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

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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 the 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, clearer and more natural in subjective evaluation, and has 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), etc., 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's a growing interest in this mysterious area of the ocean, as one of the most important data for people to study underwater resources, underwater image is particularly important [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 are absorbed less than other colors, giving the underwater image a blue-green hues [2].

This kind of problem has attracted many domestic and foreign scholars to join in the research. Among them, the histogram equalization algorithm (HE) [3] 。 is a technique used for enhancing the contrast of an image. This technique first divides the input image into small area blocks, then calculates the probability density function (PDF) of each histogram, and is used to calculate the cumulative distribution function (CDF), and then uses the CDF to map the intensity values of each block of pixels to a new range, thus creating an image with a more uniform histogram, enabling optimized underwater image contrast enhancement [4]. However, the HE algorithm only considers the probability distribution of pixel values, and does not consider the spatial distribution of pixels in the image, which will lead to the problem of brightness distortion [5]. Therefore, Pizer and others proposed an adaptive histogram equalization (AHE) algorithm [6]. The main idea is to equalize the local histogram of the underwater image, thereby improving the contrast of the underwater image and clarity. The AHE algorithm can avoid the noise introduced by the HE algorithm, enhance the local detail information of the underwater picture, and improve the visual effect. However, the underwater image enhanced by the AHE algorithm will produce artifacts, noise, and other problems. Sim et al. proposed recursive sub-image histogram equalization (RSIHE), an image enhancement algorithm based on hierarchical histogram equalization. Compared with several other improved contrast enhancement techniques, 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. RSIHE algorithm can effectively enhance the contrast and brightness of underwater images, making the photos more clear and 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 [7]. 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. In the second chapter of this paper, the traditional algorithm is introduced, followed by a discussion on the limitations of the conventional algorithm. This paper also discusses the proposed algorithm's direction and advantages. 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 MODEL

A. PRINCIPLE OF HISTOGRAM EQUALIZATION ALGORITHM

The traditional histogram equalization algorithm enhances the contrast of an image by redistributing its gray levels. 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, which is 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 section created, thus creating an image with a more uniform histogram, resulting in a significant increase in the contrast of the enhanced image [8].

The calculation formulas for the PDF and CDF of the sub-histogram corresponding to the [first, last] interval are as follows:

$$\mathrm{PDF}(k) = \frac{n_k}{N}, \tag{1}$$

$$\mathrm{CDF}(k) = \sum_{q=first}^{k} \mathrm{PDF}(q), \tag{2}$$

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

$$G(k) = first + \mathrm{CDF}(k) \times (last - first), \tag{3}$$

In the formula, $last$ represents the final value of the mapping interval, $first$ represents the starting value of the mapping interval, and the difference between them represents the mapping interval.

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 indicates how the number of pixels corresponds to each gray level in the image histogram, and its value ranges from 0 to 1. Calculating the exposure value of the image histogram enables the calculation of the exposure threshold, which can be used as the segmentation point for the image histogram. This segmentation divides the image histogram into low-exposure and over-exposure areas, allowing for separate processing of each area and improving image accuracy and efficiency [9]. The main process of the traditional histogram can be described 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, Ex represents the exposure value. The formula for the threshold is:

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

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 [10], 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 dealing with low-illuminance images with

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interference noise, the calculated exposure threshold X_a will not be ideal, resulting in indirect segmentation failure, thus affecting the final image enhancement effect [11].

