Underwater Quality Enhancement Based on Mixture Contrast Limited Adaptive Histogram and Multiscale Fusion

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***Abstract*—This paper presents a novel approach for enhancing the visual quality of underwater images using various spatial processing techniques. This research addresses the common issues encountered in underwater imaging, such as color distortion, low clarity, low contrast, bluish or greenish tints caused by light scattering and absorption, and the presence of underwater organisms. To solve these problems, we utilize various image processing methods such as white balancing, Contrast Limited Adaptive Histogram Equalization (CLAHE) in Lab and HSV color spaces, sharpening, weight map generation, and multiscale fusion. The effectiveness of the proposed approach is evaluated quantitatively using mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM). The results indicate that the optimal CLAHE parameters are a block size 4x4 and a clip limit 1.2. These parameters yielded an MSE value of 0.7594, a PSNR value of 20.7121, and an SSIM value of 0.8826, demonstrating superior performance compared to previous research. A qualitative evaluation was also conducted using eight respondents based on overall visual quality, color fidelity, and contrast enhancement. The assessment results demonstrate satisfactory outcomes, with a mean score of 4.3278 and a standard deviation of 0.7238. Overall, this research demonstrates that effective and efficient enhancement of underwater image quality through computational methods can be achieved using simple techniques with appropriate parameters and placement, thereby enabling better scientific research and exploration of the underwater world.**

Keywords—CLAHE; Color space enhancement; luminance; sharpening

I. Introduction

Underwater environments are renowned for their stunning beauty and play a vital role in various technological and research fields, such as underwater infrastructure inspection and underwater archaeology. However, underwater imaging presents significant challenges due to the degradation of image quality caused by light absorption and scattering. This often results in images with a greenish or bluish tint at certain depths [1], which can hinder practical applications like object detection and visual exploration, where accurate color representation and contrast are crucial.

Light plays a fundamental role in underwater image quality. The higher density of water compared to air leads to substantial light absorption, reducing light intensity, contrast, and visibility [2]. For instance, red light diminishes after a depth of 4-5 meters, followed by orange, yellow, green, and blue, leading to undesirable color casts [3]. These effects significantly impact the accuracy and effectiveness of underwater imaging applications.

In this context, computer vision-based image enhancement methods have emerged as effective solutions to address color cast and low contrast issues in underwater images. These methods provide advantages over traditional restoration techniques or deep learning approaches, which often require expensive hardware and extensive training datasets [4]. Among these methods, Contrast Limited Adaptive Histogram Equalization (CLAHE) has shown superior performance in enhancing contrast [5]. Despite its effectiveness, challenges related to noise and color cast persist.

This study employs CLAHE in the HSV and Lab color spaces. In the HSV model, CLAHE is applied to the saturation and value components to enhance color purity and brightness. In the Lab model, CLAHE is used on the luminance component to recover images without affecting the chrominance, which could exacerbate color casts. The proposed approach involves correcting color distortion through color balancing, applying CLAHE to enhance contrast in the Lab and HSV color spaces, and then sharpening and modifying weight maps using Multiscale Fusion. This method aims to significantly improve the quality of underwater images, contributing to advancements in automated image processing technologies.

This paper is organized as follows: Section II comprehensively reviews related works in underwater image enhancement, highlighting previous research and existing methods. Section III details the proposed method, including applying CLAHE and multiscale fusion techniques. Section IV presents the experimental results, showcasing the outcomes of our proposed method and comparing them with existing techniques. Finally, Section V concludes the paper by summarizing the key contributions and suggesting potential future research directions.

II. Related Works

Improving underwater image quality is a crucial area of research due to unique challenges such as color distortion and reduced visibility compared to standard images. Various techniques have been explored to address these issues, including color balancing, sharpening, and contrast optimization using Contrast Limited Adaptive Histogram Equalization (CLAHE) in different color spaces. CLAHE

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combined with Discrete Wavelet Transform (DWT) has been employed to enhance contrast effectively. While this approach is beneficial, it does not entirely resolve noise issues in high-frequency components [6]. Additionally, applying CLAHE in the YIQ and HSI color spaces has demonstrated improvements in image quality but introduced added complexity to the process [7]. The use of CLAHE in the Lab color space has shown significant contrast enhancement, although global illumination issues may not be fully addressed [8].

Further advancements include the application of CLAHE to luminance components in the YCbCr color space, which offers good contrast but often requires additional adjustments for varying lighting conditions [9]. Moreover, CLAHE applied to the L component in the Lab color space, in conjunction with edge detection using the Candy method, enhances edge details but may not fully improve overall color quality [10]. CLAHE applied to HSV images aids in color processing but can result in undesirable color casts [11]. Traditional enhancement techniques such as gamma correction and histogram equalization are beneficial; however, they may fall short in addressing image blur [1].

Recent approaches utilizing CLAHE-based multiscale fusion, combined with white balancing, gamma correction, sharpening, and weight map manipulation, have shown improvements in image quality. Nevertheless, issues with contrast and color cast persist [12]. Integrating Layered Difference Representation (LDR) with CLAHE for color correction has enhanced color distribution but can impact processing speed [13]. Applying CLAHE after white balancing and contrast enhancement improves image quality, although additional refinement is often necessary for optimal results [14]. Overall, the proposed methods demonstrate varying strengths and weaknesses in enhancing underwater image quality. The proposed research is anticipated to more effectively address color correction and noise removal by integrating CLAHE in color spaces such as Lab and HSV and utilizing multiscale fusion, color balancing, contrast optimization, and weight maps for more optimal results.

