Restoration and Enhancement of Underwater Under-Exposure Images with Detail-Preserving

Xujian Li
shandong university of science and technology
Ke Liu (keliucs@163.com)
Shandong University of science and technology

Research

Keywords: Edge detail enhancement, guided filter, underwater under-exposure images

Posted Date: February 27th, 2020

DOI: https://doi.org/10.21203/rs.2.24728/v1

Restoration and Enhancement of Underwater Under-Exposure Images with Detail-Preserving

Xujian Li [1], Ke Liu [2*]

[1] Shandong university of science and technology
[2] Shandong university of science and technology

Received: date; Accepted: date; Published: date

Abstract: Underwater images have great practical value in many fields such as underwater archeology, seabed mining, and underwater exploration. Due to the complex underwater environment, there are problems such as poor light, low contrast, and color degradation. Traditional underwater image processing methods cannot well achieve the goal of clear display under extreme conditions. This paper proposes a method for restoration and enhancement of underwater under-exposure images that protects edge details and enhances image color. Firstly, the underwater image was preprocessed, denoising with improved wavelet threshold function, defogging with the Multi-Scale Retinex Color Restoration (MSRCR) and guided filter method. Then, the method of adaptive exposure graph is used to enhance the under-exposure image. Finally, the deep learning algorithm combined with the Non-Subsampled Contour Transform (NSCT) technology is used to solve the problem of color degradation and edge texture weakening. Experiments show that compared with other underwater image processing methods, this method greatly improves the clarity of the image, enhances the color saturation and the edge texture details of the image, and has a better visual effect.

Keywords: Edge detail enhancement; guided filter; underwater under-exposure images

1. Introduction

At present, more and more activities are carried out underwater by human beings, such as underwater archaeology, seabed biological collection, Marine fishery breeding and so on. Due to the complicated underwater environment, the obtained images often appear dim, noisy, color degradation, detail loss and other problems, there is an urgent need for clear, high-quality underwater images.

1.1.Research status and problems

For these problems, [1] proposed a weighted mapping for each image based on some established exposure metrics, then an orderly fusion is performed. During the fusion process, each image must have different exposure information. However, this solution does not take into account the movement of the camera during the image exposure. Therefore, caused image blur; In response to this situation, [2] proposed a method using only a single under-exposure underwater image. Firstly, an LDR image was generated from a histogram. Next, the high-frequency region of the LDR image obtained in the foregoing is combined with the smooth region of the average filtered image to jointly denoise. Finally, the LDR image is fused to generate a new image. In the image fusion operation, although the edge details of the image are retained, the intensity of the image is reduced, and the color of the image is degraded, that is, the color of the image is enhanced And retaining the details is not the best of both worlds, many image fusion methods also have such problems; Some people use energy as the minimum value to obtain the best results. Reference[3] uses the energy function composed of two terms to achieve the effect of enhancing the exposed image, although it can retain the image color and edge texture However, it is necessary to increase the smoothness constraint on the image, so that the computational complexity of the image is greatly increased, and the generation efficiency is reduced; Literature [4] proposed a realization idea of the red channel.

Experiments have shown that although the color related to short wavelength can be enhanced, the method used is limited by the accuracy of the optical model and parameter estimation; Reference[5] proposed a Rayleigh-distributed color model fusion method, which not only reduced image noise, but also improved the contrast of the image to a certain extent, but led to excessive image enhancement; The enhancement method of underwater image based on defogging and color correction proposed in [6], although it solves the interference of noise and fog, however, there may also be problems with insufficient or excessive image enhancement; Reference [7] used a single underwater image restoration method by combining the blue-green channel and the red channel. First, the blue-green channel was restored by the defogging algorithm, and then the red channel was corrected by using the gray world hypothesis theory. Adapting to the exposed image and solving the problems of overexposure and underexposure largely eliminated the exposure problem of the image, but did not retain the details of the image well; Reference [8] proposed an under-exposure image enhancement method that achieves detail preservation through optimal weighted multiple exposure fusion. First, a multiple exposure image sequence is generated, and then an energy function is constructed to preserve the image color and edge detail parts. The method eliminates the exposure, retains the color of the image well, and the image enhancement effect is obvious, but the poor coloring and noise still exist in the dark area, and the calculation efficiency of the algorithm is not high.

1.2. The work of this paper

For the above-mentioned series of problems, this paper implements a method for restoration and enhancement of underwater underexposure images with preserved details. Firstly, the improved wavelet denoising function was used to remove a series of noises in the image, and the Multi-Scale Retinex with Color Restoration (MSRCR) was combined with the guided filter to solve the problem of fog in the underwater image. Because of the combination of the guided filter, it also protects the edge details, which greatly improves the image quality. Then, for the problem of low light in the image, an improved image histogram equalization method is adopted in this paper, which not only improves the brightness of the image, but also preserves and enhances the color of the image. The method of adaptive exposure combined with guided filter uses the optimal adaptive exposure map, so that the problem of uneven lighting is well solved, and the algorithm implementation is very efficient; Finally, for the underwater image after adaptive exposure processing, the color degradation of some areas may exist. This paper uses super-resolution convolutional neural network (SRCNN) combined with non-subsampled contour transform (NSCT) method, which is effective to enhances the color of underwater images, and also solves the problem of local edge texture loss. The experiments in the real image library show that compared with other methods, the MSRCR combined with the guided filter defogging method, the exposure image enhancement method, and SRCNN combined with the NSCT method are used in defogging, denoising, detail preservation and exposure enhancement Even better. The main contributions of this paper are as follows:

- A new method for defogging underwater under-exposure images is proposed, which is better than the latest method for defogging and keeps edge details.
- The super-resolution convolutional neural network is combined with the guided filter, which can enhance the color and protect the edge details of the image after adaptive exposure processing. As a result, the quality and clarity of the image is better.
- The algorithm implemented in this paper is simple and the computational efficiency is higher than other methods.

The structure of this paper is as follows: the first part briefly introduces the research method and algorithm of this paper. The second part introduces the method of image restoration. The third part introduces the image enhancement method. The fourth part is the experimental results and analysis of this method. Finally, the conclusion is given.

2. Related Work

The processing of underwater images is mainly focused on the dehazing, denoising, and enhancement of color and edge details. We discuss the background of the related works in the following sections.

2.1. Wavelet threshold function

The denoising effect of the traditional wavelet threshold function is related to the threshold function and reconstruction accuracy, while the traditional threshold function mainly includes soft threshold and hard threshold functions.

Where the hard threshold function is expressed as:

$$s_{j,k} = \begin{cases} \rho_{j,k} & |\rho_{j,k}| > \delta \\ 0 & |\rho_{j,k}| \leq \delta \end{cases} \quad (1)$$

$\rho_{j,k}$ Represents the wavelet coefficient with noise, $s_{j,k}$ Represents the output wavelet coefficient. When the hard threshold function is used, it will protect some details, but the function is discontinuous at the $\pm\delta$. Therefore, in the process of reconstruction of wavelet coefficients, Gibbs-like phenomena is easy to occur.

Soft threshold function:

$$s_{j,k} = \begin{cases} sgn(\rho_{j,k}) * (\rho_{j,k} - \delta) & |\rho_{j,k}| > \delta \\ 0 & |\rho_{j,k}| \leq \delta \end{cases} \quad (2)$$

Formula (2) can be concluded that the soft threshold function improves the flaw of the hard threshold function, that is, the soft threshold function is continuous at $\pm\delta$, but will lead to the loss of local value.

2.2. Super-resolution convolutional neural network (SRCNN)

The task goal of super resolution is to convert the input low-resolution image into high-resolution image, which is consistent with image de-noising and image de-blurring. Super-resolution focuses on how images from small to large sizes are filled with new pixels; Image de-noising is concerned with replacing the "contaminated" pixels with the correct ones without changing the image size.