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 firstly defined, and the histogram distribution range is limited by constructing a parameter m, so as to eliminate the interference noise existing in the histogram. The optimized histogram distribution range is:

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

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 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 split point is as follows:

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

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

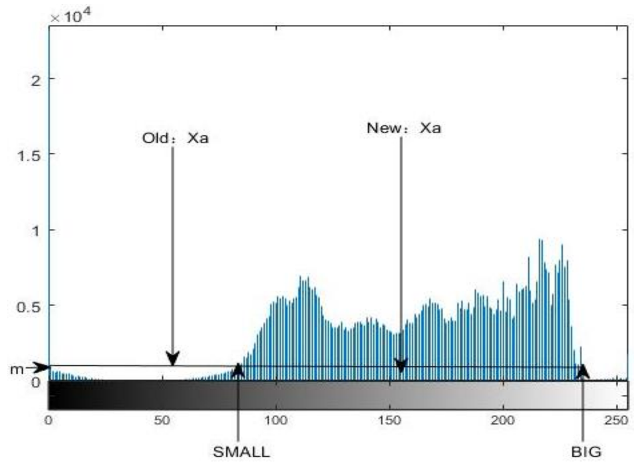

FIGURE 1. Optimization comparison chart.

Fig. 1 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 [12].

After the histogram is divided into two sub-histograms, this paper uses the mean value of the two sub-histograms as the segmentation point. Then, each sub-histogram is further divided into four sub-histograms, resulting in a total of 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 lower and upper sub-histograms respectively, and $P_{dl}(k)$ and $P_{du}(k)$ represent the PDFs of the lower and upper sub-histograms respectively.

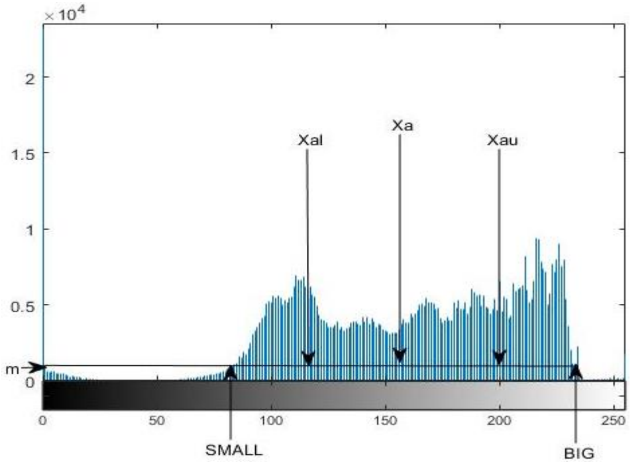

FIGURE 2. Location map of each split point.

Fig. 2 clearly displays the three segmentation points 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 the sub-histograms of each distinct region to improve the clarity of the enhanced image.

C. CONSTRUCTION METHOD BASED ON OPTIMAL CLIPPING THRESHOLD

The conventional histogram clipping method is relatively simple, and the calculation formula for clipping threshold cannot be adapted according to the distribution characteristics of the histogram. In addition, the selection of the standard clipping threshold includes the average number of gray levels but also the average value of the histogram, median and peak values, etc. Referring to the traditional clipping threshold selection method [13], 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. Among them, z is defined as the clipping parameter and a better clipping threshold value can be achieved by different values of z [14]. The calculation formula for the values in each sub-histogram is:

$$M_i = \text{median}(\text{histogramofsubimage}I_i), \tag{11}$$

Formulas of M_i represents the ith the median is the histogram. The procedure for calculating the clipping threshold of the algorithm in this paper is as follows:

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

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

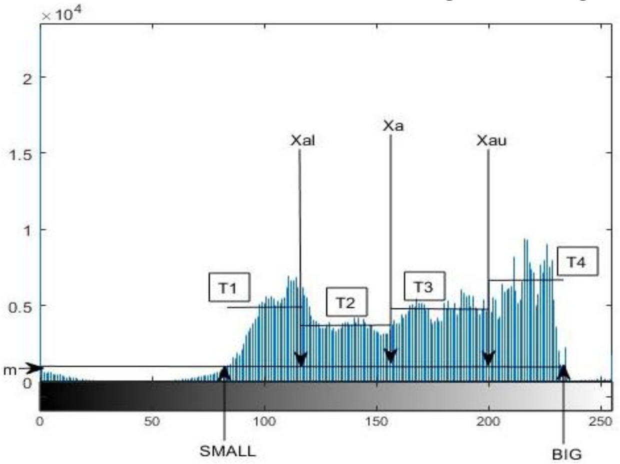

FIGURE 3. Location map of clipping threshold.

