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ADAPTATION OF ENHANCING UNDERWATER IMAGE USING MULTISCALE RETINEX

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Abstract
The Retinex theory was developed to describe the human color vision, and its derivations have resulted in practical image contrast enhancement algorithms. In this paper, strategies based on the multiscale Retinex algorithm and color constancy are presented to improve underwater images, due to medium scattering and absorption, these images have deteriorated. Preprocessing, adaptative Multi-Scale Retinex, and color constancy approach are the three critical phases of the proposed method. Consequently, consequence, the multiscale Retinex method with updated color constancy methodology is efficient and computationally cheap, delivering accurate color fidelity of roughly 28.38 dB for low-quality images. In addition, the proposed method preserves the naturalness of scenes.

1. Introduction

Because of the physical properties present in an underwater environment, underwater imaging is challenging[1]. Because of the attenuation of propagating light, largely due to absorption and scattering effects, underwater images, unlike typical images, have limited visibility[2]. Absorption reduces the energy of light, whereas scattering changes the direction of light propagation. The hazy look and contrast deterioration resulted in distant misty objects in these images[3]. In digital image capture, the reflected component of light from an object is responsible for image production[4]. Light is subject to reflection, refraction, scattering, and absorption while passing through water. The energy of the light wave determines the absorption factor[5]. Long wavelengths and low energy characterize the red-light component, whereas short wavelengths and high energy characterize the green and blue light components.[6]. Because red light has the longest wavelength and hence the least energy, it is the first to vanish in water, whereas green light has the reverse effect. Underwater photos seem blue or green due to this feature. Furthermore, because the light is randomly absorbed and dispersed by floating particles in water, picture contrast is severely harmed, resulting in brightness attenuation, and objects further than 10m from the cameras were nearly indistinguishable[7]. The red channel is the first to fade away as the distance between the imaged scene and the camera grows. The red channel map is darker, and the red channel pixels' values are reduced. The color of such an image should be adjusted in this case [8]. The color of an item is seen by human eyes regardless of the illuminant source.

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The color of the image is controlled by the lighting circumstances at the time. The technique of dealing with deteriorated images and improving their quality is known as image enhancement[9]. The fundamental goal of image enhancement is to increase an image's quality for human vision[10].

In the human visual system, an image is created in the human mind with the help of the human eye (Retina) and reasoning processing (Cortex); hence, the basis of Retinex is founded on this entire scenario of how the human vision system views a perspective. The name "Retinex" was coined from a combination of two terms (retina and cortex). Due to certain situations, it is conceivable that a picture captured with the aid machine will have a limited dynamic range or poor color consistency. There are many algorithms used to classify color, video, image, or text [34,35].

The calculation theory of color constancy perception, often known as the Retinex hypothesis, was introduced by Land in 1978. [11] Retinex can establish a balance between dynamic range compression, edge enhancement, and color constancy, unlike other linear and nonlinear algorithms that can only enhance a certain sort of image feature. As a result, diverse sorts of images can be improved adaptively. It can be viewed as a fundamental theory for the intrinsic image decomposition problem[12]. Additionally, rough set theory used also for many classifications to choose the corret pixels or text, and so on [36,37].

Single Scale Retinex (SSR)[13] If one of entire rendition or dynamic range compression is desired, SRR might be used. A Single-Scale Retinex (SSR) has the following mathematical form:

$$R_i(x, y) = \log(I_i(x, y)) - \log(I_i(x, y) \times F(x,y)) \ldots (1)$$

Ii(x,y) is the input image, $R_i(x, y)$ is the Retinex output, and F is the normalized surround function (Gaussian). This operation is performed on each color channel.

$$F(x, y) = C \exp[-(x^2 + y^2)/2\sigma^2] \ldots (2)$$

The amount of spatial detail maintained is controlled by the filter standard deviation σ, and C is a normalization factor such that:

$$\int F(x;y)dxdy = 1 \ldots (3)$$

In the meanwhile, SSR cannot give both color rendition and dynamic range compression, so Multiscale Scale Retinex is used (MSR)[14]. SSR is the foundation of Retinex, it can only execute a restricted duty on an image at a time, i.e. it may either offer an entire rendition or be used to compress the image's dynamic range. MSR may render an image in its entirety as well as reduce its dynamic range. The output of an MSR is defined as the weighted sum of the outputs of many SSRs. The multiscale Retinex formula is as follows:

$$R_{MSR_i} = \sum_{n=1}^{N} w_n R_{n_i}^{SSR} \ldots (4)$$

$$R_{MSR_i} = \sum_{n=1}^{N} w_n [log I_i(x,y) - \log(F_n(x,y) \times I_i(x,y))] \ldots (5)$$