SRCNN is the first end-to-end super-resolution algorithm using CNN architecture (that is, based on deep learning), which is better than the traditional multi-module integration method.

1)The structure of SRCNN is relatively simple. The whole convolutional network consists of three convolutional layers, even without pooling and full connection layers;

2) Convolution operation is performed on low-resolution graphs to generate n1-dimensional feature maps;

3) Conduct convolution operation on n1-dimensional feature map to generate n2 dimensional feature maps;

4) The n2 dimension feature maps are convolved to generate super-resolved images.

There are three processing processes:

1) Extract image features: extract multiple patch image blocks from low-resolution images. Each block is represented by convolution operation as a multi-dimensional vector (the dimension is equal to the number of filters), and all feature vectors constitute feature maps.

2) Nonlinear mapping: the n1 dimensional feature matrix is transformed into another n2 dimensional feature matrix through convolution operation to realize the nonlinear mapping.

3) Image reconstruction: it is equivalent to a deconvolution process, and the characteristic matrix of n2 is restored to the super-resolved image.

The objective loss of the training is to minimize the super-resolution image and the original high-resolution image X based on pixel mean square error. The definition is as follows:

$$L(\theta) = 1/n \sum_{i=1}^{n} \|F(Y_i; \theta) - X_i\|^2 \quad (3)$$

Where, n is the number of training samples, that is, the number of samples for each training. The next step is nothing more than the stochastic gradient descent method back propagation, network training to obtain the final parameter to minimize the loss , the parameter update formula is as follows:

$$\Delta_{i+1} = 0.9 * \Delta_i + \mu(\vartheta L / \vartheta W_i^{\delta}) \quad (4)$$

$$W_{i+1}^{\delta} = W_i^{\delta} + \Delta_{i+1} \quad (5)$$

2.3. Multi-scale retinex with color restoration (MSRCR)

Retinex is a combination of the words Retina and Cortex. Retinex theory mainly includes two aspects: the color of an object is determined by its ability to reflect long, medium and short waves, rather than by the absolute value of the intensity of the reflected light; The color of the object is not affected by the inhomogeneity of illumination and has consistency.

Single Scale Retinex, with a small Scale value, can better complete the dynamic range compression, and the details of the dark region can be better enhanced, but the output color is prone to distortion. When the value is larger, the color sense consistency is better.

Multi-scale Retinex can not only realize the compression of dynamic range of images, but also keep the consistency of color perception. The implementation steps are slightly different than those of a single scale, but both have problems with color skew. Multi-scale Retinex with Color Restoration (MSRCR) for better visual effects. In comparison, (1) the effect of MSRCR is much better than that of MSR, basically eliminating color bias. (2) for MSRCR, the resulting image of scale number pair is not particularly large, but the algorithm time will increase linearly with the increase of scale number. Therefore, it is more appropriate to take 3 as the general scale number.

2.4. Non-subsampled contour transform (NSCT)

The core of the Non-Subsampled Contour Transform (NSCT) transformation is Contourlet, the transformation of the edge. Non-downsampling is based on the frequency domain, that is, for an image, a frequency threshold is set first, and then the image is screened out with a filter that is greater than or equal to the threshold frequency (of course, this is not a one-time screening process, but an iterative process of using a two-channel bandpass filter without downsampling).

3. Methodology

Due to the uneven distribution of underwater light, the water body contains many impurities, and the uncertainty of the external environment at the time of shooting the images, the images obtained under water contain different levels of noise and underwater fog. In this paper, an improved wavelet threshold function is used to denoise, and a combination of MSRCR and a guided filter is used to remove underwater fog. Experiments prove that the methods of de-drying and defogging adopted in this paper are better than the current optimal methods.

3.1. Image Denoising

In order to further make up for the shortcomings in the two functions, this article has made improvements. By transforming the base value of the exponential function and the independent variable, the wavelet coefficients can be further manipulated to better solve the noise problem. And the function is uninterrupted at $|\rho_{j,k}| = \delta$., perfecting the shortcomings of the hard threshold and soft threshold functions, the formula is as follows:

$$s_{j,k} = \begin{cases} 1 + sgn(\rho_{j,k}) * \left[\rho_{j,k} - \frac{\delta}{2+\alpha} * \mu \sqrt[3]{\rho_{j,k}^2 - \delta^2} \right] & |\rho_{j,k}| > \delta \\ 1 + sgn(\rho_{j,k}) * \frac{\alpha}{2+\alpha} * b^{10*(|\rho_{j,k}| - \delta)} * |\rho_{j,k}| & |\rho_{j,k}| \leq \delta \end{cases} \quad (6)$$

$\rho_{j,k}$ Represents the wavelet coefficient with noise, $s_{j,k}$ Represents the output wavelet coefficient, δ and α are two parameters. This function performs better in denoising images than other denoising functions, and computes more efficiently. Fig.1 shows the comparison of the three functions.

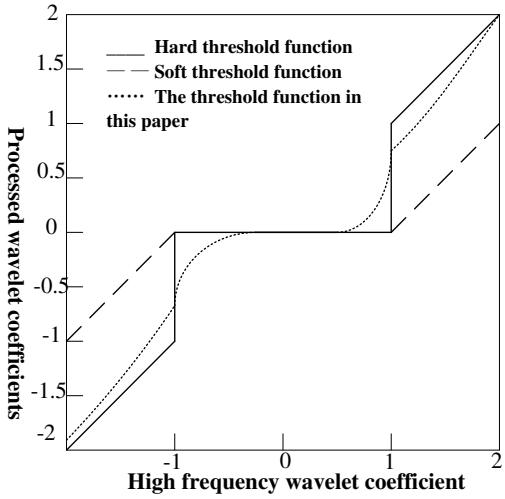


Fig.1.Comparison of different threshold function curves

The curve comparison chart of the hard threshold function, soft threshold function and the threshold function used in this paper is shown in Figure 1. Comprehensive analysis shows that the threshold function in this paper is better than the hard and soft threshold functions in processing.

In formula (6), the selection of the threshold value δ has a great influence on the de noising. If δ is selected too small, the noise will not be completely removed, resulting in unsatisfactory image effects; if δ is too large, the denoising Excessive, resulting in distortion of the image. Therefore, this paper uses the method of Bayesian threshold [9] to make the threshold of each layer automatically shrink as the wavelet decomposition scale increases:

$$\mathrm{z(X)} = \mathrm{E}(\tilde{x} - x)^2 = E_x E_{x|y}(\tilde{x} - x)^2 = \iint (n(y) - x)^2 P(y|x) P(x) dy dx = \gamma^2 \rho(\frac{\gamma_x^2}{\gamma^2}, X/\gamma) \quad (7)$$

$$\rho(\gamma_x^2, X) = \gamma_x^2 + 2(X^2 + 1 - \gamma_x^2)\varphi\left(\frac{X}{\sqrt{1+\gamma_x^2}}\right) - 2X(1 + \gamma_x^2) * \varphi(X, 1 + \gamma_x^2)) \quad (8)$$

Density function:

$$\varphi(\mathrm{x}, \gamma_{\mathrm{x}}^2) = (1/\sqrt{2\pi\gamma^2})\mathrm{e}^{(-\mathrm{x}^2/2\gamma^2)} \quad (9)$$

$$\overline{\varphi(\mathrm{x})} = \int_x^{\infty} \varphi(t, 1) dt \quad (10)$$

Threshold calculation expression:

$$X_j = \gamma^2/\gamma_x \quad (11)$$

Among them, γ^2represents the variance of noise, γ_{x} represents the standard deviation of the sub-band coefficients, and j represents a certain layer of the layer.