It can be observed from **Fig. 3** that the optimized clipping threshold is well within the range of the number of pixels in each sub-histogram. After calculating the clipping threshold, this paper clips each sub-histogram with the method that 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 Clipping threshold; and for the range where the number of pixels in the sub-histogram is less than the clipping threshold, no processing is performed. The specific calculation formula is:

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

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

D. MULTIPART FIGURES

After clipping the sub-histograms, this paper applies an independent equalization process to each sub-histogram. This process involves calculating the probability density function (PDF) of each sub-histogram [15], and using it to determine the cumulative distribution function CDF, so as to obtain the equalization transformation of each sub-histogram formula. 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:

$$G_1(k) = (X_{al} - 1) \times C_{d1}(k) \tag{16}$$

$$G_2(k) = \left((X_a - 1) - X_{al}\right) \times C_{d2}(k) + X_{al} \tag{17}$$

$$G_3(k) = \left((X_{au} - 1) - X_a\right) \times C_{d3}(k) + X_a \tag{18}$$

$$G_4(k) = ((L - 1) - X_{au}) \times C_{d4}(k) + X_{au} \tag{19}$$

Finally, the mapping function used to generate the enhanced output image is obtained by combining the mapping functions of each sub-image.

$$G = G_1(k) \cup G_2(k) \cup G_3(k) \cup G_4(k) \tag{20}$$

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. This process is repeated to get the equalized histogram of each channel. Finally, the equalized histograms of the three channels are combined to obtain an enhanced histogram, and an enhanced color image is produced as output.

Fig. 4 shows the images cited in this article, in which the comparison of the four sub-histograms of the R channel before and after equalization, and **Fig. 5** shows the comparison of the R channel histogram before and after equalization, as can be seen from the figure, the first the number of sub-histogram pixels after the second equalization becomes uniform. After the second R channel histogram equalization, the gray level is evenly mapped to the [0,255] interval so that the histogram distribution after the original histogram is enhanced is more uniform. The enhanced image contrast is more obvious, and the display effect is better.

E. THE OPTIMIZATION ALGORITHM FLOW OF THIS PAPER

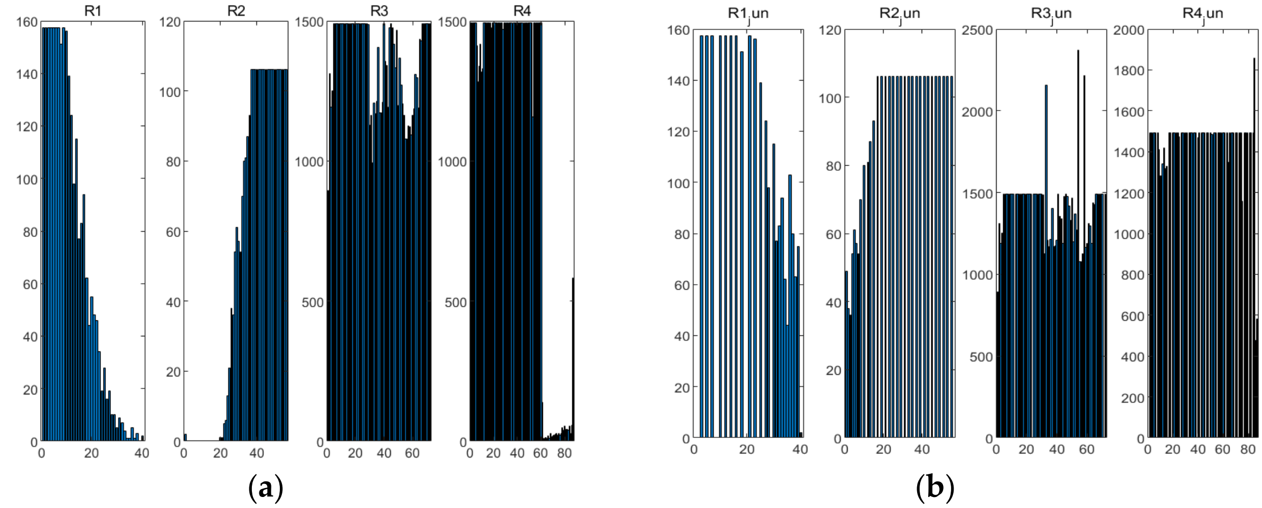

FIGURE 4. Four sub-histogram equalization of the R channel.

