IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 16 May 2023, accepted 20 June 2023, date of publication 28 June 2023, date of current version 13 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3290201

RESEARCH ARTICLE

Research on Histogram Equalization Algorithm Based on Optimized Adaptive Quadruple Segmentation and Cropping of Underwater Image (AQSCHE)

DAN XIANG[1,2], **HUIHUA WANG**[2], **DENGYU HE**[2], **AND CHENKAI ZHAI**[3]

[1]College of Information and Communication Engineering, Guangzhou Maritime University, Guangzhou 510725, China
[2]School of Electronics and Information, Guangdong Polytechnic Normal University, Guangzhou 510665, China
[3]School of Automation, Guangdong Polytechnic Normal University, Guangzhou 510665, China

Corresponding author: Dengyu He (hedengyuayn2000@163.com)

This work was supported in part by the University Scientific Research Project of the Guangzhou Education Bureau under Grant 202234607, and in part by the Special Projects in Universities' Key Fields of Guangdong Province under Grant 2020ZDZX2002.

ABSTRACT Due to the uncertain, diverse, and light-attenuating characteristics of the underwater environment, underwater images have low contrast and unclear problems. This paper proposes a histogram equalization algorithm based on optimized adaptive image quadruple segmentation and cropping (AQSCHE). Compared with the traditional histogram equalization underwater image enhancement algorithm, this algorithm introduces histogram quadruple segmentation and cropping technology. Using the exposure value and segmentation point calculation formula that optimizes the distribution range of the histogram, perform quadruple segmentation on the image to obtain a more refined histogram. The adaptive histogram clipping is realized by constructing the clipping parameter z to adjust the contrast and brightness of the image. The original image is enhanced by double equalization of the sub-histogram and the histogram of each channel. Finally, the simulation experiments verify the enhancement effect of the proposed algorithm AQSCHE on underwater images. The processed underwater image has higher contrast, is clearer and more natural in subjective evaluation, and has a better visual effect; in the image objective evaluation indicators, information entropy (Entropy), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and universal color image quality evaluator (UCIQE), this algorithm also outperforms other common algorithms such as HE and CLAHE.

INDEX TERMS Adaptive cropping, double equalization, quadruple segmentation, underwater image enhancement.

I. INTRODUCTION

Since the 21st century, with the development of the human economy and society, the exploration and development of marine resources have become increasingly important. The ocean covers 70% of the earth's surface and covers a large number of natural resources. Therefore, there is a growing interest in this mysterious ocean area as one of the most critical data for people to study aquatic resources, underwater image is essential [1]. However, the propagation process of light is quite different underwater and in the air. Due to the various media, water absorbs and scatters sunlight to varying degrees, and blue and green light is absorbed less than other colors, giving the underwater image a blue-green hue. This poses a severe obstacle to obtaining information in underwater images. Therefore, how to obtain clear and natural underwater images has become a research topic [2].

This problem has attracted many domestic and foreign scholars to join the research. Among them, the histogram equalization algorithm (HE) [3] is a technique used to

The associate editor coordinating the review of this manuscript and approving it for publication was Krishna Kant Singh.

This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License.
For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

enhance an image's contrast. This technique creates an image with a more uniform histogram by reassigning the pixel values of the histogram, thus enhancing image contrast. However, the HE algorithm only considers the probability distribution of pixel values. It does not consider the spatial distribution of pixels in the image, leading to the problem of brightness distortion [4]. Therefore, Pizer and others proposed an adaptive histogram equalization (AHE) [5] algorithm. The main idea is to equalize the local histogram of the image, thereby improving the image's contrast and clarity. The AHE algorithm can avoid the noise introduced by the HE algorithm, enhance the local detail information of the image, and improve the visual effect. However, the image enhanced by the AHE algorithm will produce artifacts, noise, and other problems. Muniyappan and others proposed an image enhancement algorithm using contrast-limited adaptive histogram equalization (CLAHE) [6]. This algorithm can control the degree of image enhancement and the intensity of contrast limitation by adjusting parameters to meet different images. However, the CLAHE algorithm requires certain experience and experiments in selecting parameters, which will limit the use of the algorithm. Sim et al. proposed recursive sub-image histogram equalization (RSIHE) [7], an image enhancement algorithm based on hierarchical histogram equalization. Compared with several other improved contrast enhancement techniques, the RSIHE algorithm is the most robust. This algorithm can effectively process high dynamic range images while avoiding the brightness distortion problem produced by the HE algorithm and the artifacts, noise, and other issues produced by the AHE algorithm. The RSIHE algorithm can effectively enhance the contrast and brightness of underwater images, making the photos clearer and more vivid. However, the RSIHE algorithm cannot equalize the entire underwater image but can only equalize the local area of the image. Therefore, when dealing with some underwater images with global equalization requirements, the RSIHE algorithm could not be suitable. Kim and others proposed a contrast enhancement algorithm based on brightness-preserving bi-histogram equalization (BBHE) [8]. This algorithm can maintain the average brightness of the original underwater image while increasing its contrast. However, the BBHE algorithm must select different parameters for different underwater images. The selection of parameters needs to be determined by experience and experiments, and adjustments may be required for some images with severe fogging.

Although the above algorithms have different degrees and aspects of enhancement for underwater images, these algorithms have their own limitations, and it is difficult to have a very balanced processing effect on the contrast, clarity, and brightness of underwater images. This paper will address these problems and propose a more balanced optimization algorithm. The second chapter of this article introduces the traditional algorithm, discusses the limitations of the traditional algorithm, and on this basis, introduces the principle and advantages of the algorithm in this paper in detail. The simulation results presented in the third chapter demonstrate that the AQSCHE algorithm achieves a more balanced enhancement effect for underwater images, resulting in superior results compared to traditional methods. Finally, the fourth chapter summarizes the full text and proposes the field of application of the algorithm and future research direction in this paper.