Where R_{MSR_i} is the i-th the MSR output's colors component, N is the number of scales, w_n is the weights of each scale, $R_{n_i}^{SSR}$ is the SSR output corresponding to the i-th color component and F *is* Gaussian function. The overall impact of retinex processing on images might affect color desaturation

and, in some situations, the intended color calculation can be regarded as a color restoration. In addition, as one of the primary goals for the retinex is to maintain a decent degree of color constancy, correction would be required.

Color constancy, as well as colors and brightness rendition, may be achieved synthetically using MSR theory, which meets the standards of human vision. As a result, MSR may be used to improve the detail of underwater images in a variety of lighting conditions[15] . In this paper, the proposed approach was evaluated by using quantitative evaluation metrics like PSNR and MSE.

MSE is the mean squared error[16] and it is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (O(i,j) - D(i,j))^2 \quad \dots (6)$$

The peak signal-to-noise ratio (PSNR) is the proportion of an image's maximum attainable power to the power of corrupting noise that affects its quality of representation. To determine the PSNR of a picture, it must be compared to an ideal clean image with the maximum possible power.

PSNR is defined as follows:

$$PSNR = 10log_{10}(\frac{(L-1)^2}{MSE}) \quad \dots (7)$$

1. Methodology of Proposed Technique

Using the Retinex theory premise, the image may be defined as:

$$I(x,y) = L(x,y)\, R(x,y) \quad \dots (8)$$

Where I(x, y) is the amount of light detected by human eyes, L(x,y) is the illumination, and R(x, y) is the reflectance of the object. Jobson et al[17] created the SSR method, which uses the center/surround Retinex model for light and image rendition as well as dynamic range compression.

Multi-Scale-Retinex (MSR) is a further development of the Single-Scale-Retinex method. MSR is most likely the most used center-surround image filter. Several previous studies have used this method for image enhancement, and video enhancement with several additional filters and other algorithms. The MSR method can also improve color in images, with low illumination. Different scales are used and given different weights to combine the advantages and eliminate the disadvantages of low and large scales. The Retinex output may be stated mathematically as shown in Equation (5).

Our Adaptive Multiscale Retinex (AMSR) proposed Technique consists of three main stages as shown in the block diagram of the proposed approach methods given in Figure 1.

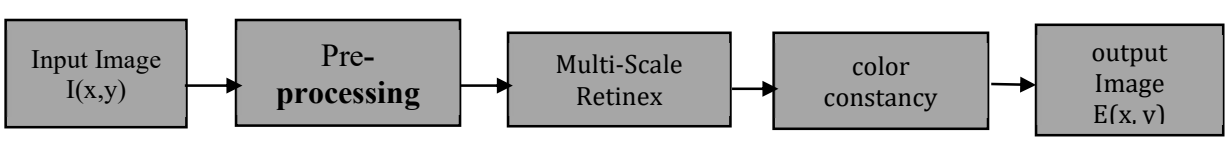

FIGURE 1: GENERAL BLOCK DIAGRAM OF THE PROPOSED TECHNIQUE

- Stage one: Pre-**processing Stage**

  Image Resizing is the first stage performed to speed the enhancement process.

- **Stage two: Adaptive Multiscale Retinex (AMSR) Stage**

In Single Scale Retinex, finding the proper scale S for the surround filter F(x, y) is critical due to the trade-off between dynamic range compression and color constancy. This paper proposes an AMSR approach for image contrast enhancement with color Constance. We sought to combine many SSR output photos such that the weight associated with each SSR scale could be determined adaptively from the information in the input image. AMSR is an SSR variant that combines the benefits of small-scale, middle-scale, and large-scale retinex to achieve a smooth balance of dynamic range compression and tonal reproduction. The AMSR result is a weighted average of many SSR outputs representing various scales. Experimental results are showed that a combination of five different scales (s1=10, s2=80, s3=90, s4=100, s5=255), with equal weights (w_1, w_2, w_3, w_4, w_5 = 1/5) are sufficient.