III. The Proposed Method

The research method employed in this study comprises several stages, as illustrated in Fig. 1. Initially, a white balancing process is applied to the underwater image using affine transformation based on cumulative histogram statistics for each channel in the RGB color space for color correction. Prior to white balancing, a compensated red channel process is performed to address the loss of the red channel that occurs in underwater images. Subsequently, the method alternates among different processes: applying the CLAHE method in the Lab color space, applying the CLAHE method in the HSV color space, and applying the unsharp masking method based on the High Pass Filter principle. Finally, Multiscale Fusion is utilized to combine the results of white balancing, CLAHE-Lab, and CLAHE-HSV images, along with the Laplacian weight map, saliency, and saturation.

To optimize the effectiveness of these methods, various parameter values are systematically tested through experiments. The goal is to observe how different parameter settings affect image quality and determine whether they yield optimal results. This optimization process involves evaluating parameter values based on the average error across multiple images, acknowledging that each image may require different settings due to its unique conditions. When an increase in error is detected, those parameter values are considered less effective and are not pursued further. Conversely, parameter values that result in reduced error are further refined and tested until improvements become minimal. This iterative approach ensures that the most effective parameter values are selected for enhancing image quality across diverse conditions.

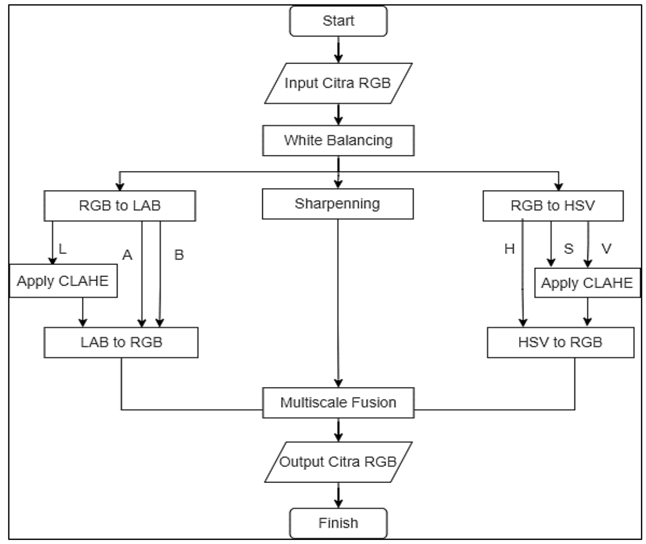

Fig. 1. Process of research method.

A. White Balancing

White balancing is an important step in correcting color casts that appear due to the absorption of colors at specific depths, resulting in bluish or greenish images. This process can be performed in two steps. First, the compensated red channel can be adjusted as in Eq. (1). Second, the RGB channels can be processed using the simplest color balance method, which neutralizes or equalizes the channels' processing, as in Eq. (2) using an affine transformation [15]. The detailed flow is in Fig. 2.

$$I_{rc}(x) = I_r(x) + \alpha.(\overline{I_g} - \overline{I_r}).(1 - I_r(x)).I_g(x) \quad (1)$$

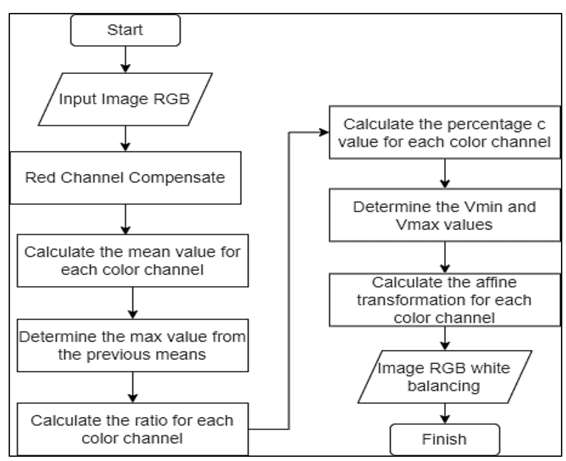

Fig. 2. Process of the white balancing algorithm.

I_r and I_g are the red and green color channels, respectively, each channel is normalized to the interval [0, 1]. $\overline{I_r}$ and $\overline{I_g}$ are the mean values of I_r and I_g.

Step 1: Calculate the average value for each color channel.

Step 2: Determine the maximum value of the average for each color channel.

Step 3: Calculate the ratio of each color channel by dividing each color by the total mean of the image, as in Eq. (2).

$$ratio(\lambda) = \frac{\max_{\lambda \in \{R,G,B\}}(mean(I_\lambda))}{mean(I_\lambda)} \quad (2)$$

Step 4: Calculate the percentage of the constant "c" for each color channel using a value of 0.005, as in Eq. (3).

$$c_{R,G,B} = 0.005 \times ratio(\lambda) \quad (3)$$

Step 5: Determine the V_{min} and V_{max} values for each color channel and convert them to one dimension.

Step 6: Calculate the affine transformation using the computed values, as in Eq. (4).

$$f(x) = \frac{(x - V_{min})}{(V_{max} - V_{min})} \times 255 \quad (4)$$

The cumulative histogram labeled "i" shows the number of pixels with low values or values equal to "i." To calculate V_{min}, we identify the lowest histogram label with a value greater than N x c_1 while V_{max} is the highest histogram label with a value lower or equal to N x (1-c_2). The pixel interval [V_{min}, V_{max}] is mapped to the range [0, 255] using an affine transformation [15].