For the calculation of γ^2 in (11), the method mentioned in [9] is used:

$$\gamma = \mathrm{median}(|s_{j,k}|)/0.6745 \quad (12)$$

$$\overline{\gamma} = 1/\mathrm{n}\sum_{i=1}^{n} s_{j,k}^2 \quad (13)$$

In formula (13), n represents the length of the decomposition wavelet coefficient of each layer, which is known from $\gamma_{\mathrm{s}}^2 = \gamma^2 + \gamma_{\mathrm{x}}^2$:

$$\gamma^2 = \sqrt{\max(\gamma_s^2 - \gamma^2, 0)} \quad (14)$$

Therefore, according to (12) (13) (14), the Bayesian threshold is jointly obtained, that is, the adaptiveness of the Bayesian threshold between different layers is obtained, thereby highlighting the benefits of the algorithm in this paper.

For the parameters δ and α in the improved threshold function, this paper uses the particle swarm optimization algorithm mentioned in [10] to solve.

By applying the improved wavelet threshold function to the de-noising problem of underwater images, a series of noises appearing in the image are fully solved, and the visual effect of the image is greatly improved. The de-noising effect is shown in Fig.2.

(a) Original image (b) Denoised image

Fig.2. Denoising results

3.2. Image defogging

In order to overcome the problem of the color deviation of Multi-Scale Retinex(MSR) and the image enhancement effect is not ideal, reference [11] used the MSRCR algorithm to deal with the problem of image enhancement. Although the effect of MSR color shift was largely eliminated, the image still has the problem of faded details. Aiming at such problems, this paper proposes a method of combining the MSRCR algorithm with a guided filter to complete the defogging of underwater images.

$$\mathrm{RMSRCR(x,y)'} = \mathrm{G} \cdot \mathrm{RMSRCR(x,y)} + \mathrm{b} \quad (15)$$

$$\mathrm{RMSRCR(x,y)} = \mathrm{C(x,y)RMSR(x,y)} \quad (16)$$

$$\mathrm{C(x,y)} = \mathrm{f}\left[\frac{\mathrm{I'(x,y)}}{\sum I(x,y)}\right] C_i(x,y) = f[I_i'(x,y)] = f[I_i(x,y)\sum j] \quad (17)$$

$$\mathrm{f[I'}(x,y) = \beta \log[\alpha I'(x,y)] = \beta\{\log[\alpha I'(x,y)] - \log[\sum I(x,y)]\} \quad (18)$$

Among them, G represents the gain Gain (usually 5), b represents the offset Offset (usually 25), $\mathrm{I(x,y)}$ represents the image of a channel, C represents the color recovery factor of a channel, adjust the ratio of the color of the three channels, $\mathrm{f}(*)$ represents the mapping relationship of the color space, β refers to the gain constant (valued as 46), and α refers to the controlled non-linear intensity (valued as 125).

Experiments prove that MSRCR can remove the fog phenomenon in the original underwater image well, and enhance the contrast and saturation of the color in the image. The guide filter can protect the edge details and also has a certain defogging function. The combination of the two methods not only makes the defogging effect more efficient, but also enhances the color of the image to a certain extent and the edge details more clearly, thereby improving the efficiency of the algorithm. Fig.3 is an image result of continuing the defogging based on Fig.2. It is obvious from figure 3 that the de-fogging method adopted in this paper has a very ideal de-fogging effect.

(the original image on the left; the image after the defogging on the right)

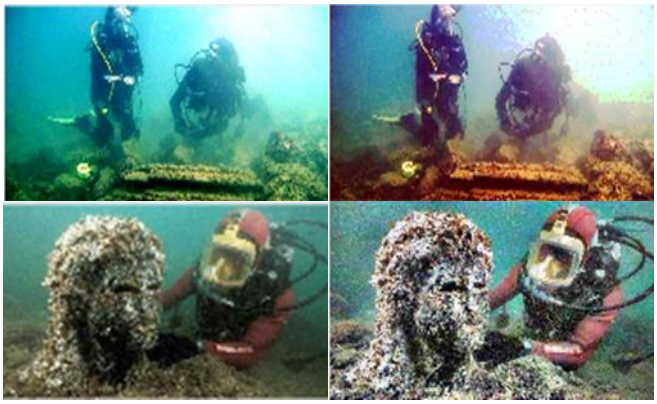
Fig.3. Dehazing effect

3.3. Underwater image enhancement

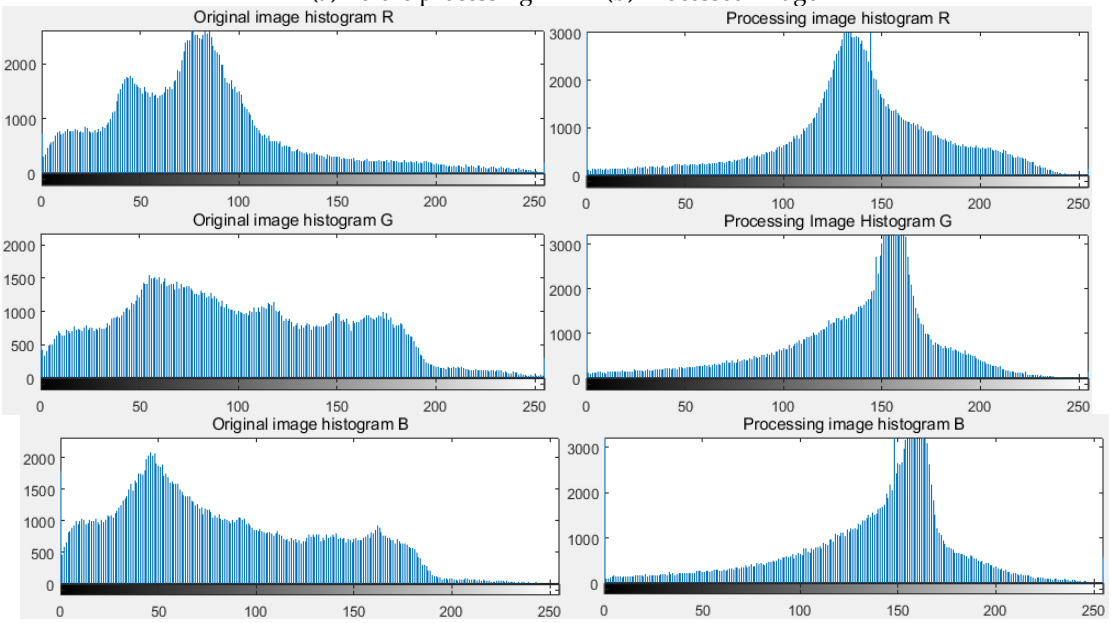
For underwater archaeology and Marine biological collection, it is difficult to obtain clear underwater images due to the change of underwater water flow, uneven lighting and other

practical conditions, but the practical value is becoming higher and higher. Therefore, it is very important to enhance the underwater under-exposure image.

After the previous image restoration stage, to some extent, some information can be obtained from the current image, but there is still the problem of low image bright ness. In response to this problem, this paper uses the improved histogram equalization image enhancement method proposed by Dong Lili et al. [12] to process the image, which has two effects:1) Improved the bright- ness of underwater under-exposure images;2) It also has a great effect of maintaining and enhancing the color of the image, avoiding the appearance of Artefact. However, experiments have shown that in the process of increasing the brightness of this method, some images may cause some areas of the resulting image to appear lighter or darker. See Figure 4.