II. THEORETICAL MODELING

This chapter first gives the flow chart of the algorithm proposed in this paper and then introduces the principle of the traditional histogram equalization algorithm. On this basis, it details the principle of each innovative module in the overall flow chart.

A. PRINCIPLE OF HISTOGRAM EQUALIZATION ALGORITHM

The traditional histogram equalization algorithm enhances the contrast of an image by redistributing its pixel values. The main process of the algorithm involves calculating the probability density function (PDF) and cumulative distribution function (CDF) of the histogram and then using these values to generate a pixel mapping table, the conversion formula of histogram equalization. Then, using the normalized CDF, the intensity values of the pixels in each block are mapped to the new parts created, creating an image with a more uniform histogram, thus enhancing the image's contrast [3].

For the histogram of the $[first, last]$ interval, the corresponding calculation formulas of PDF and CDF are:

$$PDF\left(k\right)=\frac{n_k}{N} \tag{1}$$

$$CDF\left(k\right)=\sum\nolimits_{q=first}^{k} PDF\left(q\right) \tag{2}$$

where k is the gray level, n_k is the number of pixels corresponding to the k gray level in the image histogram, and N is the total number of pixels in the interval. Therefore, the transformation formula for histogram equalization is:

$$F\left(k\right)=first+CDF\left(k\right)\times\left(last-first\right) \tag{3}$$

In the formula, the $last$ represents the final value of the mapping interval, the $first$ represents the starting value, and the difference between them represents the mapping interval length. In the traditional histogram equalization conversion formula, the $last$ is 255, and the $first$ is 0.

The conventional histogram equalization algorithm faces difficulties in handling low-exposure and high-exposure underwater images, thus requiring the integration of histogram segmentation technology into the traditional algorithm. Exposure value and exposure threshold are two parameters introduced in the histogram segmentation. The exposure value reflects the distribution of the number of pixels corresponding to each gray level in the image histogram, and its value ranges from 0 to 1. By calculating the exposure value of the image histogram, the exposure threshold can be calculated. The exposure threshold can be used as the segmentation point of the image histogram, which divides the image histogram into low-exposure areas and over-exposure areas, and then performs separate processing for each area, thereby improving the accuracy and efficiency of the image [9].

The traditional calculation formula for exposure value is as follows:

$$Ex = \frac{\sum_{k=1}^{L} n_k \times k}{L \sum_{k=1}^{L} n_k} \tag{4}$$

where L represents the total number of gray levels, and Ex represents the exposure value. The formula for the exposure threshold is:

$$X_a = L\left(1 - Ex\right) \tag{5}$$

B. CALCULATION METHOD OF EXPOSURE VALUE BASED ON OPTIMIZED HISTOGRAM DISTRIBUTION RANGE

When the traditional segmentation algorithm based on exposure value encounters a narrow distribution range in the histogram, the calculated exposure threshold may fall outside the area with a non-zero histogram distribution range, leading to a failure in histogram segmentation. And when the algorithm is processing low-light images and images with interference noise, the calculated exposure threshold X_a will not be ideal, resulting in indirect segmentation failure, thus affecting the final image enhancement effect [10].

Therefore, this paper proposes a calculation method of exposure value based on optimizing the distribution range of the histogram. In this method, a new histogram distribution range is first defined, and the histogram distribution range is limited by constructing a parameter m to eliminate the interference noise existing in the histogram. The optimized histogram distribution range is:

$$\begin{cases} SMALL = \min\left(n_k \geq m\right), k \in [0, L-1] \\ BIG = max\left(n_k \geq m\right), k \in [0, L-1] \end{cases} \tag{6}$$

It can be seen from the formula that the distribution range of the optimized histogram is changed to the interval formed by the minimum and maximum values of the statistics in the histogram not less than m. Different from the distribution range of the traditional histogram, the new calculation method of the histogram distribution range can effectively remove the interference noise in the histogram. Consequently, it improves the accuracy of the exposure value calculation and the image enhancement effect. The corresponding formula for calculating the new exposure value and the split point is as follows:

$$EX = \frac{\sum_{k=SMALL}^{BIG} n_k (k - SMALL + m)}{(BIG - SMALL) \times \sum_{k=SMALL}^{BIG} n_k} \tag{7}$$

$$X_a = SMALL + (1 - EX) \times (BIG - SMALL) \tag{8}$$

Fig.2 illustrates the histogram of a low-light underwater image affected by interfering noise. It can be observed from the figure that using the optimized histogram distribution range to calculate the new exposure value and exposure threshold results in a more accurate calculation, and the optimal position of the exposure threshold can be precisely determined based on the distribution characteristics of the histogram [11].

After segmenting the histogram into two sub-histograms, this paper uses the mean value of the two sub-histograms as the segmentation point. It segments two sub-histograms again to obtain four sub-histograms to be enhanced. The formula for calculating the Mean of the two sub-histograms is:

$$X_{al} = \sum_{k=SMALL}^{k=X_a-1} P_{dl}(k) \times k \tag{9}$$

$$X_{au} = \sum_{k=X_a}^{k=BIG-1} P_{du}(k) \times k \tag{10}$$

where X_{al} and X_{au} represent the means of the two sub-histograms respectively, and $P_{dl}(k)$ and $P_{du}(k)$ represent the PDFs of the two sub-histograms, respectively.

Fig.3 clearly shows the positions of the three segmentation points X_{al}, X_a and X_{au} calculated by the optimization algorithm. From the calculation formula, these three segmentation points are all calculated according to the distribution characteristics of the histogram, which can effectively divide the image's histogram into sub-histograms with different features. Then, different enhancement processing is performed on each distinct region's sub-histograms to improve the enhanced image's clarity.