B. CLAHE Lab Dan HSV

CLAHE is a local histogram equalization technique that enhances contrast in an image by dividing it into sub-images and performing contrast enhancement on each sub-image based on the characteristics of the pixels surrounding it. After equalization, neighboring sub-images are combined using bilinear interpolation to eliminate any artificial boundaries in the image. Moreover, CLAHE can also mitigate noise in an image by constraining the contrast in homogeneous areas.

CLAHE has two primary parameters: block size and clip limit. The block size parameter is used to partition the image into sub-images. In contrast, the clip limit parameter reduces noise in the image by trimming the histogram at a specified value before calculating the Cumulative Distribution Function (CDF). These two CLAHE parameters serve to set the quality of the enhanced image [16].

The CLAHE method enhances image quality in two color spaces: Lab and HSV. In the Lab color space, as illustrated in Fig. 3, CLAHE is applied to the Luminance (L) component to improve image brightness. After histogram equalization on the L component is completed, the L, a, and b components are recombined and converted back to RGB, resulting in the CLAHE-Lab image. Conversely, in the HSV color space, as depicted in Fig. 4, CLAHE is applied to the Saturation (S) and Value (V) components, separately or together. Before converting back to RGB, a comparison is made to evaluate the application of CLAHE to S, V, or both. The evaluation involves determining the optimal clip limit and block size based on MSE error values. Different images are obtained for each combination, with lower MSE values approaching zero, indicating better image quality. The general steps of the CLAHE method are as follows:

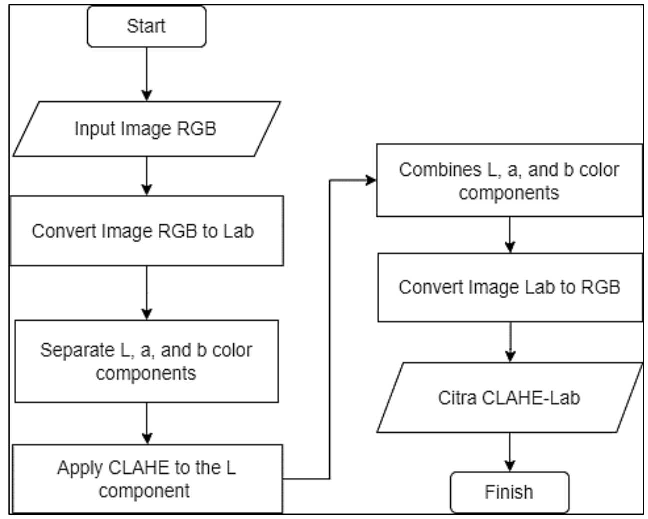

Fig. 3. Process of the CLAHE-Lab algorithm.

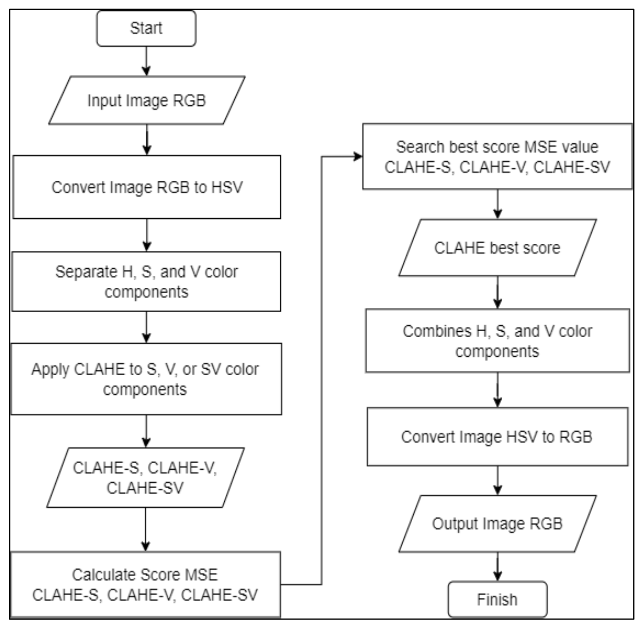

Fig. 4. Process of the CLAHE-HSV algorithm.

Step 1: Divide the image into sub-images or blocks with a size M×N.

Step 2: Normalize the histogram by calculating the image's Cumulative Distribution Function (CDF) value. CDF is defined as the running sum of the intensity I divided by the number of pixels in the image, as in Eq. (5). Here, f is the cumulative distribution, N is the maximum pixel value, M is the image size, and K is the frequency of occurrence of the pixel value.

$$f_{i,j}(n) = \frac{(N-1)}{M} \cdot \sum_{k=0}^{n} h_{i,j}(K) \quad (5)$$

Step 3: Calculate the maximum clip limit value in the histogram, as in Eq. (6). The clip limit (CL_ is influenced by an independent factor, the clip factor (α), which controls the illumination level. The clip factor range is from 0 to 100. Here, M is the size of the image region, N is the maximum pixel value (256), and Smax is the maximum pixel value in the region.

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \tag{6}$$

Step 4: After dividing the image into blocks, perform histogram normalization by finding the CDF in each region. The probability distribution is found by dividing the frequency of occurrence by the region's size. The cumulative distribution is obtained by adding the pixel probability distribution to the previous pixel value probability. This process is repeated for each pixel value in each region.

