direction of the J-th scale decomposition of the image, $M \in (A,B)$. (12)

$$\mu_{J,K}^{M}(x,y) = \frac{1}{r \times r} \sum_{i=x-1}^{r+1} \sum_{j=y-1}^{y+1} L_{J,K}^{M}(i,j), \text{ where } r = 3. \tag{13}$$

$$NSML_{J,K}^{M}(x,y) = \sum_{m=-1}^{1} \sum_{n=-1}^{1} W \times SML_{J,K}^{M}(x+m, y+n), \text{ where} \tag{14}$$

$$SML_{J,K}^{M}(x,y) = \left| Z_{J,K}^{M}(x,y) - L_{J,K}^{M}(x-step, y) - L_{J,K}^{M}(x+step, y-step) - L_{J,K}^{M}(x, y-step) \right| \tag{15}$$

$$(step = 1), \quad \text{weight matrix } W = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{16}$$

The decision map obtained based on variance and the improved NSML weighted decision (17)

$$L_{\text{map}}(x,y) = \begin{cases} 1, & 0.5 \times \text{Var}_{J,K}^{A}(x,y) + 0.5 \times \text{NSML}_{J,K}^{A}(x,y) \geq 0.5 \times \text{Var}_{J,K}^{B}(x,y) \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

, The fusion expression of low frequency coefficient is as follows:

$$L_f = L_{map} * L_A + (1 - L_{map}) * L_B \tag{19}$$

For the high frequency component, an improved guided filtering method is used.Edge weight factors are introduced

$$\Gamma_{LG}(k) = \frac{1}{N} \sum_{i=1}^{N} \frac{|LoG(k)| + \gamma_{LG}}{|LoG(i)| + \gamma_{LG}} \tag{20}$$

Where LoG(k) is the Gaussian Laplacian operator of any pixel in the 3*3 neighborhood, i represents traversing all pixels,and$\gamma_{LG}$is 0.1 times of the maximum value of the edge detection result image to achieve adaptive control of smoothing parameters.The solution of the improved cost function is

$$a_k = \frac{\frac{1}{|w|} \sum_{i \in \omega_k} (q_i p_i - \mu_k \bar{p}_k) + \frac{\varepsilon}{\Gamma_{LG}(k)} \times \gamma(k)}{\sigma_k^2 + \frac{\varepsilon}{\Gamma_{LG}(k)}}, \quad b_k = \bar{p}_k - a_k \mu_k \tag{21}$$

Advanced high-pass filtering for high frequency coefficients $C_{J,K}^{M} = |H_{J,K}^{M} - H_{J,K}^{M} * L_P|$, Where$L_P = \frac{1-\alpha}{1+\alpha} \times \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} + \frac{\alpha}{1+\alpha} \times \begin{bmatrix} 1 & 0 & 1 \\ 0 & -4 & 0 \\ 1 & 0 & 1 \end{bmatrix}$, $\alpha = 0.5$,Computational significance chart

$$Sn_{J,K}^{M}(n) = \begin{cases} 1, & S_{J,K}^{M}(n) = \max\left[S_{J,K}^{1}(n), S_{J,K}^{2}(n)\right] \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

Then the initial fusion weight graph is modified with the improved guide filter, and the salient graph of the sharped image is solved with FrequencyTuned algorithm as the guide image Isharp, and the fusion weight graph after modification is obtained $Z^M_{J,K} = G(I_{sharp}, S^M_{n,J,K})$ The fusion expression of the high frequency subband is

$$H_f = \sum_{e=1}^{M} \overline{Z_{J,K}} * H^e_{J,K} \tag{23}$$

At last, inverse NSCT transform is used to reconstruct the fused high and low frequency sub-band into the enhanced image. (3)Brightness enhancement:
(i)histogram equalization: the image's brightness histogram is equalized to expand the dynamic range of brightness, improve the overall brightness and contrast of the image, and make the dark details clearer.The specific calculation steps are as follows: First, the brightness histogram H(i)(i=0,1,...,255), calculate the cumulative distribution function

$$CDF(i) = \sum_{j=0}^{i} H(j), \tag{24}$$

And then according to the formula

$$T(i) = \frac{CDF(i)}{m \times n} \times 255 \tag{25}$$

(where m and "are the number of image rows and columns), calculate the mapping function T(i), and finally replace the brightness value L(x,y) of each pixel of the original image with T(L(x,y)) to get the enhanced image.