(a) Before processing **(b)** Processed image



(c) Is the histogram of the second image in (a)

Fig.4. Improved histogram equalization results

In view of the above phenomena, this paper uses an adaptive exposure map method. First, we further improved the adjustment results based on the adaptive exposure map [13], and obtained the adaptive image exposure map f (x) from the solution of the optimal value in this document:

$$\min_{f} \sum_{x}\{[2 - f(x)Y_{J(X)}/Y_{I(x)}]^2 + \alpha[f(x) - 2]^2\} + \varphi(f) \quad (19)$$

Among them, f (x) represents the adaptive risk map, $Y_{J(X)}$ represents the light intensity of the restored image, $Y_{I(x)}$ represents the light intensity of the input image, α is a constant 0.3, and $\varphi(*)$ represents a smooth positive Regularization.

The optimization solution is divided into two steps. The first is to solve f(x) when $\varphi(*)$ is ignored, which is an auto-closed value; the second is to introduce the guided filter into the solution, which leads to the ideal answer. Here, the estimation function is obtained as:

$$\mathrm{f(x)} = GF_I\left[\left(Y_{J(X)}Y_{I(x)} + \alpha Y_{I(x)}^2\right)/\left(Y_{J(x)}^2 + \alpha Y_{I(x)}^2\right)\right] \quad (20)$$

Further draws:

$$\mathrm{OutputExp} = J^c(x).* f(x), c \in \{r, g, b\} \quad (21)$$

Among them, $J^c(x)$ represents a restored image, and f(x) represents an adaptive exposure image.

Under-exposure images, the processed images have the problem of edge detail dilution to varying degrees, accompanied by the occurrence of local edge color degradation. To this end, the improved super-resolution convolutional neural network (SRCNN) combined with the non-sub sampled contour transform (NSCT) technology is used to enhance the image color and edge details. Based on the super-resolution based on color features proposed in reference [14-15], this paper makes some improvements. Firstly, the initial image is optimized by SRCNN, which contains three convolutional neural layers. The original image is divided into three parts, namely RGB channel. Then, using CNN to perform training operation on the image, three new images are obtained, and the new images are fused with each other to obtain the fused image. Finally, the fused image is processed by NSCT [16-17] to obtain the final ideal image.

Step 1: channel processing. Cut the initial image into three channels: R, G and B, and each channel can get its own information. The formula is as follows:

$$Y_i = image(Y_i) \quad (i = R, G, B) \quad (22)$$

In equation (22), i represents three channels of R, G, and B, and Y represents the original image of CNN.

Step 2: CNN training. The formula is as follows:

$$Y_i = \max\left(0, S_i * Y_{i(i-1)} + C_i\right) \quad (i = 1,2,3) \quad (23)$$

In equation (23), S_i represents the convolution kernel of each layer of the CNN, C_i represents the bias of each layer of the CNN, and $Y_{i(i-1)}$ represents the output result after the fifth convolution.

Step 3: Image fusion. The formula is as follows:

$$\mathrm{Y} = \mathrm{cat}(Y_R, Y_G, Y_B) \quad (24)$$

Step 4: NSCT algorithm processing. The NSCT operation is performed on the fused image. This method uses a tower decomposition algorithm to decompose the initial image into two parts, high-pass and low-pass. Then use NSDFB (Non-Subsampled Directional Filter Banks) to decompose the high frequency sub-band into several directional sub-bands, and for the low frequency part, continue to de-compose according to the method described above. The final image is obtained.

By using deep learning convolutional neural network and NSCT technology to enhance the color, the ideal goal has been achieved. NSCT can achieve rapid trans- formation at different scales and directions. The experiment proves that the method combining SRCNN and NSCT can not only further enhance the degree of idealization of color, but also maintain and enhance the edge details of the image to the greatest extent.

As mentioned above, the method of adaptive exposure graph is used to deal with the exposure problem, and the color and edge details are enhanced by combining SRCNN and NSCT technology, which plays an irreplaceable role in improving the image clarity, enhancing the color and edge details.

4. Experimental Results

The method proposed in this paper systematically illustrates how to transform an underwater image full of noise, underwater fog and dim light into a high-quality image that can be clearly read by people from two aspects of image restoration and enhancement. Among them, it is better than other methods in defogging underwater under-exposure images, enhancing image color, maintaining and enhancing local edge details.

4.1.Experimental result and theoretical analysis

In order to further verify the superiority of the method used in this paper, this paper compares the methods of other literatures in the image restoration and image enhancement stages, as follows:

The first stage. This paper compares the method of YUJIE LI et al. [18] and the method of Pan-wang PAN et al. [19], and the results are shown in Fig.5.

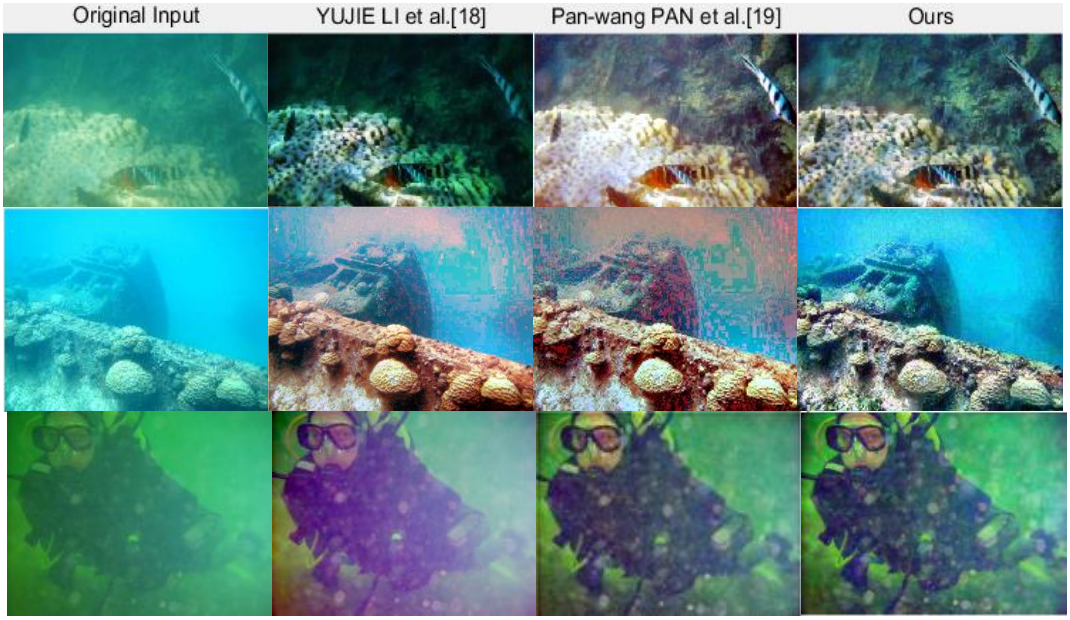


Fig.5. Comparison of the results of different image restoration methods

It can be clearly seen from the comparison of the three sets of images in Fig. 5 that the literature [18] is relatively good in defogging and maintaining details of the image, but the color of the local area is darker, and the color difference from the normal image is too large. And a certain blur appears in the image after denoising. Literature [19] is relatively good at defogging and color control, but there is also a certain degree of blurring in the image, and it does not make much contribution to the retention of edge details, resulting in the desalted detail texture of the processed image and the lack of clarity. The method used in this paper is better than other methods in denoising, fogging, preserving details and protecting colors of underwater under-exposed images. In order to further illustrate the clarity comparison of different methods, signal to noise ratio (SNR) is adopted, as shown in table 1.

Table 1 SNR comparison

No.	References [18]	References [19]	Ours
Fig.4(a)	36.46	37.52	40.67
Fig.4(b)	38.61	39.27	42.39
Fig.4(c)	36.53	37.14	40.13

The second stage. The method in this paper will be compared with the method proposed by D. Wang et al. [20] and T. Uemura et al. [21]. The qualitative comparison is shown in Fig.6.