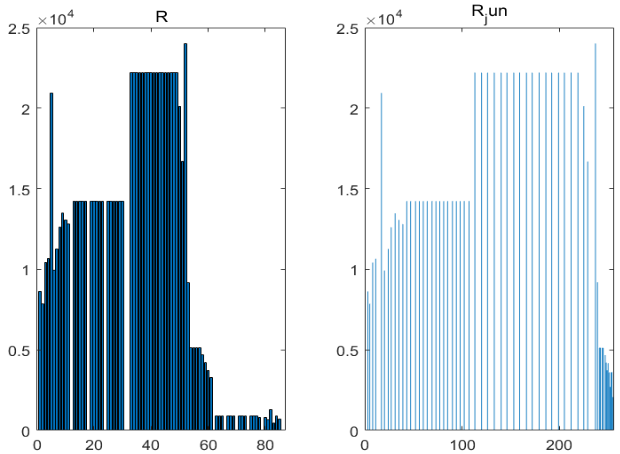

FIGURE 5. R channel histogram equalization.

The previous sections mainly introduce the three detailed steps of the algorithm in this paper image segmentation, cropping, and equalization. The following describes the detailed process of the algorithm in this paper. As shown in **Table I**.

III. RESULTS AND ANALYSIS

The database selected in this paper is EUVP (European Visual Plankton Archive), which 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 acquisition; among which in the paired data, there are 111,670 images of Underwater Dark, 8,670 images of Underwater ImageNet, and 4,500 images of Underwater Scenes. The unpaired data contains 6,665 images of poor quality and good quality, and these images have different acquisition times and space. The comprehensive information provided by in-depth analysis covers a wide range of scenarios and is highly informative, which can be utilized to validate and analyze the results of the algorithm proposed in this paper. The experimental simulation software and system parameters are shown in **Table II.**

A. SUBSECTION EVALUATION OF IMAGE QUALITY

In order to verify whether the subjective evaluation of the algorithm in this paper is better for underwater image enhancement, this paper conducts comparative experiments with six other common underwater image enhancement algorithms. These algorithms include CLAHE, RD, AHE, HE, BBHE, and RGHS. From the perspective of the universality of the verification algorithm, this paper selects some representative underwater image data from the three modules of Underwater Dark, Underwater ImageNet, and Underwater Scenes in the EUVP database for simulation experiments and demonstrates the enhancement effect of each algorithm.

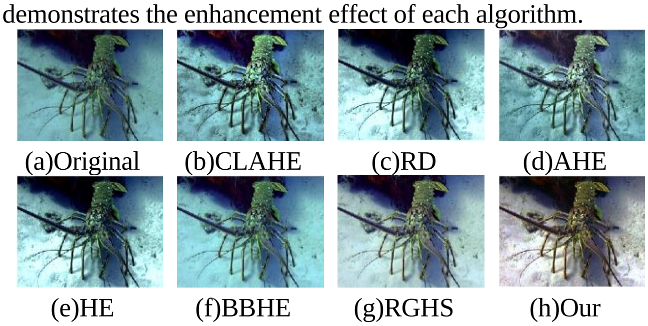

FIGURE 6. Example Figure 1 Subjective Comparison Chart

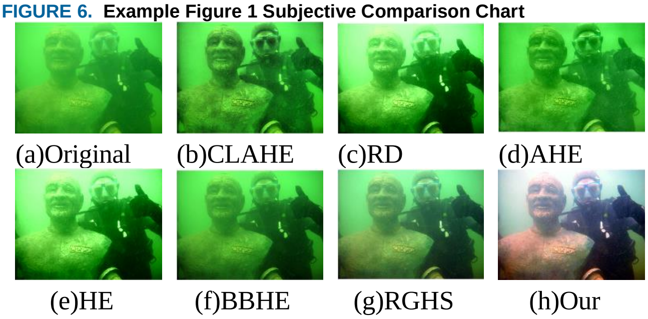

FIGURE 7. Example Figure 2 Subjective Comparison Chart.