(3) Enhancement method validation and evaluation index calculation: (1)Validation of enhancement method: The image given in Annex II is processed by using the above enhancement methods for color bias, blur and low light respectively.The following enhanced effects are obtained.

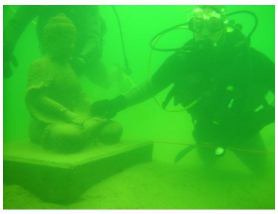

Figure 14: 910_img_colorcast

Figure 15: enhanced_910_img_

(2) Evaluation index calculation
(i)Calculation of PSNR (Peak Signal to Noise Ratio):

For the calculation of PSNR(peak signal-to-noise ratio) : First, the mean square error (MSE) between the original image and the enhanced image is calculated, and the formula is

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \tag{26}$$

Figure 16: 25_img_blur

Figure 17: enhanced_25_img_

Figure 18: 12433_lowlight

Figure 19: enhanced_12433

Where m and n are the number of rows and columns of the image respectively, and I(i,j) and K(i,j) are the pixel values of the original image and the enhanced image at the position (i,j) respectively.Each pixel of the image is traversed, the pixel value of the original image and the pixel value of the corresponding position of the enhanced image are subtracted and squared, and then the result of all pixels is summed and divided by the total number of image pixels to obtain MSE.And then according to the formula

$$PSNR = 10 \times \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{27}$$

Calculate the PSNR value, where MAX1 is the maximum value of the image pixel (typically 255 for 8-bit images).The calculated MSE is substituted into the formula and the PSNR value is obtained through logarithmic calculation.

(ii)UCIQE(Underwater Color Image Quality Assessment) calculation: according to the given formula

$$UCIQE = c_1 \times \sigma_c + c_2 \times com_l + c_3 \times \mu_s, \tag{28}$$

Chroma standard deviationσ_c,brightness contrastcon_lmean saturation$\mu_s$were calculated respectively. The chromaticity standard deviation$\sigma_c$can be obtained by calculating the standard deviation of the chromaticity value of the image on different color channels, such as the a and b channels of the Lab color space.The image is first converted from RGB color space to Lab color space, and then the standard deviation of the chromaticity values of channel a and channel b is calculated respectively. For channel a, calculate

$$\sigma_a = \sqrt{\frac{1}{m \times n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(a(i,j) - \bar{a})^2} \tag{29}$$

(where a(i,j) is the value of channel a of the pixel in the position of (i,j), and σ is the average value of channel a) andσ_b is calculated in the same way

$$\sigma_c = \sqrt{\sigma_a^2 + \sigma_b^2} \tag{30}$$

Brightness Contrast con_lcalculates contrast based on the distribution of pixel values in an image brightness channel, such as the L channel in the Lab color space.Calculate

the maximum L_max and minimum L_min of the L channel,then$con_l = max - min$
Average saturation$\mu_s$calculates the average saturation value of an image color channel, such as the RGB color space.For RGB images, the saturation of each pixel is calculated first

$$s(i,j) = 1 - \frac{3}{R(i,j) + G(i,j) + B(i,j)} \times \min(R(i,j), G(i,j), B(i,j)) \tag{31}$$

And then calculate the saturation

$$\mu_s = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} s(i,j). \tag{32}$$