Step 5: Find the clip limit value by specifying the clip factor within the range of 0 to 100.

Step 6: Normalize the histogram by multiplying each pixel's cumulative distribution by the maximum value of the pixel value in the region.

Step 7: Perform clipping by adding the pixel result from the normalization multiplication to the clip limit. If the resulting value exceeds the maximum pixel value, which is 255, it is replaced with the maximum pixel value.

Step 8: After equalization, the sub-images are combined using bilinear interpolation to eliminate artificial boundaries and produce a smoother and better-combined result.

C. Sharpening

The method used in this study to enhance image sharpness is the unsharp masking method, designed to enhance unclear details in the image. The unsharp masking process involves several stages, starting with a low-pass filter process that produces a blurred image, followed by a high-pass filter that enhances the details in the image by subtracting the original image from the blurred image. The unsharp masking process consists of several stages. Firstly, a low-pass filter process is used to create a blurred image. Secondly, a high-pass filter enhances image details by subtracting the original image from the blurred image. Thirdly, a histogram stretching process is implemented to increase or decrease the image contrast by expanding or compressing the range of pixel intensity values. Finally, a normalized unsharp masking process normalizes image sharpness without parameter adjustment. The detailed flow of sharpening is shown in Fig. 5.

$$S = (I + N\{I - G \times I\})/2 \tag{7}$$

where, I represents the input or original image, G×I represents the blurred image generated by convolving the Gaussian filter with the original image, and N represents the linear normalization operator that adjusts histogram stretching. Operator N shifts and scales all color pixel intensities in the input image such that the transformed set of pixel values encompasses the full dynamic range. The normalized unsharp masking process, which does not require any parameter adjustments, appears to be more effective in enhancing image sharpness, as indicated by previous studies [1].

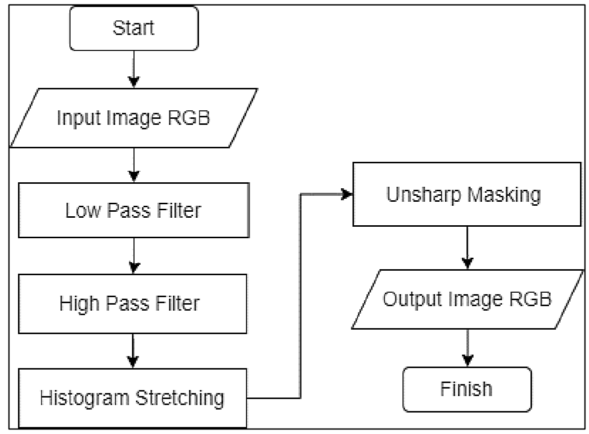

Fig. 5. Process of the sharpening algorithm.

The unsharp masking process effectively enhances sharpness; however, it can result in undesirable halo effects caused by excessive sharpening. To overcome this issue, a multi-scale fusion strategy was used to minimize artifacts that may arise during image merging, producing a final outcome free of halo effects.

D. Weightmap Generation

After implementing several methods and generating three image results, namely CLAHE-Lab, CLAHE-HSV, and sharpening, the next step is to create three weights from these results. These weights, namely Laplacian Contrast (W_L), Laplacian Saliency (W_S), and Laplacian Saturation (W_{Sat}), aim to explore the spatial relationship of degraded regions. Each pixel weight is generated based on the object's characteristics, such as hue, saturation, and contrast [1].

1) Laplacian Contrast (W_L) computes the global contrast by applying the absolute value of the Laplacian filter to each input luminance channel. Convolution is run using the Laplacian kernel, as in (8), where f(x) represents the input image on the Luminance component, and g(x) represents the Laplacian kernel.

$$W_L = |f(x) * g(x)| \tag{8}$$

2) Laplacian Saliency (W_S) is used to identify the most prominent objects that lack superiority in the underwater scene. A saliency map is generated to highlight the relevant areas. To detect the saliency level, we employed the Laplacian Saliency algorithm based on the regional contrast object proposed [17] This algorithm uses histogram-based contrast methods, as in Eq. (9) [18], to consider both global contrast and spatial coherence.

$$W_{sal}(I_p) = \sum_{i=1}^{N}\left(I_{p,q} - \overline{I_k}\right)^2 \tag{9}$$

Where, I_p represents the matrix value in the Lab color space, N denotes the number of rows (p) and columns (q), and $\overline{I_k}$ signifies the average value of each L, a, and b component.

3) Laplacian Saturation (W_{Sat}) employs a fusion algorithm to extract chromatic information from highly saturated areas by measuring color intensity values in the image. The presence of saturated colors enhances the clarity of the image. The weight map calculates the deviation for each pixel position between the color channel and illumination, as in Eq. (10).

$$W_{sat} = \frac{\sqrt{[(R_k - L_k)^2 + (G_k - L_k)^2 + (B_k - L_k)^2]}}{3} \quad (10)$$

Where, I_k represents the input value of each L, a, and b component, and R_k, G_k, B_k signify the input values of each R, G, and B component and luminance L_k of the kth input (each pixel value position).

Furthermore, the weight map (W_k) is generated by combining these three weights using as in Eq. (11)

$$\overline{W_k}(x, y) = \frac{W_k(x,y)+\delta}{\sum_{k=1}^{N} W_k(x,y)+\delta} \quad (11)$$

Where W_k represents the normalized weight map for the kth input. N is the normalized aggregate map of each pixel, and the weight of each pixel in each map is divided by the total weight of the same pixel. Here, we set N to a constant coefficient of 2, and δ is a constant set to 0.001 to ensure that each weight map contributes to the result and prevents it from becoming 0 [19].