TABLE I
ALGORITHM FLOW OF THIS PAPER

Algorithm steps in this article
1. Input a color image
2. Generate the R, G, and B three-channel histograms of the input image respectively
3. For the histogram of each channel, find the distribution range of the histogram limited by the m value
4. Use the histogram distribution range limited by the m value to calculate the exposure value and the segmentation point X_a
5. Calculate the mean value X_{al} and X_{au} of each sub-histogram, and use it as a split point to divide each sub-histogram into two sub-histograms to obtain four sub-histograms
6. Use the adaptive clipping parameter z to find the clipping threshold, and clip each sub-histogram
7. Equalize each sub-histogram obtained by splitting and clipping the three channels
8. Perform secondary equalization on each histogram of the three channels after splicing
9. Merge the equalized histograms of the three channels to obtain an enhanced histogram
10. Enhance image output

TABLE II
ALGORITHM SYSTEM PARAMETERS

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

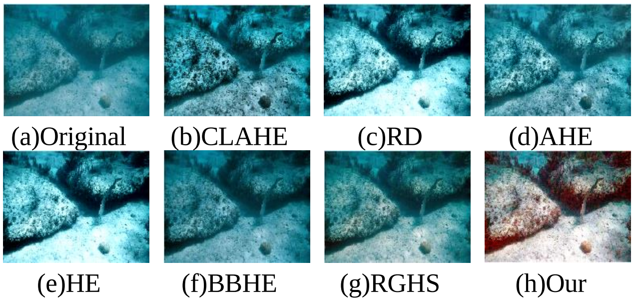

FIGURE 8. Example Figure 3 Subjective Comparison Chart.

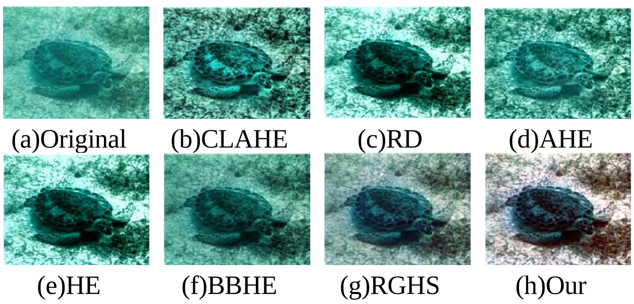

FIGURE 9. Example Figure 4 Subjective Comparison Chart.

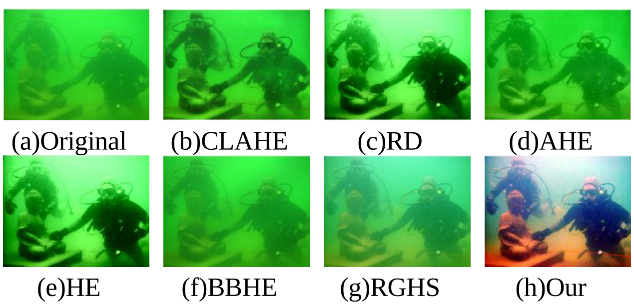

FIGURE 10. Example Figure 5 Subjective Comparison Chart.

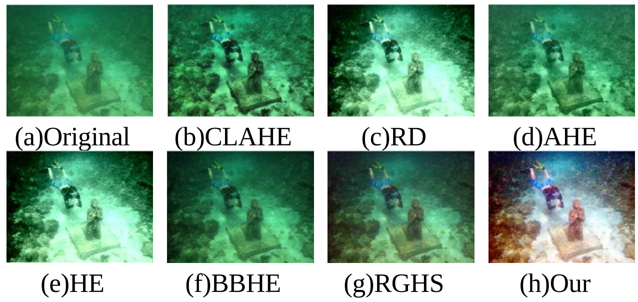

FIGURE 11. Example Figure 6 Subjective Comparison Chart.