C. CONSTRUCTION METHOD BASED ON OPTIMAL CLIPPING THRESHOLD

The traditional histogram clipping method is relatively simple, and the clipping threshold calculation formula cannot be clipped according to the distribution characteristics of the histogram. In addition, the selection of common clipping thresholds also includes the average number of occurrences of gray levels, the Mean, median, and peak values of the histogram, and so on. Referring to the traditional clipping threshold selection method, this paper proposes an adaptive histogram clipping algorithm, which uses a value between the Mean and median of each sub-histogram as the clipping threshold [12]. Among them, z is defined as the clipping parameter and a better clipping threshold value can be achieved by different values of z [13]. The calculation formula for the median value of each sub-histogram is as follows:

$$M_i = median\left(histogramofsubimageI_i\right) \tag{11}$$

In the formula, M_i represents the median value of the ith sub-histogram. The formula for calculating the clipping threshold is:

$$T_i = z\left(\frac{Q_i}{L_i} - M_i\right) + M_i \tag{12}$$

where T_i represents the clipping threshold of the ith sub-histogram, Q_i represents the total number of pixels of the ith

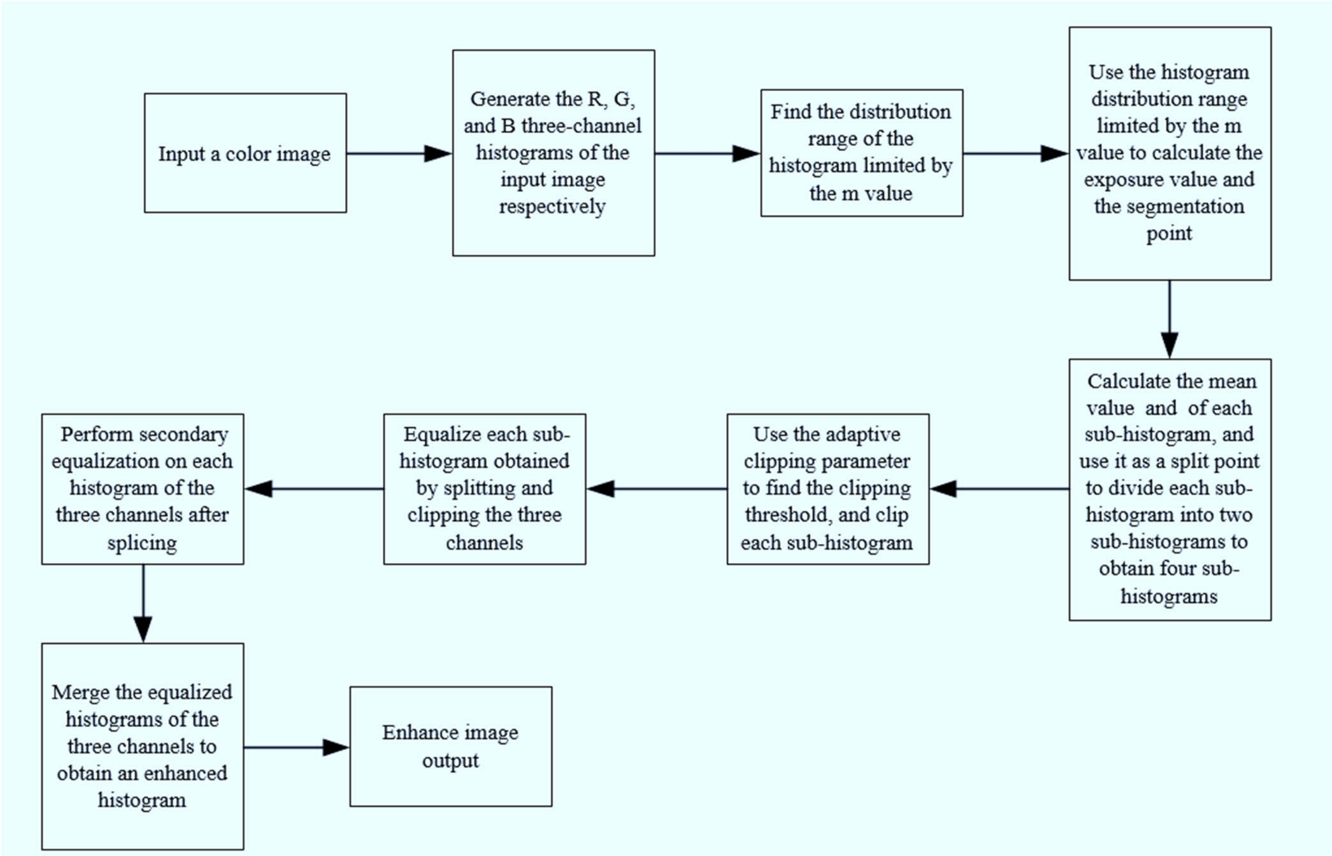

FIGURE 1. The overall flow chart of the algorithm in this paper.

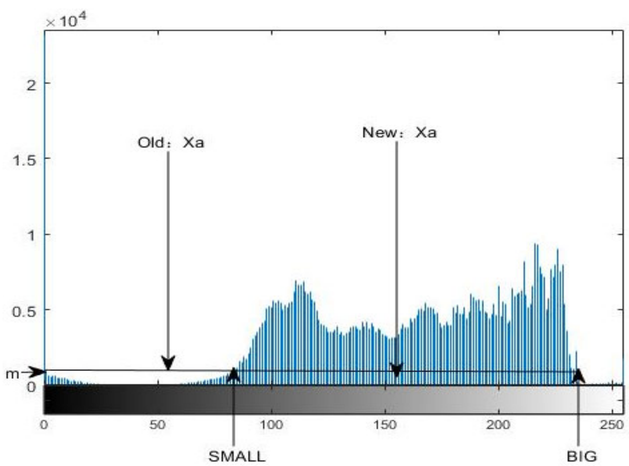

FIGURE 2. Location map before and after $X_a$optimization.