Fig. 6. Comparison of the results of different image enhancement methods

From left to right, the four sets of images in Fig.6 are the original image, D. Wang et al. [20], T. Uemura et al. [21], and the method of this paper. It can be seen that the results achieved by D. Wang et al.'S method can achieve a dehazing effect, but the image clarity and color have not achieved the desired effect. Although the method of T. Uemura et al. Has achieved the effect of defogging, and can make a certain degree of effort in terms of color preservation and enhancement, it fails to improve the degradation of edge details. However, the method in this paper not only fully realizes the efficient defogging effect, but also enhances the image color and edge texture, making the image sharper and achieving the ideal visual effect.

Next, the paper uses the image Entropy and gradient average value(AVG) to calculate and analyze the corresponding implementation results of different methods in Fig.6, as shown in Table 2. Among them, the entropy of the image can be used to represent the statistical characteristics of the image. It shows the average signal amount. The size of the entropy value intuitively highlights the quality and clarity of an image. The gradient average value can not only reflect the sharpness of the image, but also can indicate changes in edge texture details. As the gradient average value becomes larger, the blurriness of the image will become smaller, that is, the more the image will be the clearer.

Table 2 Comparison of entropy and AVG

Image	Method	Entropy	AVG
Image1	D.Wang	7.4218	0.1179
	T.Uemura	7.6126	0.1258
	Our	7.7829	0.1324
Image2	D. Wang	7.3852	0.1098
	T.Uemura	7.4635	0.1175
	Our	7.5397	0.1253
Image3	D. Wang	7.3758	0.1137
	T.Uemura	7.5461	0.1248
	Our	7.6283	0.1309
Image4	D. Wang	7.4106	0.1135
	T.Uemura	7.4913	0.1268
	Our	7.5372	0.1325

It is obvious from the image entropy and gradient average values in Table 2 that the method used in this paper is better than the other two methods. Experiments show that the method used in

this paper is very effective in solving the problems of noise, fog, dim light, color degradation and loss of edge details in underwater images. Therefore, it is known from experiments and qualitative analysis that the method used in this paper is superior to the other two methods, and further improves the visual effect of underwater images.

4.2.Application under other circumstances

The experimental verification shows that the method in this paper also plays a certain role in restoring and enhancing non-underwater images. It can also deal with foggy and noisy underexposure images taken in daily life, and the processing results are considerable. See Fig.7.

(a) original image **(b)** processed image

Fig.7. Processing effect of underexposure in other cases

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.

5. Discussion

In the first stage of this paper (section 4.1), the restoration of underwater under-exposure images is carried out, including two experiments of underwater image de-noising and de-fogging. The specific implementation method and experimental results are shown in sections 2.1 and 2.2. An improved wavelet threshold function is used for denoising, in which the Bayesian threshold is used, and the threshold of each layer can be adaptively reduced as the wavelet decomposition scale increases, and it is also used in [10] Particle swarm optimization algorithm, its benefits are that the algorithm is simple and easy to implement, the convergence speed is fast, and fewer parameters are set; Use the method of MSRCR combined with the guide filter to remove fog. Among them, MSRCR can not only remove the fog, but also can greatly protect the color of the image during the processing. The restoration effect of the image is remarkable, and the efficiency of the algorithm is improved. In Fig. 5, the experimental results of this paper are compared with YUJIE LI et al. [18] and the method of Pan-wang PAN et al. [19]. YUJIE LI et al. [18] first performed defogging and gamma correction on the original image, then SRCNN is used to enhance the color of the image, the contribution of this paper is that the color of the image is well protected and enhanced, the disadvantage is that the enhancement of the edge details of the image has not achieved the desired effect, and the brightness processing also did not achieve good results. Pan-wang PAN et al. [19] first adopted a multi-scale iterative framework to remove underwater scattering, then refined it through an adaptive bilateral filter, and finally used NSCT to perform edge denoising. The

advantage of this paper is the use of deep learning methods to remove the color distortion of the image, the disadvantage is that there are no targeted measures for underwater fog, which results in the processed image is not very clear. From the experimental results and the signal-to-noise ratio of the image, it can be seen that the method of restoration and enhancement of underwater underexposure images with preservation of details used in this paper is optimal.

The second stage (Section 4.2) of this paper is to enhance the underwater image, including the exposure processing of the underwater image, the enhancement of image color and edge details, the method of adaptive exposure map combined with a guided filter is adopted. After the first stage, the overall effect of the image is dark, although after the improved histogram equalization process, there is still a certain degree of poor exposure for the local area of the image, so the method of solving the optimal value of the adaptive exposure map combined with the guided filter method perfectly solves this problem. Finally, for the phenomenon that the processed underwater image may not have obvious local area colors and lost edge details, this paper uses the method of SRCNN combined with NSCT, which has the best effect on enhancing the local color and edge texture. In comparison experiments with D. Wang et al. [20] and T. Uemura et al. [21], it can be concluded that there are different degrees of shadows in their implementation effects, and the sharpness and saturation of colors in the images is not as effective as the method of this paper. Further, by comparing the experimental results with those in Table 2, we can see that the method used in this paper is the best.

6. Conclusions

To solve the problem of underwater underexposure image restoration and enhancement, this paper adopts the method of image preprocessing and SRCNN. First, the improved wavelet threshold function was used to solve the image noise problem, and then the MSRCR combined guided filter was proposed to remove the underwater fog. Experiments show that the effect of defogging is better than the existing methods, and the efficiency of calculation is higher, which is also a great innovation of this paper. Then, the improved histogram equalization is used to improve the brightness of the image and play a role in enhancing the color of the image. Finally, SRCNN algorithm combined with NSCT technology is used to further improve the phenomenon of local area edge detail dilution and color degradation in the image after exposure processing. The experimental results show that the underwater underexposure image restoration and enhancement method is better than other methods and achieves the desired goal. However, there are still some shortcomings in the method in this paper. For underwater images with heavy noise, too much fog and too little light, the advantages are not obvious after image processing. Next, it will make further consummation in this respect.

List of abbreviations

Abbreviations	Meaning
SRCNN	Super-resolution convolutional neural network
MSRCR	Multi-scale retinex with color restoration
NSCT	Non-subsampled contour transform
AVG	Gradient average value
MSR	Multi-Scale Retinex
SNR	Signal to noise ratio
CNN	Convolutional Neural Networks
NSDFB	Non-Subsampled Directional Filter Banks

Acknowledgements

Thanks to my teachers and classmates for their help in the paper writing; It was with their encouragement and guidance that I finally finished this paper.

Authors' contributions

The first draft of the paper、Formula analysis、review of articles and experimental data are completed by Ke Liu, Revision, review and fund management of papers are completed by Xujian Li.

Authors' information

Xujian Li, Associate professor, master tutor, he is currently working at the school of computer science, shandong university of science and technology, Qingdao, Shandong, China. Main research areas: graphics and image processing, computer vision, cloud computing.

Ke Liu, Master degree, he is currently studying at the school of computer science, shandong university of science and technology, Qingdao, Shandong, China. Main research areas: graphic image processing, deep learning.

Funding

The authors acknowledge this paper was supported by the National Key Research and Development Program of China under Grant 2017YFC0804406.

Availability of data and materials

Data and implementation codes for all experiments are based on python and matlab.