E. Multiscale Fusion

Gaussian pyramids are formed for each weight (Wk) in each image by convolving each layer of the pyramid with a Gaussian filter. We then create Laplacian pyramids for each color channel based on the levels determined in each image. Finally, a merging process between the Gaussian and Laplacian pyramids for each color channel (R, G, and B) based on the levels, as in Eq. (12).

$$R_{l,k}(x) = \sum_k G_l[\overline{W_k}(x, y)]\, L_l[I_k(x, y)] \quad (12)$$

The formula consists of $R_{l,k}(x)$, which represents the l layer of the image pyramid for input image k, $G_l[\overline{W_k}(x, y)]$, which is the input of the pyramid from Gaussian filtering and $L_l[I_k(x, y)]$, which is the normalized weight map before Laplacian filtering on the image. The pyramid is then reconstructed by merging images based on color channels, as in Eq. (13), resulting in a new pyramid for each color channel (fusion). Normalization is performed on the resulting fusion image by scaling it from 0 to 255 with data type uint8.

$$E_{res}(x, y) = \sum_l U\left[R_{l,k}(x, y)\right] \quad (13)$$

where, $E_{res}(x, y)$ is obtained by adding the combined contribution from all levels in the Gaussian-Laplacian pyramid, where l represents the pyramid level and k represents the number of input images. $U\left[R_{l,k}(x, y)\right]$ represents the output of the image pyramid. The merging process can reduce unnecessary image information or improve image quality from a lower-quality image to a higher-quality image. To evaluate the quality of the method used in this study, an error value is calculated. Fig. 6 illustrates the detailed flow of the multiscale fusion process.

F. Evaluation Metrics

Quantitative evaluation will be conducted by calculating the Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR) [3], and Structural Similarity Index (SSIM) between the processed images and ground truth images. Higher PSNR values and lower MSE values indicate better-quality underwater images that more closely match the ground truth. In comparison, higher SSIM values reflect better image structure and texture preservation. Additionally, the proposed method will be compared with several existing methods to assess its performance [20].

To demonstrate the quantitative improvements achieved by the proposed method in mitigating color cast and enhancing contrast in underwater images, the Universal Image Quality Metric (UIQM) will be computed. The UIQM consists of three components: the Underwater Image Color Metric (UICM) to assess color fidelity, the Underwater Image Sharpness Metric (UISM) to evaluate sharpness, and the Underwater Image Contrast Metric (UIConM) to measure contrast. The overall UIQM value is obtained by aggregating these three metrics. A higher UIQM value indicates better image quality and results that align more closely with human visual perception.

Qualitative evaluation will also be performed using a Google Forms survey. Respondents will rate the effectiveness of the proposed method in producing noticeable improvements compared to the original images. Ratings will range from 5 (Excellent) to 1 (Bad). The average score and standard deviation of the survey responses will be calculated to provide insights into the method's subjective assessment.

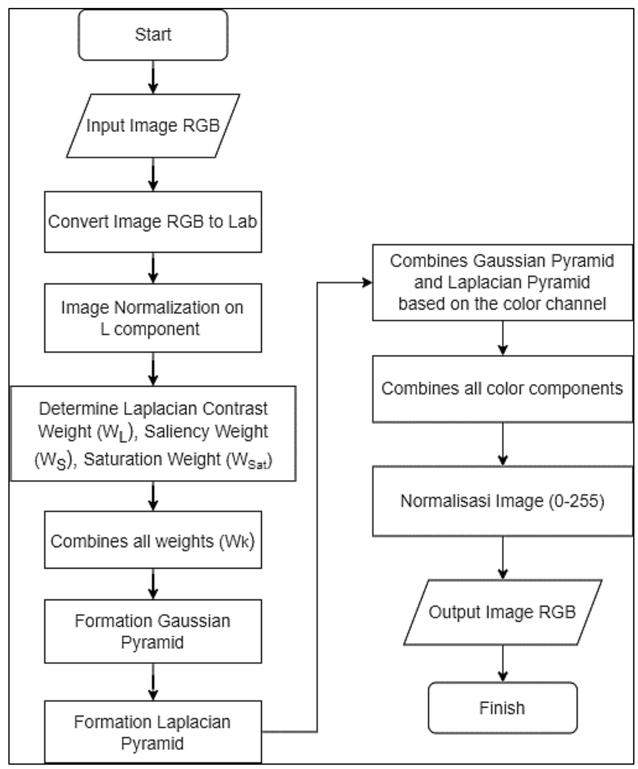

Fig. 6. Process of the multiscale fusion algorithm.

IV. Experimental Results

The UIEB dataset consists of 950 underwater images from Google, YouTube, and prior research. These images were enhanced using nine methods: fusion-based, two-step-based, retinex-based, UDCP, regression-based, GDCP, Red Channel, histogram prior, and blurriness-based. For each original image, nine enhanced versions were produced using different methods. Fifty respondents evaluated these versions to select the best one as the reference image (ground truth), without knowing the enhancement method used. The effectiveness of the enhancement methods was assessed by comparing error values across techniques. For quantitative and qualitative evaluation, a subset of 90 images from the 950 was used to ensure consistency in the comparative analysis [20]. The proposed method will be implemented using Python in Google Colab.