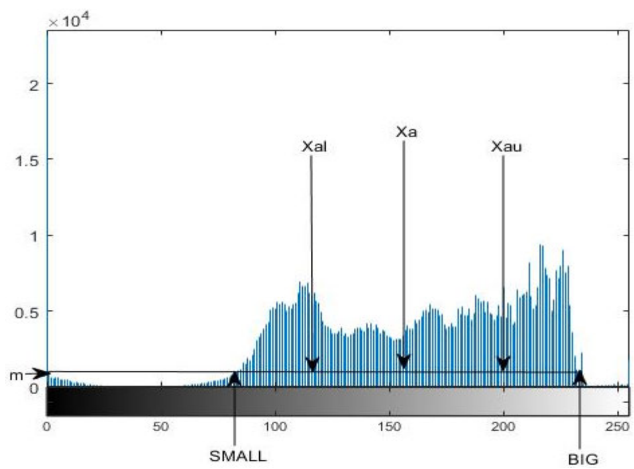

FIGURE 3. Location map of each split point.

sub-histogram, L_i represents the interval length of the ith sub-histogram, z represents a clipping parameter, and the value range is [0, 1], so the value range of the clipping threshold is between the median and the Mean of a single sub-histogram.

It can be seen from **Fig.4** that the clipping threshold calculated after optimization falls well within the interval of the number of pixels in each sub-histogram. After calculating the clipping threshold, this paper clips each sub-histogram with a clipping method in which the maximum number of pixels in the histogram is limited to the clipping threshold. For the range where the number of pixels in the sub-histogram is greater than the clipping threshold, the number of pixels in the sub-histogram is defined as a clipping threshold. It will not be processed for the sub-histogram whose number of pixels

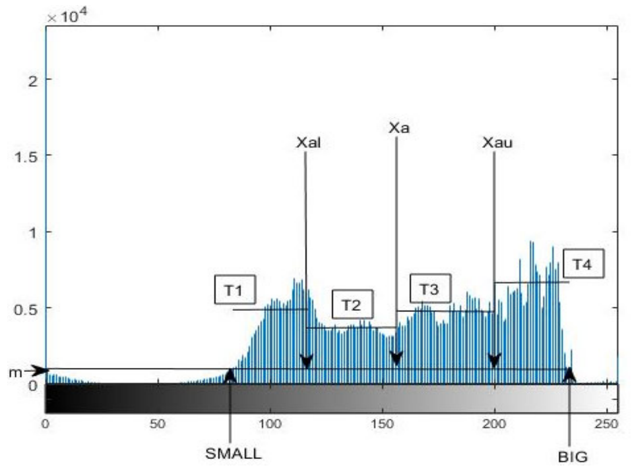

FIGURE 4. Location map of each clipping threshold.

is less than the range of the clipping threshold. The specific calculation formula is: [14]:

$$y_i(k) = \begin{cases} T_i, \text{ if } y_i(k) \geq T_i \\ y_i(k), \text{ if } y_i(k) < T_i, \quad i = 1, 2, 3, 4 \end{cases} \tag{13}$$

where $y_i(k)$ represents the clipping histogram and T_i represents the clipping threshold of the i sub-histogram.

D. SUB-HISTOGRAM DOUBLE EQUALIZATION

After obtaining the four sub-histograms, this paper first performs independent equalization on each sub-histogram, including calculating the probability density function PDF of each sub-histogram and using the PDF to determine the cumulative distribution function CDF to obtain the transformation formula of each sub-histogram. The formulas for calculating the probability density function (PDF) and cumulative distribution function (CDF) of each sub-histogram are as follows:

$$P_{di}(k) = \frac{y_i(k)}{N_i} \tag{14}$$

$$C_{di}(k) = \sum_{k=N}^{k=M} P_{di}(k) \tag{15}$$

The value of $[N, M]$ is determined according to the distribution range of each sub-histogram after segmentation and clipping.

Then, based on the CDF and the distribution range of each sub-histogram, the conversion formula for each sub-histogram is obtained:

$$F_1(k) = (X_{al} - 1) \times C_{d1}(k) \tag{16}$$

$$F_2(k) = ((X_a - 1) - X_{al}) \times C_{d2}(k) + X_{al} \tag{17}$$

$$F_3(k) = ((X_{au} - 1) - X_a) \times C_{d3}(k) + X_a \tag{18}$$

$$F_4(k) = ((L - 1) - X_{au}) \times C_{d4}(k) + X_{au} \tag{19}$$

Finally, by combining the mapping functions of each subimage, the mapping function of the enhanced output image is obtained.

$$F = F_1(k) \cup F_2(k) \cup F_3(k) \cup F_4(k) \tag{20}$$

After obtaining the four equalized sub-histograms of each channel, this paper combines them to obtain a complete histogram of each channel and then applies a second equalization on each channel's histogram. Repeat the above operation to obtain the equalized histogram of each channel. Finally, the three-channel equalized histograms are accumulated to obtain an enhanced histogram, and an enhanced color image is finally output.

Fig.5 (a) shows the four sub-histograms before R channel equalization, and **Fig.5 (b)** shows the corresponding sub-histogram after equalization. **Fig.6** shows the comparison before and after the equalization of the entire R channel. It can be seen from the figure that the number of sub-histogram pixels after the first equalization becomes uniform, and after the second equalization of the entire R channel histogram, The gray level is evenly mapped to the [0,255] interval so that the enhanced histogram distribution of the original histogram is more uniform, the contrast of the enhanced image is more obvious, and the display effect is better.