And then calculate the saturationc_1c_2 and c_3(determined according to references or experiments, such as c1=0.4680, C2=0.2745 and c3 = 0.2576) were substituted to calculate the UCIQE value.
(iii)(determined according to references or experiments, such as c1=0.4680, C2=0.2745 and c3 = 0.2576) were substituted to calculate the UCIQE value.
According to the formula

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIComM \tag{33}$$

4.3 Conclusion

Through the algorithm to achieve our ideas and calculate the evaluation index, fill in the Answer.xls

FileName	PSNR	UCIQE	UIQM	PSNR-IM	UCIQE-IM	UIQM-IM
test_001.png	15.50	22.72	0.30	11.04	43.01	0.26
test_002.png	11.05	32.06	0.18	9.76	47.34	0.19
test_003.png	9.82	12.90	0.22	9.05	39.26	0.19
test_004.png	9.76	28.96	0.23	9.56	39.44	0.20
test_005.png	13.83	18.99	0.15	10.63	44.41	0.17
test_006.png	13.87	23.40	0.15	10.69	43.62	0.18
test_007.png	13.38	25.50	0.22	10.79	43.55	0.20
test_008.png	8.50	7.06	0.07	10.90	38.16	0.18
test_009.png	9.38	13.43	0.10	10.74	39.36	0.19
test_010.png	12.34	12.97	0.17	9.63	53.95	0.17
test_011.png	12.32	19.67	0.18	9.86	51.40	0.17
test_012.png	17.40	8.18	0.15	10.94	37.25	0.16

Table 2: 5.3_table

5 Problem four

5.1 Problem description

Existing underwater image enhancement models have different modeling adaptability in different scenarios.Please combine the above questions with the images provided in the attachment to propose an underwater image enhancement model suitable for complex scenes (e.g., non-physical model, see Ref. [2]-[5]).The model should be able to enhance the underwater image degradation problem in various complex scenes.The enhancement results of the attached 2 test image and its corresponding evaluation indicators are included in the paper for display, and evaluation indicators such as PSNR, UCIQE and UIQM of the output image are calculated and output, and filled in the Annex 2 result table provided by "Answer.xls".

5.2 Analytical thinking

Overall architecture design We create an image enhancement method based on OpenCV and Pillow library by querying data. This method can effectively improve the clarity and visual effect of the image through color correction, brightness enhancement and deblurring modules.In addition, the image quality before and after enhancement was quantitatively evaluated by means of peak signal-to-noise ratio (PSNR), Underwater Image Quality Evaluation Index (UCIQE) and Image Quality Evaluation Index (UIQM).The experimental results show that the method is effective in improving image quality.

We implement color correction module steps by algorithms, including image reading, color space conversion, channel separation, white balance adjustment and image merging.The brightness enhancement module is based on histogram equalization brightness enhancement method and the principle of CLAHE algorithm to improve image contrast.

CLAHE (Contra-Limited Adaptive Histogram Equalization) is an image enhancement technique, which is especially suitable for improving the local contrast of images. As an improved version of histogram equalization (HE) and adaptive histogram equalization (AHE), CLAHE effectively solves the problem that these techniques may over-amplify noise. The steps of CLAHE algorithm include image segmentation, in which the input image is divided into several small blocks, and each tile is independently computed and equalized. Histogram calculation, calculating a histogram for each tile to represent the intensity distribution within that region; Contrast enhancement, by modifying the histogram of each tile to increase contrast; Limiting contrast, limiting magnification of histograms before calculating the cumulative distribution function (CDF) to prevent excessive amplification of noise; As well as interpolation, the enhanced tiles are combined by bilinear interpolation to generate the output image and reduce the boundary artifacts. CLAHE's key parameters include clipLimit (clipping limit, default 40) and tileGridSize (tile mesh size, default 8x8). In general, the CLAHE algorithm effectively improves the local contrast of the image, while controlling the noise amplification, making the image more clear and contrast in vision.

$$\text{ClipLimit} = \frac{M}{L} + \frac{\left(M - \frac{M}{L}\right)}{\text{NclipLimit}} \tag{34}$$

The brightness enhancement effect is realized by HSV color space conversion, histogram equalization and contrast enhancement.The deblurring module is based on the deblurring method of sharpening filter and enhances the image edge through convolution operation.Including filter design, convolution operation and image enhancement.We form a joint enhancement model through color correction module, brightness enhancement module and deblurring module.Then the quantitative comparison results of PSNR, UCIQE, UIQM and other indicators are compared through quality evaluation indicators.