We conducted a series of experiments to optimize the CLAHE method by varying the block sizes (2×2, 4×4, 6×6, 8×8, and 12×12) and clipping limits (ranging from 0.2 to 2.0 with increments of 0.2). Optimal kernel usage during the sharpening stage also contributed to the improved final results of the proposed method. After performing white balancing, we combined the processed image results from CLAHE-Lab, CLAHE-HSV, and Sharpening. The enhancement in underwater image quality, based on the average error of the proposed method, indicated superior performance. 90 underwater images were used to determine the best parameter combination.

The experimental results reveal that the optimal clipping limit for the CLAHE method is 1.2 with a block size of 4×4, yielding the lowest Mean Squared Error (MSE) of 0.7594. Comparative values for different block sizes and clipping limits are presented in Table I, with corresponding evaluation graphs shown in Fig. 7. The Peak signal-to-noise ratio (PSNR) obtained was 20.7121. Values for block sizes and clipping limits are detailed in Table II, and the evaluation graph is illustrated in Fig. 8. Additionally, the Structural Similarity Index (SSIM) recorded a value of 0.8826. Details for block sizes and clipping limits are shown in Table III, with the evaluation graph displayed in Fig. 9. The sharpening process, using a 3×3 kernel with a sigma value of 5, was also assessed and demonstrated better results compared to other parameter settings.

TABLE I. EVALUATION RESULTS OF MSE FOR VARIOUS BLOCK SIZES DAN CLIP LIMITS

BLOCK SIZE	CLIP LIMIT				
	1.2	1.4	1.6	1.8	2.0
2x2	0.7712	0.7808	0.7944	0.8122	0.8316
4x4	**0.7594**	0.7648	0.7753	0.7838	0.8009
6x6	0.7647	0.7686	0.7786	0.7838	0.7967
8x8	0.7663	0.7676	0.7723	0.7770	0.7896
12x12	0.7881	0.7860	0.7928	0.7976	0.8078
BLOCK SIZE	CLIP LIMIT				
	0.2	0.4	0.6	0.8	1.0
2x2	0.8493	0.8223	0.7980	0.7808	0,7730
4x4	0.8428	0.8137	0.7904	0.7723	0,7633
6x6	0.8457	0.8178	0.7956	0.7801	0,7693
8x8	0.8617	0.8183	0.7952	0.7790	0.7708
12x12	0.8543	0.8316	0.8127	0.7985	0.7903

Our findings suggest that the proposed method can compete with more complex techniques while requiring lower computational resources. As summarized in Table IV, our method outperforms several previous studies regarding MSE, PSNR, and SSIM. The method's stability against error variations is notable, with the proposed method exhibiting more excellent stability than competing methods. Although a larger clip limit reduces error, excessive values increase error.

To assess whether color cast and contrast have been improved from the original images, we also performed quantitative testing using the Underwater Image Quality Metric (UIQM), which includes the Underwater Image Colorfulness Metric (UICM), Underwater Image Sharpness Metric (UISM), and Underwater Image Contrast Metric (UIConM). The UIQM evaluation demonstrated improved values compared to the original images. The UICM for color was 3.1474, UISM for sharpness was 4.4132, UIConM for contrast was 0.2374, and UIQM for overall Human Visual System (HVS) assessment was 2.2408. The proposed method achieved values of UICM 4.8774, UISM 5.6065, UIConM 0.3134, and UIQM 2.9136.

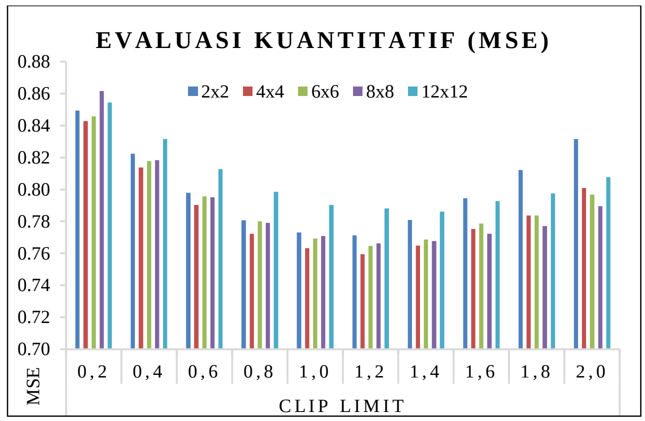

Fig. 7. Quantitative Evaluation Results (MSE).

TABLE II. EVALUATION RESULTS OF PSNR FOR VARIOUS BLOCK SIZES DAN CLIP LIMITS

BLOCK SIZE	CLIP LIMIT				
	0.2	0.4	0.6	0.8	1.0
2x2	20.4632	20.5596	20.6266	20.6596	20.6199
4x4	20.4942	20.6105	20.6893	20.7387	20.7332
6x6	20.4881	20.6012	20.6817	20.7246	20.7426
8x8	20.4887	20.6135	20.7063	20.7568	20.7784
12x12	20.4604	20.5480	20.6128	20.6447	20.6635
BLOCK SIZE	CLIP LIMIT				
	1.2	1.4	1.6	1.8	2.0
2x2	20.5583	20.4111	20.2486	20.0791	19.9032
4x4	**20.7121**	20.6128	20.4758	20.3496	20.2104
6x6	20.7370	20.6771	20.5645	20.4765	20.3605
8x8	20.7818	20.7654	20.6870	20.6299	20.5242
12x12	20.6331	20.6206	20.5266	20.4426	20.3367