III. RESULTS AND ANALYSIS

The databases selected in this paper are ImageNet-O (ImageNet-Opponent) and EUVP (European Visual Plankton Archive). ImageNet-O was created by the ImageNet team and is dedicated to underwater image research. The dataset contains more than 2,000 categories of nearly 50,000 underwater images. These images cover a variety of underwater scenes and objects, including marine life, coral reefs, marine environments, underwater machinery and equipment, and more. The sources of images include real underwater images collected by underwater drones, submersibles, underwater cameras, and other equipment. EUVP is a database that collects images of plankton in different waters in Europe, including thousands of high-quality, high-resolution images and detailed information about image collection. There are 111,670 pieces of Underwater Dark, Underwater ImageNet among the paired data. There are 8670 images, Underwater Scenes has 4500 images, and the unpaired data contains 6665 images with poor quality and good quality. The images in the two data sets have different acquisition time, space, and depth information and are of various types and rich in scenes. They are very representative and are very convincing for the experimental analysis of the algorithm in this paper. The experimental simulation software and system parameters are shown in **Table 1.**

A. SUBJECTIVE EVALUATION OF IMAGE QUALITY

In order to verify whether the subjective effect of this algorithm on underwater image enhancement is better, this paper conducts comparative experiments with six other common underwater image enhancement algorithms. These algorithms include CLAHE, RSIHE, AHE, HE, BBHE, and RGHS. From the perspective of verifying the universality of

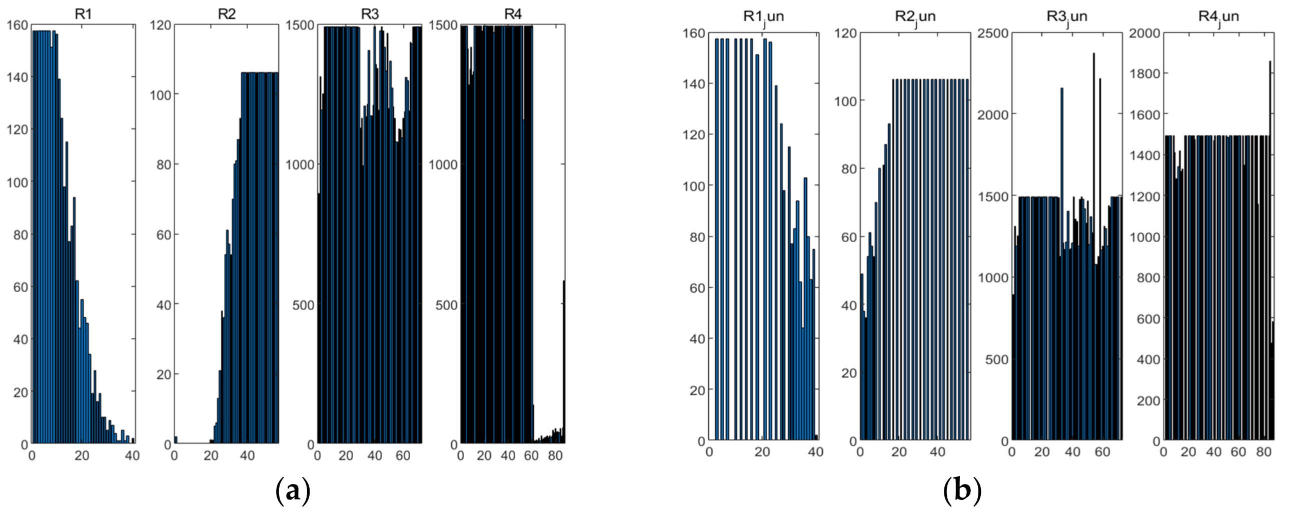

FIGURE 5. Comparison chart before and after equalization of the four sub-histograms of the R channel. (a) means before equalization, (b) means after equalization.

TABLE 1. Experiment system parameters.

Simulation platform and model	CPU	Memory	operating system	GPU
MATLAB R2021a	Itel(R)Core(TM) i5-12500H	16GB	Windows11(64bit)	RTX2050-4G

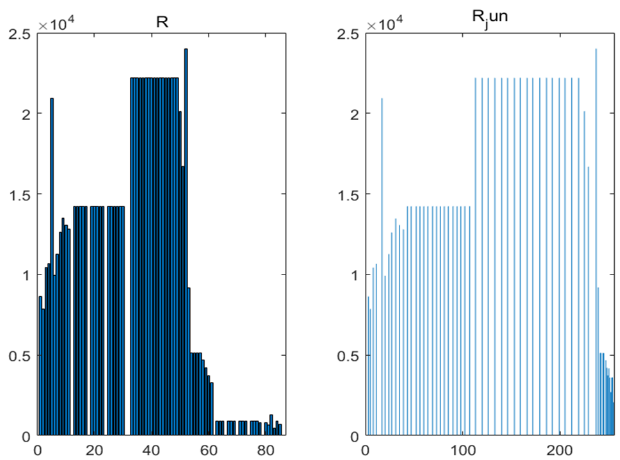

FIGURE 6. Comparison chart before and after R channel equalization.

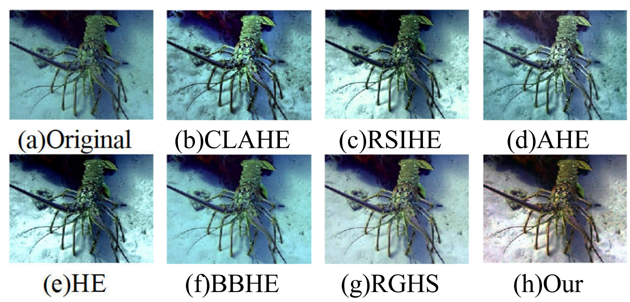

FIGURE 7. Subjective comparison figure 1.

FIGURE 8. Subjective comparison figure 2.

the algorithm, this paper selects some representative underwater image data from the EUVP and ImageNet-O databases for simulation experiments and shows the enhancement effect of each algorithm [15].