This article selects six underwater images of different tones, and each comparison image shows the comparison between the underwater image enhanced by seven algorithms and the original image. The results are shown in the above six images. While the CLAHE and AHE algorithms enhance image contrast and preserve some details and local features, excessive enhancement can cause distortion. The RD algorithm can adaptively adjust the degree of enhancement, avoiding over- and under-enhancement, but may not produce significant improvement for images with blue-green tones.

The HE algorithm can produce clearer images, but may result in loss of details in some areas, leading to unnatural visual effects. The image enhanced by the BBHE algorithm and the RGHS algorithm can enhance the detailed information in the image very well, but the enhancement effect of RGHS is not good when processing low-contrast images, and the phenomenon of gray value aggregation occurs when BBHE processes high-contrast images, resulting in Image color is distorted. Through the above comparison, it can be seen that the contrast of the image processed by the algorithm in this paper is enhanced, the problem of image edge blur is improved, the image is clearer, the color is more natural, and the local details of the image are enhanced, which has a better visual effect.

TABLE III
ENTROPY EVALUATION INDEX RESULTS

Images	CLAHE	RD	AHE	HE	BBHE	RGHS	OUR
Exp.1	7.69	7.32	7.77	7.30	7.73	7.60	**7.98**
Exp.2	7.12	7.18	7.45	7.19	7.42	7.40	**7.88**
Exp.3	7.84	7.41	7.39	7.42	7.54	7.77	**7.89**
Exp.4	7.68	7.27	7.52	7.41	7.41	7.45	**7.94**
Exp.5	7.46	7.26	7.28	7.14	7.32	7.51	**7.92**
Exp.6	7.12	7.31	7.82	7.34	7.24	7.31	**7.92**

TABLE IV
MEAN EVALUATION INDEX RESULTS

Images	CLAHE	RD	AHE	HE	BBHE	RGHS	OUR
Exp.1	117.18	**128.54**	121.48	120.04	109.45	112.36	128.02
Exp.2	115.08	127.90	122.67	127.90	125.43	106.51	**128.11**
Exp.3	95.33	123.56	101.62	123.56	105.78	119.87	**128.37**
Exp.4	78.36	113.48	90.31	96.49	101.35	115.62	**129.16**
Exp.5	77.49	114.11	88.33	114.12	92.83	96.28	**128.73**
Exp.6	95.33	125.40	109.19	130.40	113.64	115.60	**128.34**

TABLE V
THE AVERAGE RESULTS OF THE UCIQE, PSNR, AND SSIM EVALUATION METRICS

Target	CLAHE	RD	AHE	HE	BBHE	RGHS	OUR
UCIQE	0.433	0.445	0.387	0.443	0.415	0.396	**0.470**
PSNR	29.987	29.596	30.132	30.485	30.070	28.784	**33.063**
SSIM	0.809	0.757	0.830	0.745	0.811	0.836	**0.875**

B. OBJECTIVE EVALUATION OF IMAGE QUALITY

In addition to verifying that the improved algorithm in this paper 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 to evaluate the quality of the image. This paper selects some image objective evaluation indicators, and each image parameter is verified and analyzed.

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 mean value, on the other hand, represents the overall intensity level of the image. Increasing Mean values correspond to higher average brightness of the image and generally indicate better image quality; the Universal Color Image Quality Index (UCIQE) is a method that compares the brightness, contrast, and chromaticity differences between the distorted image and the original image. To evaluate the objective index of color image quality, its value range is [0,1]; the more significant the image quality is better; the peak signal-to-noise ratio (PSNR) is a full measure of the distortion between the image, and the original image Refer to the objective index; the larger the PSNK, the smaller the distortion between the image to be evaluated and the reference, and the better the quality; the structural similarity (SSIM) reflects the structural similarity between the image to be evaluated and the reference image, and the value range of SSIM It 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.