Competing interests

Not applicable

Author details

[1] Associate professor, master tutor, member of jiusan society, Shandong university of science and technology, 266000; xjlee@163.com. Tel: +86-13863963003

[2,*] Master, school of computer science and engineering, Shandong university of science and technology, 266000; keliucs@163.com. Tel: +86-18354238263

References

1. S. Li and X. Kang, "Fast multi-exposure image fusion with median filter and recursive filter," IEEE Trans. Consum. Electron. May 2012,vol. 58, no. 2,pp. 626–632.
2. J. Im, J. Jeon, M. H. Hayes, and J. Paik, "Single image-based ghostfree high dynamic range imaging using local histogram stretching and spatially-adaptive denoising," IEEE Trans. Consum. Electron. Nov. 2011, vol. 57,no. 4, pp. 1478–1484.
3. M. Bertalmío and S. Levine, "Variational approach for the fusion of exposure bracketed pairs," IEEE Trans. Image Process. Feb. 2013, vol. 22, no. 2,pp. 712–723.
4. A. Galdran z, D. Pardo, A. Picon, and A. Alvarez-Gila, '"Automatic red-channel underwater image restoration,"Journal of Visual Communication and Image Representation. 2015 , vol. 26, pp. 132–145,.
5. A. S. A. Ghani and N. A. M. Isa, "Underwater image quality enhancement through integrated color model with rayleigh distribution," Applied Soft Computing, 2015, vol. 27, pp. 219–230.
6. C. Li and J. Guo, "Underwater image enhancement by dehazing and color correction," Journal of Electronic Imaging, 2015,vol. 24, pp. 033023–033023.
7. Chongyi Li1, Jichang Guo1, Yanwei Pang1, Shanji Chen2, Jian Wang." SINGLE UNDERWATER IMAGE RESTORATION BY BLUE-GREEN CHANNELS DEHAZING AND RED CHANNEL CORRECTION", 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 20-25 March 2016.
8. Shiguang Liu,Yu Zhang. Detail-Preserving Under-exposure Image Enhancement via Optimal Weighted Multi-Exposure Fusion[J]. IEEE Transactions on Consumer Electronics, Aug.2019, vol.65,no.3, 303 – 311.
9. Israt Zahan Nishu ; Muhammad Fuad Tanjim ; A. S. M. Badrudduza ; Md. Al Mamun. A New Image Despeckling Method by SRAD Filter and Wavelet Transform Using Bayesian Threshold[C]. 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), 7-9 Feb. 2019.

10. Tang peng, guo baoping. Wavelet de-noising analysis of improved threshold function optimization method [J]. Signal processing. 2017, 33(1).102-110.
11. Yuhong Liu ; Hongmei Yan ; Shaobing Gao ; Kaifu Yang. Criteria to evaluate the fidelity of image enhancement by MSRCR[J]. IET Image Processing. May 2018, vol.12,no,6.
12. Dong lili, ding chang, xu wenhai. Two improved methods for image enhancement based on histogram equalization [J]. Chinese Journal of Electronics, 2018.10: 2367-2375.
13. K. Tang, J. Yang, and J. Wang, "Investigating hazerelevant features in a learning framework for image dehazing," in Computer Vision and Pattern Recognition,2014 IEEE Conference on. IEEE, 2014, pp. 2995–3002.
14. Nahla M. H. Elsaid ; Yu-Chien Wu. Super-Resolution Diffusion Tensor Imaging using SRCNN: A Feasibility Study*[C]. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),July 2019.
15. Yongpeng Dai ; Tian Jin ; Yongping Song ; Hao Du ; Dizhi Zhao. SRCNN-Based Enhanced Imaging for Low Frequency Radar[C]. 2018 Progress in Electromagnetics Research Symposium (PIERS-Toyama),1-4 Aug 2018.
16. Zhishe Wang; Jiawei Xu; Xiaolin Jiang; Xiaomei Yan. Infrared and visible image fusion via hybrid decomposition of NSCT and morphological sequential toggle operator[C]. Optik.2019.12.
17. Liu Jiahuan ; Zhang Jian ; Du Yunfei. A Fusion Method of Multi-spectral Image and Panchromatic Image Based on NSCT Transform and Adaptive Gamma Correction[C]. 2018 3rd International Conference on Information Systems Engineering (ICISE), 4-6 May 2018.
18. YUJIE LI , CHUNYAN MA, TINGTING ZHANG, JIANRU LI,ZONGYUAN GE, YUN LI, AND SEIICHI SERIKAWA. Underwater Image High Definition Display Using the Multilayer Perceptron and Color Feature-Based SRCNN[J]. IEEE Access. ENVIRONMENTS. June 2019, vol.7.
19. Pan-wang PAN, Fei YUAN, En CHENG. De-scattering and edge-enhancement algorithms for underwater image restoration[J]. Frontiers of Information Technology & Electronic Engineering, 2019, Vol.20 (6), pp.862-871.
20. H. Lu, D. Wang, Y. Li, J. Li, X. Li, H. Kim, S. Serikawa, and I. Humar,''CONet: A cognitive ocean network,'' IEEE Wireless Commun. to be published. July.2019, vol.26,no.3,90-96.
21. H. Lu, Y. Li, T. Uemura, H. Kim, and S. Serikawa, ''Low illumination underwater light field images reconstruction using deep convolutional neural networks,'' Future Gener. Comput. Syst. May 2018, vol. 82, pp. 142–148.