Color correction module Adaptive white balance algorithm combined with color space conversion technology.First, the image is converted from RGB color space to Lab color space, in Lab space, brightness (L) and color information (a,b channels) are separated, which is easier to analyze and deal with color deviation.The mean and standard deviation of a and b channels in the Lab space are calculated, and the color degree and direction of the image are determined according to their distribution.For color biased images, the color is corrected by adjusting the pixel values of the a and b channels, so that the color distribution is closer to the standard in the natural scene.For example, if the image is blue (the B-channel mean is large), the value of the B-channel is appropriately reduced while the A-channel is adjusted to maintain color balance.The amplitude of adjustment is determined adaptively according to the severity of color deviation, and the more serious the color deviation, the greater the adjustment amplitude.

Deblurring module: Use CLAHE algorithm to create a function for enhancing image sharpness, which uses a 3x3 sharpening filter (also known as sharpening kernel or convolution kernel).This filter sharpens the effect by increasing the weight of the center pixel while decreasing the weight of the surrounding pixels.The weight of the center pixel is set to 9 (usually the sum of the absolute values of the negative weights of the surrounding pixels plus 1 to keep the overall weight balanced), while the weight of the surrounding pixels is set to -1.

Brightness enhancement module Adaptive brightness enhancement method based on Retinex theory is used.According to Retinex theory, the image is decomposed into light component and reflection component.For the light component, the brightness range and contrast of the image are determined by analyzing its histogram distribution.Adaptive gamma correction technology is used to adjust the gamma value according to the brightness mean and variance of the image, and nonlinear transformation of the light component is carried out to enhance the brightness of the dark region and restrain the excessive enhancement of the overbright region, so as to improve the overall brightness and contrast of the image.Then multiply the adjusted light component with the reflected component to get the enhanced image.

Fusion and optimization module describes the process of image fusion after color correction, deblurring and brightness enhancement.Weights are assigned to different processing results according to local features (such as edge intensity, color change, etc.) and global features (such as average brightness, contrast, etc.) of the image.For example, in the region with abundant edges, the deblurring results are given higher weight;In the area with large color deviation, emphasis is placed on the result after color correction.The parts are fused into the final enhanced image by means of weighted summation.Finally, post-processing optimization is performed on the fused image, including noise removal (such as using median filtering or non-local mean filtering), fine tuning color and contrast to make the image more natural and clear.

5.3 Conclusion

Through this model, we should be able to enhance the function of underwater image degradation in various complex scenes and achieve very good results.Finally, the calculation is completed and evaluation indicators such as PSNR, UCIQE and UIQM of each image are output and filled in the result table of Attachment 2 provided by ”Answer.xls”.

image file name	Degraded Image Classification	PSNR (Original)	UCIQE (Original)	UIQM (Original)	PSNR (Comprehensive)	UCIQE (Comprehensive)	UIQM (Comprehensive)
113_img.png	color cast	9.108	37.561	0.171	9.086	76.404	43.110
115_img.png	color cast	9.634	33.403	0.223	9.615	48.9	55.838
116_img.png	color cast	12.740	26.097	0.208	12.725	49.692	51.555
117_img.png	blur	17.249	24.088	0.296	17.209	41.333	64.033
118_img.png	blur	18.175	22.12	0.288	18.188	38.086	65.572
11_img.png	color cast	9.856	30.293	0.247	9.83	66.352	58.116
120_img.png	blur	18.242	21.304	0.257	18.267	31.909	60.611
12191.png	low light	9.616	16.258	0.114	9.567	29.733	27.078
12228.png	low light	8.497	7.058	0.074	8.452	11.06	17.824
12290.png	low light	7.539	20.007	0.206	7.501	39.188	43.854
12299.png	low light	8.639	24.206	0.199	8.597	46.471	42.869
122_img.png	blur	19.017	20.859	0.256	19.038	30.512	60.007