This article selects six underwater images of different tones, and each comparison chart shows the contrast between the underwater image enhanced by seven algorithms and the original image. The result is shown in **Fig.7 - Fig.12**. It can be seen from the subjective renderings that although the CLAHE and AHE algorithms enhance the image contrast and retain some details and local features, excessive enhancement leads to image distortion. The local enhancement effect of the image processed by the RSIHE algorithm is obvious, but

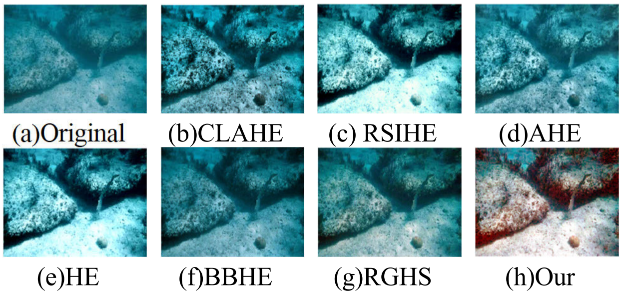

FIGURE 9. **Subjective comparison figure 3.**

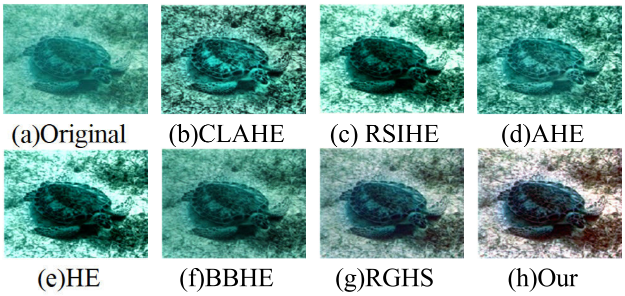

FIGURE 10. **Subjective comparison figure 4.**

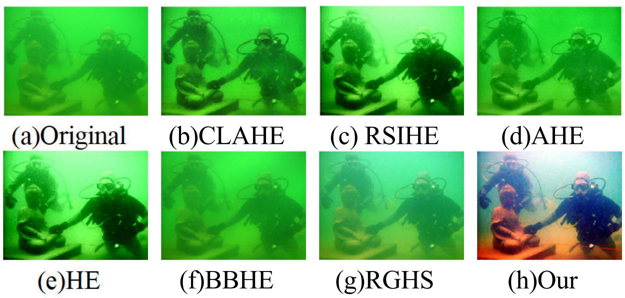

FIGURE 11. **Subjective comparison figure 5.**

the overall enhancement effect of the image is not ideal. The HE algorithm can produce sharper images but may cause a loss of detail in some areas, resulting in unnatural visual effects. The images enhanced by the BBHE algorithm and RGHS algorithm can enhance the detail information in the image very well, but the enhancement effect of RGHS is not good when processing low-contrast images, and BBHE will appear with gray value aggregation when processing high-contrast images, resulting in image color distortion. From the comparison above, it can be seen that the contrast of the image processed by the algorithm in this paper has been enhanced, the problem of image edge blur has been improved, the image is clearer, the color is more natural, and the local details have also been enhanced. The enhanced image has a better visual effect overall.

B. OBJECTIVE EVALUATION OF IMAGE QUALITY

In addition to verifying that the improved algorithm is better than the other six enhancement algorithms from the subjective comparison chart, this paper also uses some mathematical algorithms and models to calculate and analyze the image processed by the algorithm to evaluate the improved algorithm's superiority. This paper selects some image objective evaluation indicators and verifies and analyzes each evaluation parameter of the image.

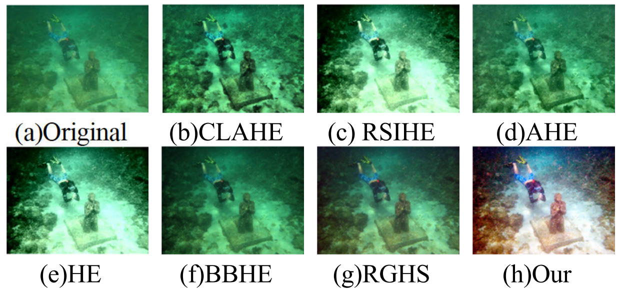

FIGURE 12. **Subjective comparison figure 6.**

Information entropy (Entropy) is a no-reference objective index used to evaluate the amount and complexity of image information. The higher the information entropy of an image, the greater its amount of information and complexity, leading to a better visual effect. The average value represents the overall brightness level of the image. A higher average value corresponds to a higher average brightness of the image and generally indicates better image quality. The Universal Color Image Quality Index (UCIQE) is an objective indicator for evaluating the quality of color images by comparing the brightness, contrast, and chromaticity differences between the distorted image and the original image, and its value range is [0,1]. The larger the value, the better the image quality. The peak signal-to-noise ratio (PSNR) is a full-parameter objective evaluation index that reflects the distortion between the image and the original image. The larger the PSNR, the smaller the distortion between the image to be evaluated and the reference image, and the better the image quality to be evaluated. Structural similarity (SSIM) reflects the structural similarity between the image to be evaluated and the reference image. The value range of SSIM is [0,1]. The larger the value, the more similar the image is to the image to be evaluated and the better the quality of the image to be evaluated.

Firstly, this paper uses two non-parametric objective evaluation indexes, Entropy and Mean, to analyze the data of the six underwater images selected above. According to the data in **Table 2**, it can be seen that the entropy values of the six sample images enhanced by the algorithm in this paper are greater than those of other algorithms, indicating that the gray-level distribution of the image histogram is more uniform, and the details and textures contained in the image are richer. From the data in **Table 3**, the Mean value of the algorithm in this paper is relatively close to that of the RSIHE algorithm, but judging from the overall effect of the six example diagrams, the algorithm in this paper is still better than the RSIHE algorithm, and the other five algorithms. It shows that the average brightness of the image enhanced

TABLE 2. Entropy evaluation index results.

Images	CLAHE	RSIHE	AHE	HE	BBHE	RGHS	OUR
Exp.1	7.69	7.43	7.77	7.30	7.73	7.60	**7.98**
Exp.2	7.12	7.24	7.45	7.19	7.42	7.40	**7.88**
Exp.3	7.84	7.32	7.39	7.42	7.54	7.77	**7.89**
Exp.4	7.68	7.51	7.52	7.41	7.41	7.45	**7.94**
Exp.5	7.46	7.37	7.28	7.14	7.32	7.51	**7.92**
Exp.6	7.12	7.46	7.82	7.34	7.24	7.31	**7.92**

TABLE 3. Mean evaluation index results.