First, 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 III**, it can be seen that the Entropy values of the six sample images enhanced by the algorithm of this paper are greater than those of other algorithms, indicating that the distribution of gray levels in the image enhanced by the algorithm of this paper is more uniform. The details and textures contained are more abundant. From the data in **Table IV**, the Mean value of the algorithm in this paper is relatively close to that of the RD algorithm, but judging from the overall effect of the six example diagrams, the algorithm in this paper is still better than the RD algorithm, and the other five algorithms, indicating that the algorithm in this paper is enhanced the average brightness of the image is higher, the overall brightness is better, and the visual effect is better.

This paper also selects 300 high-definition underwater images in EUVP database for full-parameter image objective evaluation. The following are 300 long-length underwater images enhanced by seven algorithms and their three full-parameter objective evaluations of UCIQE, PSNR, and SSIM Data analysis of the mean value of the indicator. **Table V** Average results of UCIQE, PSNR and SSIM evaluation indicators [16].

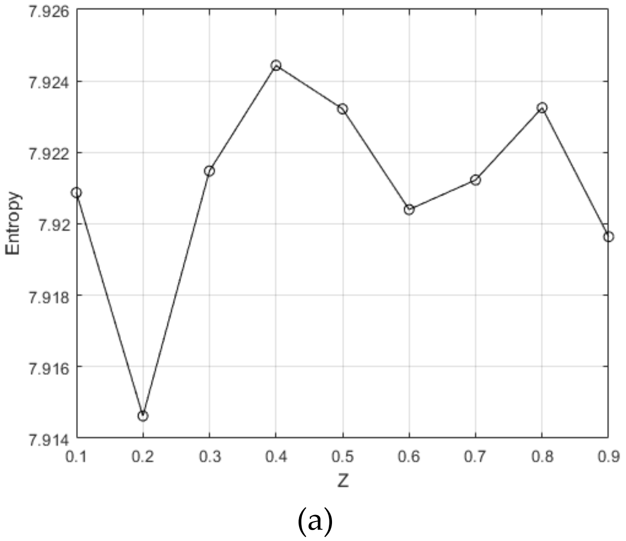

FIGURE 12. **Entropy and mean average line chart.**

According to the data in **Table V**, the algorithm of this paper is superior to other algorithms in terms of three comprehensive objective indicators, indicating that the image enhanced by the algorithm of this paper has better performance in terms of color, contrast, sharpness and details, and the overall quality is higher [17]. 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

In this paper, the value range of the clipping parameter z is set to [0,1], and the clipping parameter is taken from 0.1 to 0.9 with nine different values. The Entropy and Mean values are calculated for the six selected underwater images, and the average values of the six images are analyzed to determine the optimal range of clipping parameter values.

Fig. 12 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 algorithm for histogram equalization of underwater images. First, the exposure value and split point are calculated by optimizing the distribution range of the histogram. The histogram is first segmented, and then the sub-histogram is divided into four parts by using the mean value of the sub-histogram as the splitting point twice. Secondly, use the histogram clipping technique to clip different regional features of each sub-histogram, and then perform secondary equalization on the clipped histogram. Finally, the equalized sub-histograms of each channel are combined to obtain an enhanced color image as output. The subjective and objective evaluation experiments of the algorithm in this paper show that the image output by the algorithm in this paper is better than the comparison algorithm in terms of Entropy, Mean. Some comprehensive metrics show that the proposed algorithm is effective, and it is also simple and easy to understand, making it applicable to various underwater scenarios, such as deep-sea exploration, underwater archaeology, and underwater photography. The future research direction is to overcome the limitations of the algorithm proposed in this paper in processing the details of underwater images, and to develop a more refined histogram segmentation and cropping method that can preserve the details of underwater images with different characteristics.

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