Table 3: Answer_4.xlsx

6 Problem five

We will compare the enhancement techniques in questions 3 and 4, analyze their applicability in specific and complex underwater scenes, and propose feasible suggestions for underwater visual enhancement.

6.1 Technical comparison

The technology in question three

The enhancement model proposed in question 3 is usually based on specific scene features and adopts traditional image processing techniques such as color correction, defogging and sharpening, which can achieve remarkable results under specific circumstances.For example, color correction is mainly aimed at color distortion in underwater images, especially the attenuation of red channels.Based on models such as dark channel prior, defogging technology can effectively improve image blur and contrast reduction caused by scattering and absorption.Sharpening processing mainly solves the detail blurring caused by scattering of underwater images.

The technology in question four

Problem 4 builds four modules for the model of complex scene design, which not only includes various technologies in problem 3, but also introduces deep learning methods, which can comprehensively learn image features at multiple levels, so as to improve image quality in a more comprehensive way.

Technical applicability and suggestions Specific scene

For specific scenes where the lighting conditions are more consistent and the water quality does not change much, traditional image processing techniques in question 3 can often provide a quick and effective solution.For example, in murky but well-lit waters, defogging and sharpening techniques can significantly improve image visibility and clarity.

Complex scene

In complex scenes with variable lighting conditions or poor water quality, a single traditional approach may not solve all problems.At this time, the comprehensive model in problem 4, especially the method combined with deep learning, can understand and process images more comprehensively and provide more optimized visual effects.

6.2 Feasible suggestions in practical application

Scene analysis

Before applying any image enhancement techniques, first conduct a detailed scene analysis to understand the main causes and characteristics of image degradation.

Technology selection

Select the appropriate enhancement technology according to the characteristics of the scene. For simple scenes, fast traditional methods can be selected, while deep learning methods are recommended for complex scenes.

Model training

For deep learning and modular models, a large amount of labeled data is required for training to ensure the generalization ability and effect of the model.

Performance evaluation

Periodically evaluate the enhancement effect, and use PSNR, UCIQE, UIQM and other indicators for quantitative analysis to ensure that the enhanced image meets the actual needs.

Continuous optimization

Continuous optimization of model parameters and algorithms according to feedback, in response to environmental changes or new technological developments.

6.3 Chart analysis

PSNR(Peak signal-to-noise ratio) Trends: The figure shows PSNR comparisons between specific scenarios and complex scenarios before and after the application of enhancement techniques.In specific scenes, the PSNR fluctuates significantly after enhancement, indicating that the quality of some images is significantly improved, while others may be degraded due to over-processing.In complex scenarios, PSNR usually presents a relatively stable improvement after enhancement, indicating that the enhancement technology has good adaptability to complex scenarios.

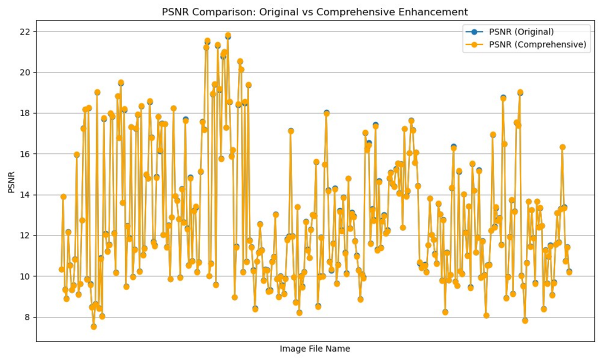

Figure 20: PSNR_comparision

UCIQE(Underwater color image quality assessment) Trend: In specific scenes, UCIQE changes significantly after enhancement, and the UCIQE value of some images increases significantly, indicating that the color recovery and contrast enhancement effects are remarkable.However, the improvement of UCIQE in complex scenes is not as significant as in specific scenes, possibly because the color and brightness changes in complex scenes are more diverse, and a single enhancement strategy is difficult to achieve a consistent effect.