- **Stage three: Color Constancy**

The primary disadvantage of AMSR is that it will either enhance noise in a huge dark region or generate an artificial image with lost global brightness contrast. With arbitrary RGB limits, the AMSR process may produce negative and positive RGB values. To overcome this challenge, the range of data must be translated into the visible domain [0: 255]. Before being shown, the Retinex output must be handled, with each (r,g,b) channel being adjusted by the absolute Minimum and Maximum of the three color bands using the colors Constancy equation (9)[18]:

$$\boldsymbol{MSRcc} = 255 \times \frac{MSRc(x,y) - \text{MIN}\,(\text{MIN}(R)\,,\text{MIN}(g)\,,\text{MIN}(b))}{Max(\text{MAX}(R)\,,\text{MAX}(g)\,,\text{MAX}(b)) - \text{MIN}\,(\text{MIN}(R)\,,\text{MIN}(g)\,,\text{MIN}(b))} \quad \ldots(9)$$

The proposed AMSR Technique with all stages can be shown in Figure 2

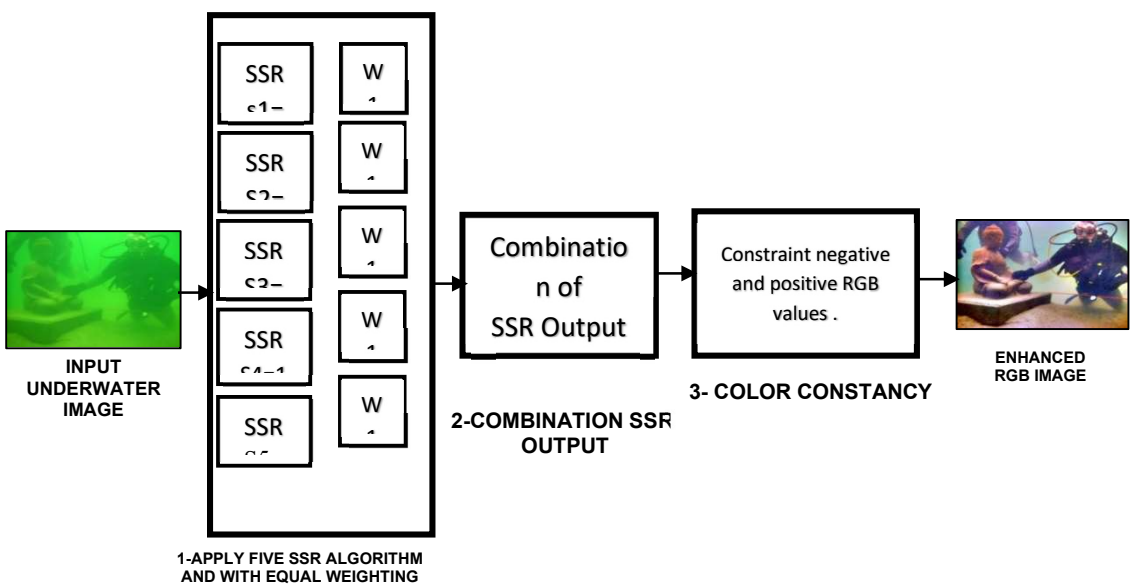

FIGURE 2: MULTISCALE RETINEX AND COLOR CONSTANCY STEPS

Algorithm (1) is illustrated as AMSR implementations with color restoration are performed to the three-color channels.

Algorithm (1): AMSR implantation

Input: I(x, y) underwater image; s_1, s_2, s_3, s_4, s_5 the scales, n is the number of scales
Output: Enhanced color image

Begin:
resize I(x, y) to I(MxN)
For each C € {r,g,b} do
Foreach σ_i do

$$SSR = (I(x,y) - log(I(x,y) * G\sigma i$$

SSR= $w_n * SSR$
End

$$MSR = \sum_{i=0}^{n-1} \frac{1}{n} SSR$$

$$MSRcc = 255 \times \frac{MSRc(x,y) - \text{Min}\ (\min(R), \min(g), \min(b))}{Max(\max(R), \max(g), \max(b)) - \text{Min}\ (\min(R), \min(g), \min(b))}$$

$I(x, y)_{output} = MSR_{cc}$
End
End

Table1 shows the list of constants in the implementation of AMSR; the scales are: s_1, s_2, s_3, s_4, and s_5, and N is the number of scales.

Table1: the control parameters

Constant	N	σ_1	σ_2	σ_3	σ_4 w	σ_5
Value	5	15	80	90	100 1/5	250

2. Experiment Results

In order to test the transferability of our proposed AMSR approach to diverse datasets, we employed a real-world dataset. On the Underwater Image Datasets, Figure 3 shows some visible results of our proposed method. The model is can generalized to other images. In addition to providing a good underwater image, one of our key aims is to handle such variety.