Figures

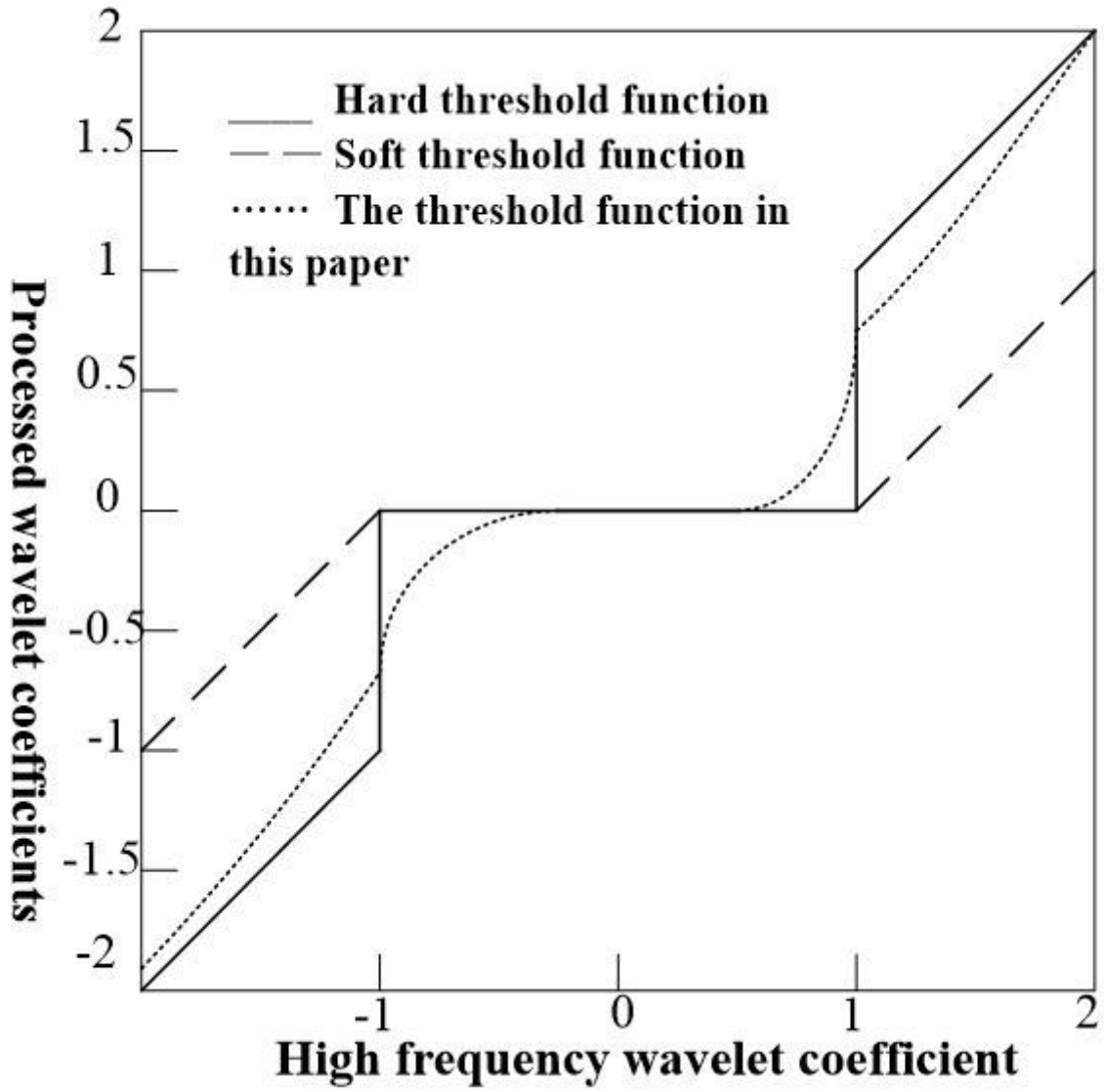


Figure 1

Comparison of different threshold function curves

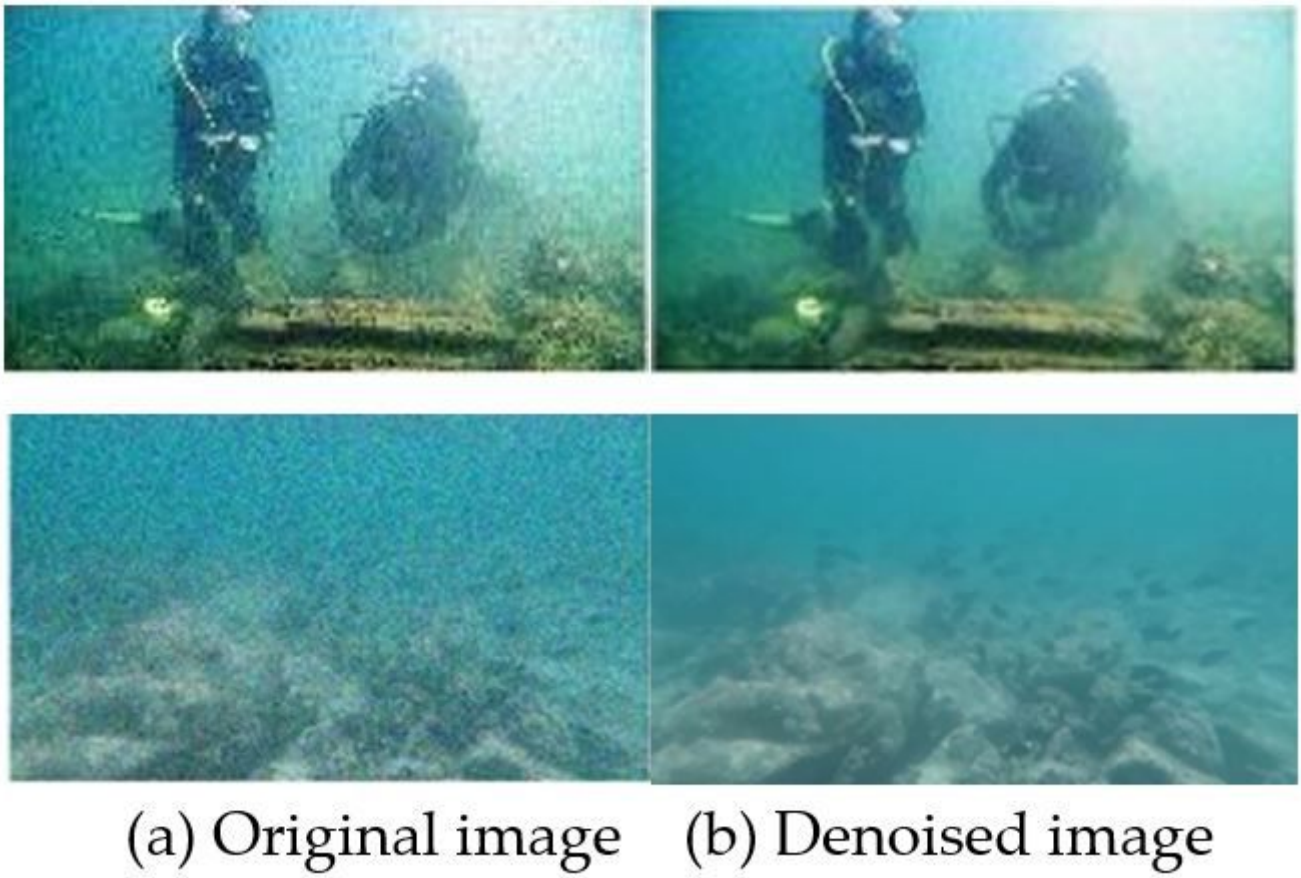


Figure 2

Denoising results

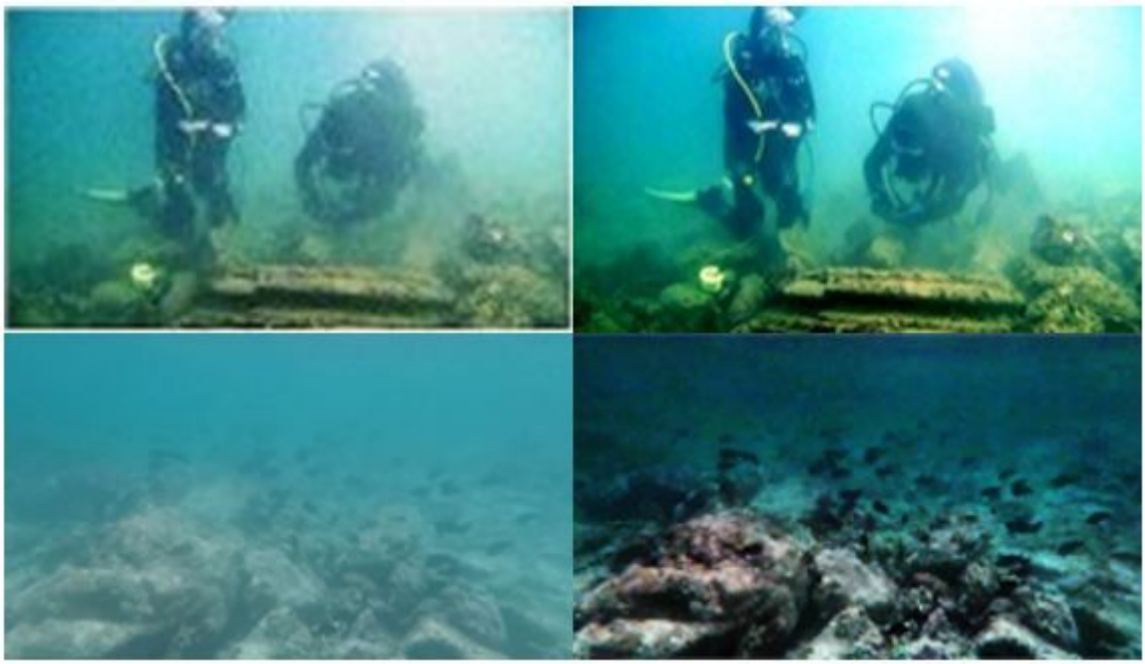


Figure 3

Dehazing effect (the original image on the left; the image after the defogging on the right).