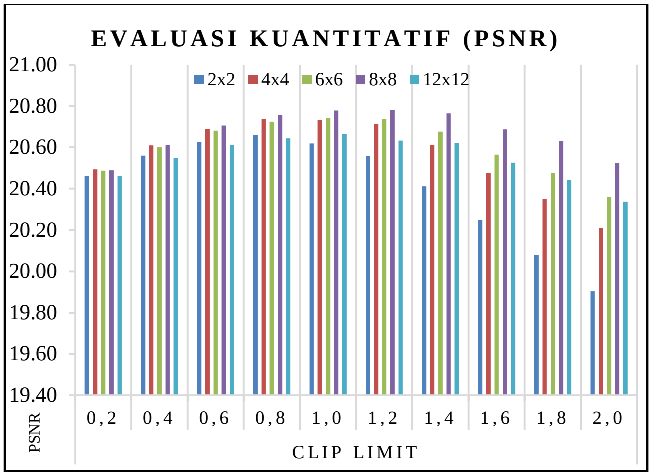

Fig. 8. Quantitative Evaluation Results (PSNR).

TABLE III. EVALUATION RESULTS OF SSIM FOR VARIOUS BLOCK SIZES DAN CLIP LIMITS

BLOCK SIZE	CLIP LIMIT				
	0.2	0.4	0.6	0.8	1.0
2x2	0.8728	0.8759	0.8791	0.8814	0.8826
4x4	0.8737	0.8774	0.8804	0.8823	**0.8830**
6x6	0.8740	0.8777	0.8804	0.8805	0.8828
8x8	0.8728	0.8781	0.8811	0.8824	0.8823
12x12	0.8740	0.8778	0.8801	0.8806	0.8810
BLOCK SIZE	CLIP LIMIT				
	1.2	1.4	1.6	1.8	2.0
2x2	0.8825	0.8811	0.8792	0.8765	0.8735
4x4	**0.8826**	0.8813	0.8788	0.8746	0.8726
6x6	0.8821	0.8804	0.8776	0.8746	0.8713
8x8	0.8820	0.8802	0.8777	0.8748	0.8709
12x12	0.8802	0.8785	0.8748	0.8715	0.8673

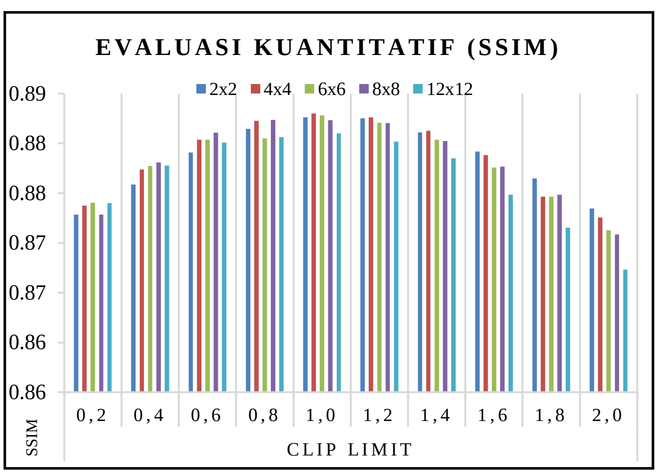

Fig. 9. Quantitative Evaluation Results (SSIM).

Furthermore, a qualitative evaluation was conducted through a survey of eight respondents from diverse backgrounds, including experts such as faculty members specializing in underwater image quality enhancement and non-experts such as students interested in image processing, divers, and students outside the field of image processing. Respondents rated the images on a scale of 1-5 (very poor to very good). The average score and standard deviation for two expert respondents were 3.9444 and 0.5953, respectively. For six non-expert respondents, the average score was 4.4556, with a standard deviation of 0.7181. The overall average score for all respondents was 4.3278, with a standard deviation of 0.7238. The qualitative evaluation categorized the proposed method as "Good," with a score of 4, reflecting favorable results from a subjective perspective.

The survey revealed that images with initial color cast and low contrast received the highest ratings after enhancement. Conversely, images with minimal color cast and high noise but already visually good exhibited decreased rating post-processing, as the method focuses more on correcting color cast and blur or lack of detail. Nonetheless, the results from the proposed method closely approach ground truth images with improved MSE, PSNR, and SSIM values compared to the original images. These findings indicate that a more straightforward method can yield better images with lower computational cost. Spatial methods in underwater image processing must be applied carefully, as incorrect method placement can worsen subsequent processing stages. Several sample images from all tested methods are shown in Fig. 10.

A qualitative evaluation was performed by surveying the proposed method for 90 underwater images and comparing the results with the original images. The survey involved eight respondents from diverse backgrounds, including experts such as professors who specialize in enhancing underwater image quality, and non-experts such as students who focus on image processing research, students who are passionate about the beauty of the underwater world (divers), and students outside the image processing field. The respondents rated the results on a 1-5 scale (very poor to excellent).

Based on the calculation of the average score and standard deviation from two expert respondents, the average score was 3.9444 and a standard deviation of 0.5953. The average score for the six non-expert respondents was 4.4556, and a standard deviation of 0.7181. Overall, the average score for all respondents was 4.3278, with a standard deviation of 0.7238. The qualitative evaluation results of the proposed method fall within the 'Good' category with a score of 4, indicating positive outcomes from a subjective perspective.