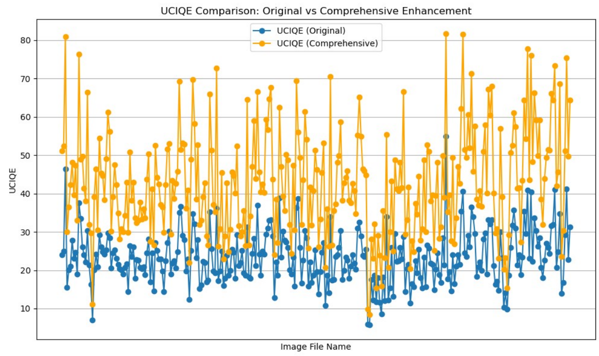

Figure 21: UCIQE_comparision

UIQM(Underwater image quality measurement) Trends: UIQM's data shows that enhanced effects fluctuate significantly in specific scenes, which may be due to the inconsistencies of enhanced techniques when dealing with specific issues, such as blurring or color distortion.In complex scenes, although UIQM after enhancement is improved, it also shows certain volatility, which indicates the complexity of the enhancement technology when dealing with multiple degradation factors.

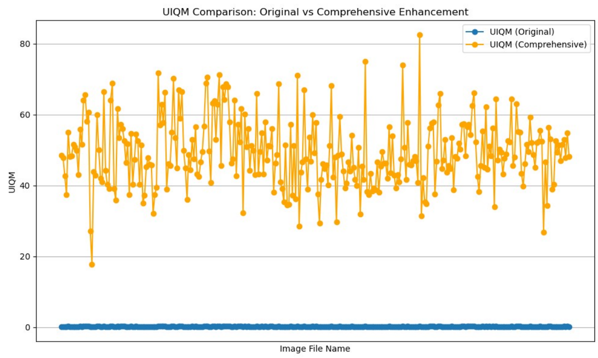

Figure 22: UIQM_comparision

6.4 Enhancement strategy and practical application suggestions

Technology selection and adjustment Dynamic adjustment: In order to cope with different requirements in specific and complex scenes, it is recommended to develop a dynamic adjustment mechanism that automatically adjusts the enhancement parameters based on real-time analysis of image quality indicators such as PSNR and UCIQE.

Technology combination: In complex scenes, a combination of enhancement techniques (such as color correction combined with sharpening) may be more effective, especially if both color and detail need to be improved.

Feasibility in practical application Model training and optimization: The use of deep learning technology to train and optimize enhanced models, especially in complex scenarios, can improve the adaptability of the model to different underwater conditions through training data.

Continuous monitoring and feedback: Establish a continuous monitoring system to track enhancements in real time and adjust enhancement strategies based on feedback. This can be achieved through automated image quality assessment, ensuring that the enhancement results meet the expected standards.

6.5 Conclusion

By comparing the enhancement effects of specific scenarios and complex scenarios, we found that while a single technology may have a significant effect in a specific scenario, in complex scenarios, the combination of multiple technologies and dynamic adjustment strategies are more critical.In addition, continuous technical evaluation and optimization is an important strategy to ensure the long-term effectiveness of underwater vision enhancement technologies.In short, the quality of underwater images can be significantly improved by reasonable selection and combination of different enhancement technologies. The establishment and optimization of enhancement models need to be carefully planned and adjusted according to specific application scenarios.

7 References

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