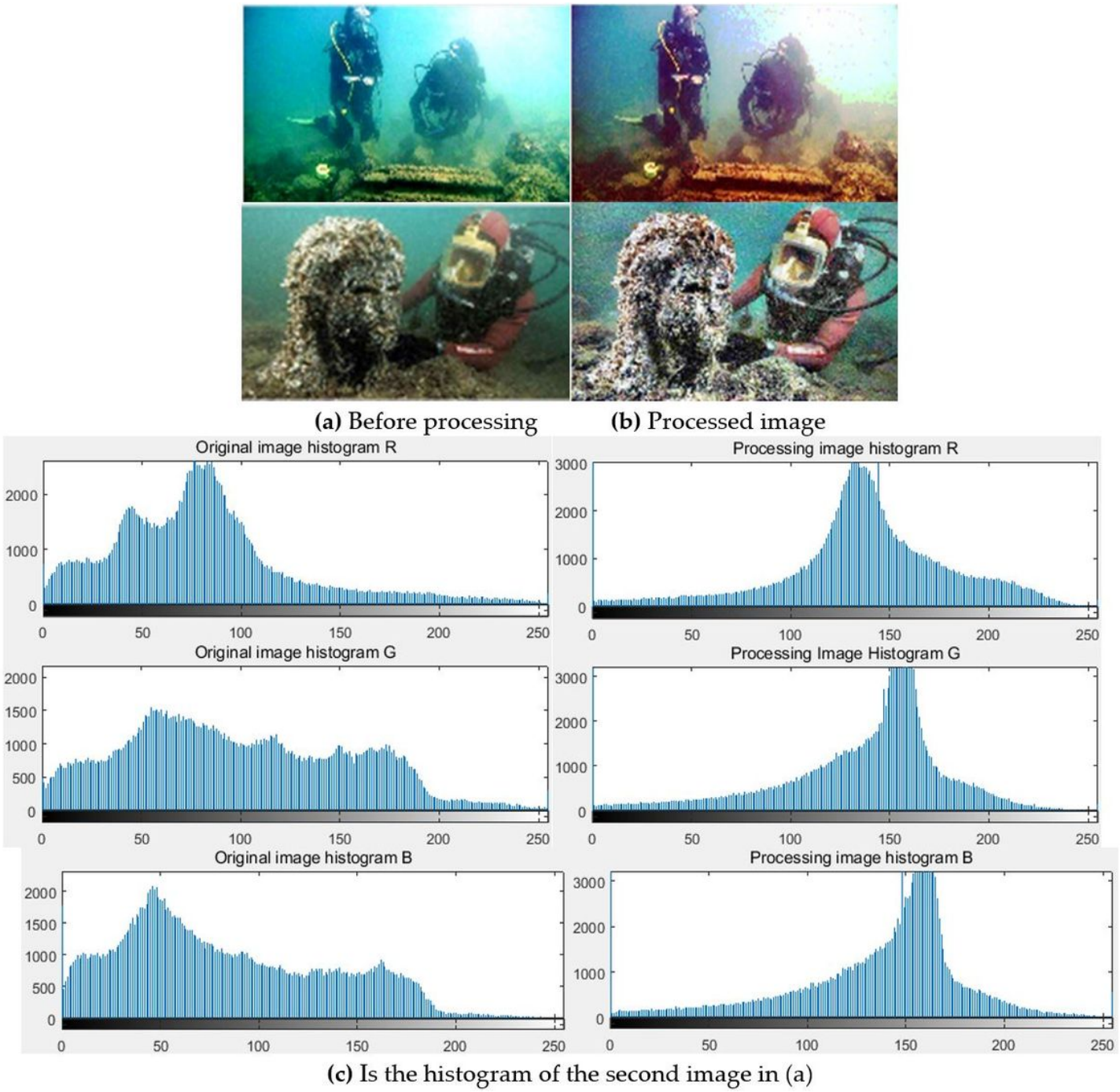


Figure 4

Improved histogram equalization results

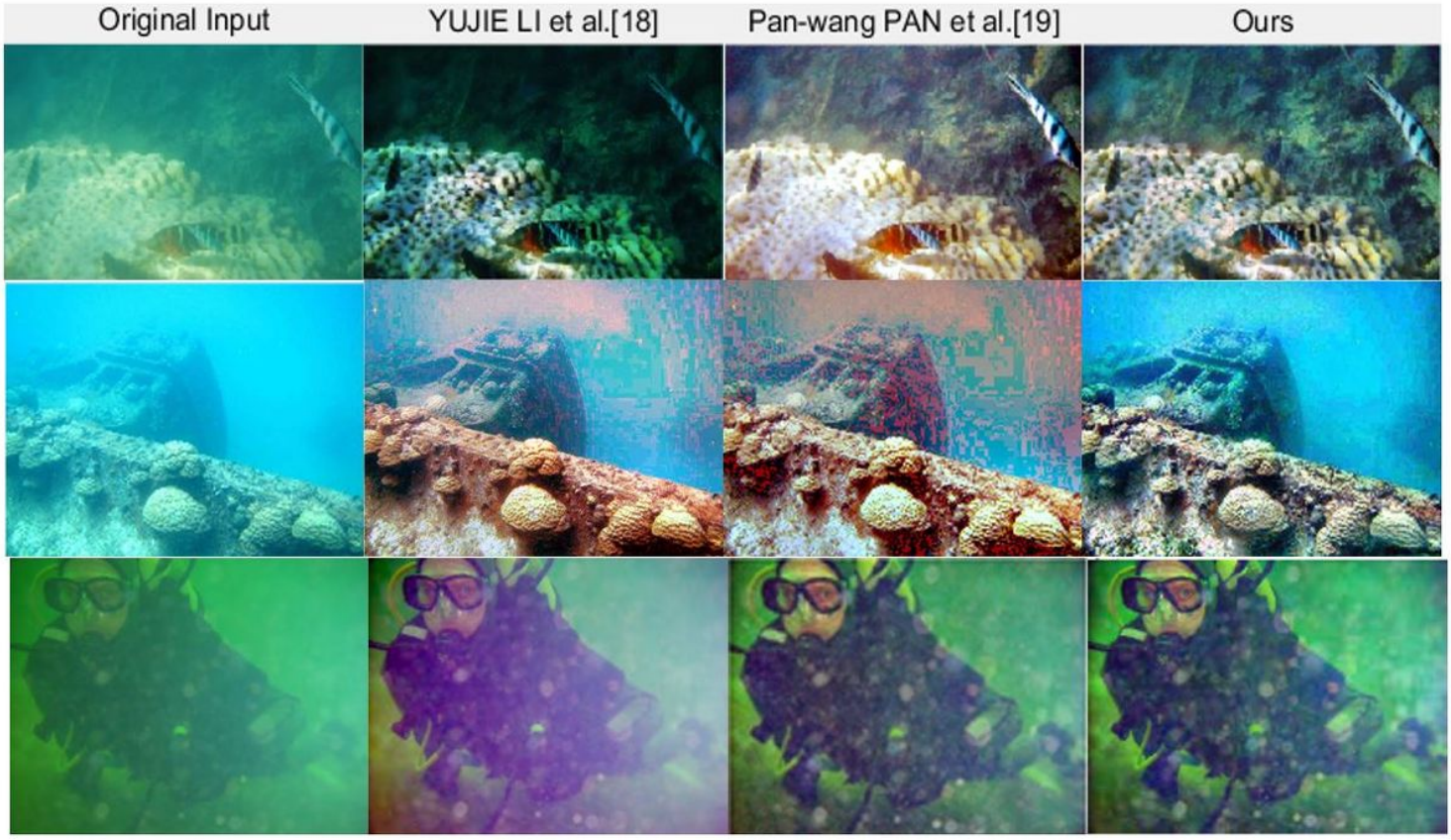


Figure 5

Comparison of the results of different image restoration methods

Figure 6

Comparison of the results of different image enhancement methods

Figure 7

Processing effect of underexposure in other cases