Images	CLAHE	RSIHE	AHE	HE	BBHE	RGHS	OUR
Exp.1	117.18	**128.74**	121.48	101.34	109.45	112.36	128.02
Exp.2	115.08	126.44	122.67	101.48	125.43	106.51	**128.11**
Exp.3	95.33	120.34	101.62	86.33	105.78	119.87	**128.37**
Exp.4	78.36	111.56	90.31	74.34	101.35	115.62	**129.16**
Exp.5	77.49	121.78	88.33	72.69	92.83	96.28	**128.73**
Exp.6	95.33	124.30	109.19	86.30	113.64	115.60	**128.34**

TABLE 4. TIME evaluation index results.

Images	CLAHE	RSIHE	AHE	HE	BBHE	RGHS	OUR
Exp.1	1.95	1.59	1.67	0.53	1.74	2.24	1.45
Exp.2	1.98	1.62	1.68	0.58	1.79	2.56	1.46
Exp.3	1.83	1.46	1.60	0.49	1.64	2.25	1.34
Exp.4	1.85	1.49	1.62	0.51	1.69	2.19	1.36
Exp.5	2.10	1.58	1.73	0.61	1.83	2.38	1.49
Exp.6	1.92	1.48	1.65	0.52	1.68	2.33	1.38

TABLE 5. The average results of the UCIQE, PSNR, and SSIM evaluation metrics.

Target	CLAHE	RSIHE	AHE	HE	BBHE	RGHS	OUR
UCIQE	0.433	0.438	0.387	0.324	0.415	0.396	**0.470**
PSNR	29.987	28.694	30.132	24.368	30.070	28.784	**33.063**
SSIM	0.809	0.823	0.830	0.745	0.811	0.836	**0.875**

by the algorithm of this paper is higher, the overall brightness is better, and the visual effect is better.

Secondly, to verify the proposed algorithm's comprehensive efficiency, this paper also compared the processing time of 6 algorithms with the algorithm in this paper. From the overall data results in Table 4, it can be seen that the processing time of the algorithm proposed in this paper is shorter than that of the other five algorithms except HE, indicating that the algorithm in this paper has a better effect and high efficiency with a shorter processing time.

This paper also selects 300 high-definition underwater images in the EUVP database for objective image evaluation of the full parameters. The average data of UCIQE, PSNR, and SSIM, three full-parameter objective evaluation indicators of 300 underwater images enhanced by seven algorithms, are shown in **Table 5** [16].

According to the data in **Table 5**, the algorithm of this paper is superior to the other six algorithms in the three comprehensive and objective evaluation indicators, indicating that the image enhanced by the algorithm in this paper is better in

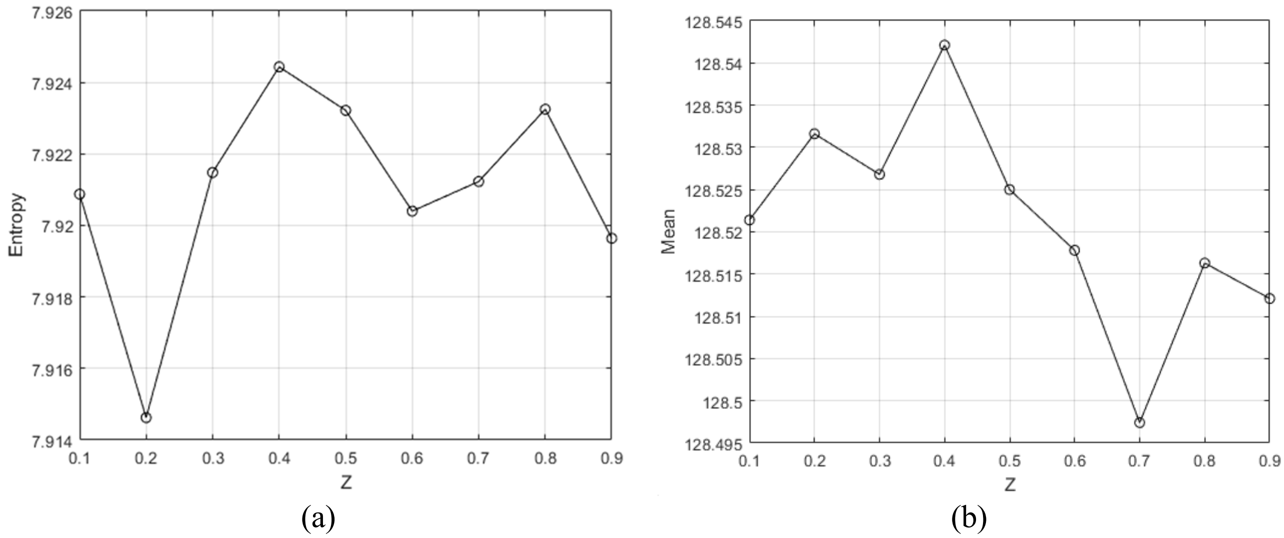

FIGURE 13. Entropy and mean average line chart.

terms of color, contrast, clarity, and the overall image quality is higher [17]. Moreover, compared with the selected high-definition image, the image enhanced by the algorithm in this paper has the least distortion, is most similar to the original high-definition image, and has the highest quality.

C. EXPERIMENTAL ANALYSIS OF DIFFERENT CLIPPING PARAMETER Z VALUES

The value range of the clipping parameter z defined in this paper is [0,1]. This section takes nine different values for the clipping parameter z from 0.1 to 0.9 and calculates the Entropy and Mean values of the six underwater images selected above. The optimal value range of cropping parameters is determined by analyzing the average value of two data in six images.

Fig. 13 shows the average curves of Entropy and Mean of six underwater images obtained by different clipping parameter z values. It can be seen from the figure that when z is 0.4, the average values of Entropy and Mean both reach the highest point. Therefore, in the algorithm of this paper, when the clipping parameter z is 0.4, the calculated clipping threshold is the optimal value, the clipping effect on the histogram is the best, and a better underwater enhanced image will be obtained.