Based on the survey results, the image characteristics that received the highest scores were images with color cast and low contrast, respectively. After enhancement, these images appeared significantly better than their original versions. Conversely, the original images with little color cast and high noise decreased in quality compared to the original because of the proposed method's emphasis on improving underwater images with color cast and low contrast.

Despite this, the proposed image produced results closer to the ground truth image, with better values for the MSE, PSNR, and SSIM calculations than the original image. Fig. 10 shows some image samples resulting from all the methods employed in this research.

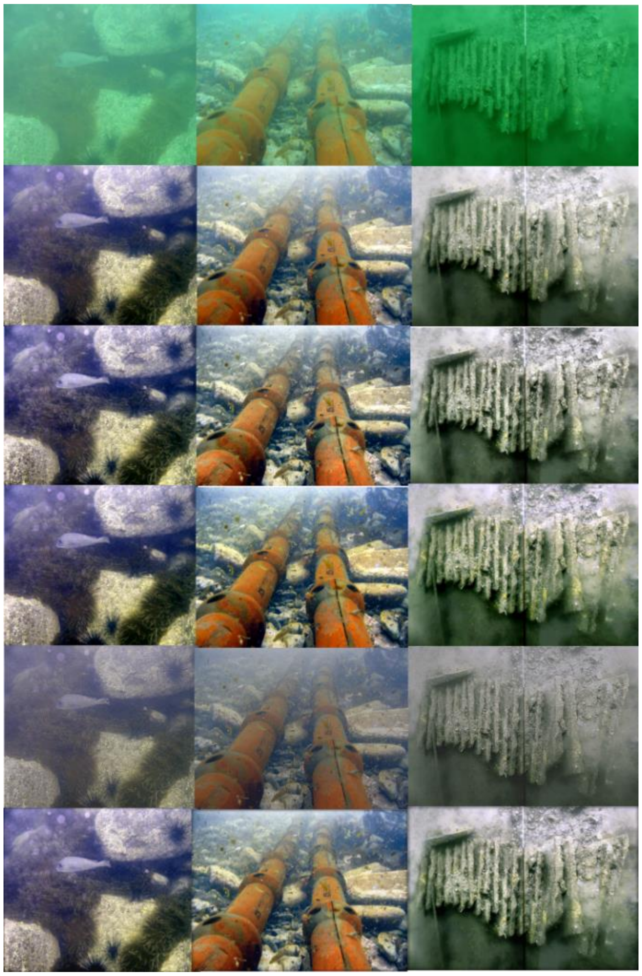

Fig. 10. The image samples of all processing stages, including the initial image (first row), the image after white balancing (second row), the image after CLAHE-Lab (third row), the image after CLAHE-HSV (fourth row), the image after sharpening (fifth row), and the image after multiscale fusion (sixth row).

TABLE IV. QUANTITATIVE EVALUATION RESULTS OF IMAGE QUALITY ASSESSMENT USING MSE, PSNR, AND SSIM

Method	MSE (10^{-3})	PSNR (dB)	SSIM
Fusion-based [21]	1.1280	17.6077	0.7721
Retrinex-based [22]	1.2924	17.0168	0.6071
GDCP [23]	4.0160	12.0929	0.5121
Histogram prior [24]	1.7019	15.8215	0.5396
*Blur*riness-based [25]	1.9111	15.3180	0.6029
Water CycleGAN [26]	1.7298	15.7508	0.5210
Dense GAN [27]	1.2152	17.2843	0.4426
Water-Net [20]	0.7976	19.1130	0.7971
Mixture CLAHE-Fusion (method in this study)	0.7594	20.7121	0.8826

V. CONCLUSION

This research proposes a method of enhancing underwater image quality aimed at the problem of color cast and low contrast in underwater images caused by light scattering and absorption. The white balance method effectively corrects the color cast commonly found in bluish or greenish underwater images. Histogram equalization has been shown to reduce image errors by using clipping and block size techniques in the CLAHE method, along with color space conversion to Lab and HSV. The use of image sharpening methods also helps in the process of enhancing edges in underwater images, although the results obtained may still be insufficiently sharp for pattern recognition purposes. The final output is obtained by combining the results using Multiscale Fusion, which employs three weights, namely the Laplacian Contrast Weight (WL), Saliency Weight (WS), and Saturation Weight (WSat).

Based on the quantitative evaluation results, the proposed method showed a significant improvement in the average values, with the initial MSE value of 2.2497 reduced to 0.7594, the initial PSNR value of 15.7480 increased to 20.7121, and the initial SSIM value of 0.7299 increased to 0.8826. Additionally, the qualitative evaluation results indicated that the average and standard deviation values chosen by the eight respondents showed good results, with a score of 4 (Good) from a subjective perspective. The calculation of the average score and standard deviation from eight respondents showed an average value of 4.3278 and a standard deviation of 0.7238. Based on these evaluation results, it can be concluded that utilizing a simple method to enhance underwater image quality with appropriate parameter settings and method placement can considerably enhance the quality of underwater images and expedite the computation time.

Despite successfully enhancing the quality of underwater images, further development is necessary due to its effectiveness only for not very deep depths. When capturing images at deeper depths, the lighting conditions become affected, resulting in lower contrast and color cast. Therefore, future research could focus on developing or combining the proposed method with others, such as dehazing, adaptive methods, or machine learning, to address additional challenges in underwater image processing.

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