IV. CONCLUSION

This paper proposes an optimization-based adaptive quadruple segmentation and cropping histogram equalization algorithm, which is mainly used in underwater image enhancement. First, the algorithm uses the method of optimizing the distribution range of the histogram to calculate the exposure value and the segmentation point, divides the histogram for the first time, and then uses the mean value of the sub-histogram as the segmentation point to perform secondary segmentation on the sub-histogram to obtain four sub-histograms. Secondly, use the histogram clipping technique to clip different regional features of each sub-histogram, and then perform secondary equalization on the clipped histogram, and finally output the enhanced color image. Through the subjective and objective evaluation experiments of the algorithm in this paper, it is shown that the image output by the algorithm in this paper is better than the comparison algorithm in terms of Entropy, Mean, and some comprehensive indicators, and the algorithm is simple and easy to understand and can be used in deep-sea exploration, underwater archaeology and Application scenarios such as underwater photography. The future research direction is to address the shortcomings of the algorithm in this paper in the processing of underwater image details and develop a more refined histogram segmentation and cropping method to achieve the preservation of details of underwater images with different characteristics.

REFERENCES

[1] G. Singh and A. Mittal, ''Various image enhancement techniques—A critical review,'' *Int. J. Innov., Sci. Res.*, vol. 10, no. 2, pp. 267–274, Oct. 2014.

[2] Y. Peng and P. C. Cosman, ''Underwater image restoration based on image blurriness and light absorption,'' *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1579–1594, Apr. 2017.

[3] T. Celik, ''Two-dimensional histogram equalization and contrast enhancement,'' *Pattern Recognit.*, vol. 45, no. 10, pp. 3810–3824, Oct. 2012.

[4] H. Yeganeh, A. Ziaei, and A. Rezaie, ''A novel approach for contrast enhancement based on histogram equalization,'' in *Proc. Int. Conf. Comput. Commun. Eng.*, Kuala Lumpur, Malaysia, May 2008, pp. 256–260.

[5] S. M. Pizer, E. P. Amburn, J. D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. ter Haar Romeny, J. B. Zimmerman, and K. Zuiderveld, ''Adaptive histogram equalization and its variations,'' *Comput. Vis., Graph., Image Process.*, vol. 39, no. 3, pp. 355–368, Sep. 1987.

[6] A. M. Reza, ''Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement,'' *J. VLSI Signal Process.-Syst. Signal, Image, Video Technol.*, vol. 38, no. 1, pp. 35–44, Aug. 2004.

[7] K. S. Sim, C. P. Tso, and Y. Y. Tan, ''Recursive sub-image histogram equalization applied to gray scale images,'' *Pattern Recognit. Lett.*, vol. 28, no. 10, pp. 1209–1221, Jul. 2007.

[8] Y.-T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," *IEEE Trans. Consum. Electron.*, vol. 43, no. 1, pp. 1–8, Feb. 1997.
[9] K. Singh, R. Kapoor, and S. K. Sinha, "Enhancement of low exposure images via recursive histogram equalization algorithms," *Optik*, vol. 126, no. 20, pp. 2619–2625, Oct. 2015.
[10] U. K. Acharya and S. Kumar, "Image sub-division and quadruple clipped adaptive histogram equalization (ISQCAHE) for low exposure image enhancement," *Multidimensional Syst. Signal Process.*, vol. 34, no. 1, pp. 25–45, Mar. 2023.
[11] K. Singh and R. Kapoor, "Image enhancement via median-mean based sub-image-clipped histogram equalization," *Optik*, vol. 125, no. 17, pp. 4646–4651, Sep. 2014.
[12] Z. Yao, Z. Lai, C. Wang, and W. Xia, "Brightness preserving and contrast limited bi-histogram equalization for image enhancement," in *Proc. 3rd Int. Conf. Syst. Informat. (ICSAI)*, Shanghai, China, Nov. 2016, pp. 866–870.
[13] M. Zarie, A. Parsayan, and H. Hajghassem, "Image contrast enhancement using triple clipped dynamic histogram equalisation based on standard deviation," *IET Image Process.*, vol. 13, no. 7, pp. 1081–1089, May 2019.
[14] C. H. Ooi and N. A. Mat Isa, "Quadrants dynamic histogram equalization for contrast enhancement," *IEEE Trans. Consum. Electron.*, vol. 56, no. 4, pp. 2552–2559, Nov. 2010.
[15] S. Patel and M. Goswami, "Comparative analysis of histogram equalization techniques," in *Proc. Int. Conf. Contemp. Comput. Informat. (IC3I)*, Mysore, India, Nov. 2014, pp. 167–168.
[16] L. Lu, Y. C. Zhou, K. Panetta, and S. Agaian, "Comparative study of histogram equalization algorithms for image enhancement," *Proc. SPIE*, vol. 7708, Apr. 2010, Art. no. 770811.
[17] H. Lu, Y. Li, Y. Zhang, M. Chen, S. Serikawa, and H. Kim, "Underwater optical image processing: A comprehensive review," *Mobile Netw. Appl.*, vol. 22, no. 6, pp. 1204–1211, Apr. 2017.

DAN XIANG was born in Yichang, Hubei, China, in 1980. She received the Ph.D. degree from the South China University of Technology, Guangzhou, Guangdong. Currently, she is with Guangzhou Maritime University, she has 20 years of teaching experience and industry experience in electronics and communications, mainly researching underwater target recognition and underwater image processing.

HUIHUA WANG was born in Huizhou, Guangdong, China, in 1999. He is currently pursuing the master's degree in new generation of electronic information with the School of Electronics and Information, Guangdong Polytechnic Normal University. His research interest includes underwater image enhancement.

DENGYU HE was born in Fuyang, Anhui, China, in 2000. He is currently pursuing the master's degree in new generation of electronic information with the School of Electronics and Information, Guangdong Polytechnic Normal University. His research interest includes underwater image enhancement.

CHENKAI ZHAI was born in Anyang, Henan, China, in 1997. He is currently pursuing the master's degree in control science and engineering with the School of Automation, Guangdong Polytechnic Normal University. His research interests include control theory and application and underwater sensors.