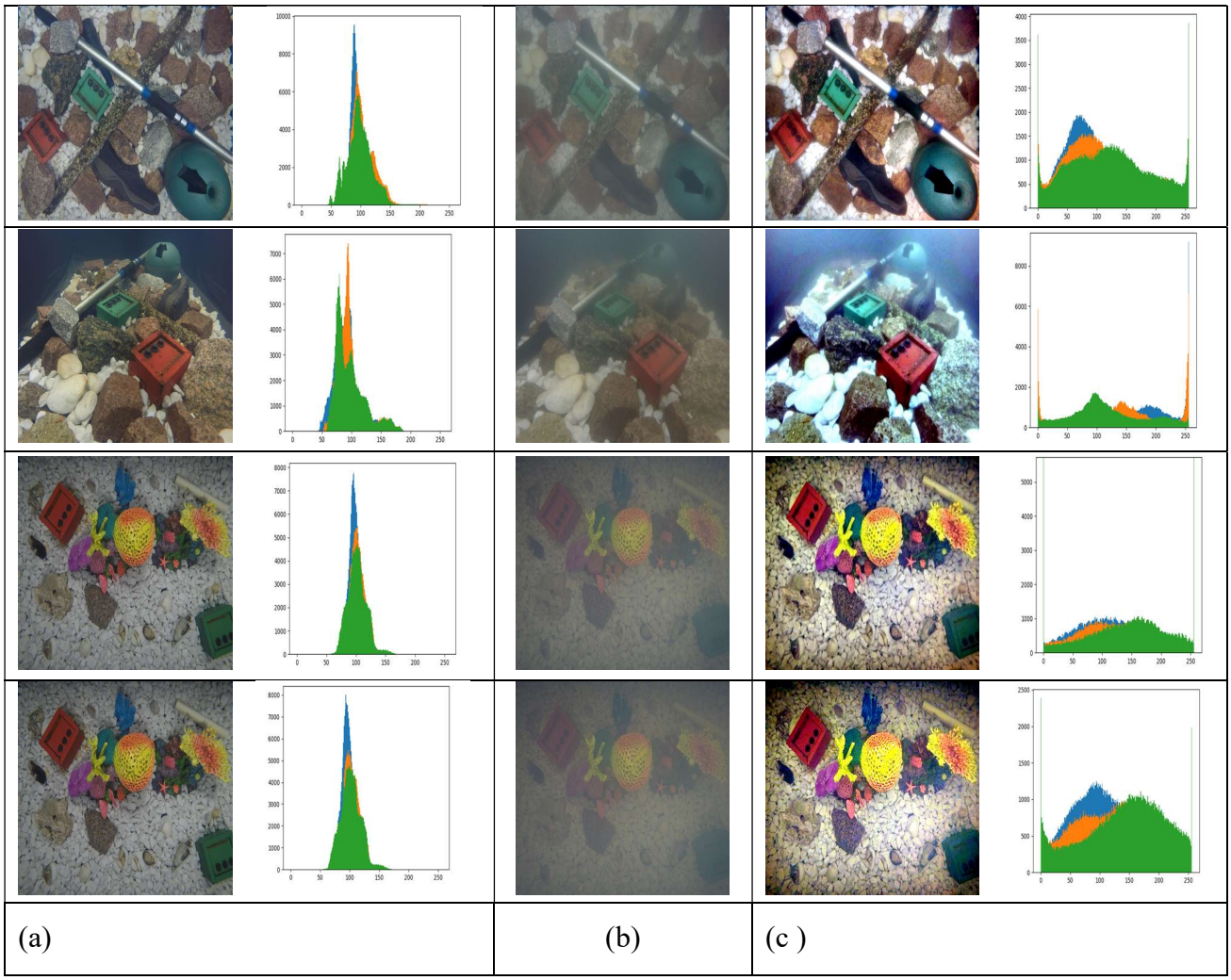

Figure 3: Samples of image enhancement using AMSR: a) the ground truth image and its histogram, b) underwater images, and c) Enhanced images and their histogram

In Figure 3, the TURBID dataset is used, which has a reference image and corresponding degraded images of varying degrees. We try to enhance different degraded varying degree turbid images.

In Figure 4, We experiment with our framework with the images on the EUVP dataset. We try to enhance different degraded varying degree turbid images.

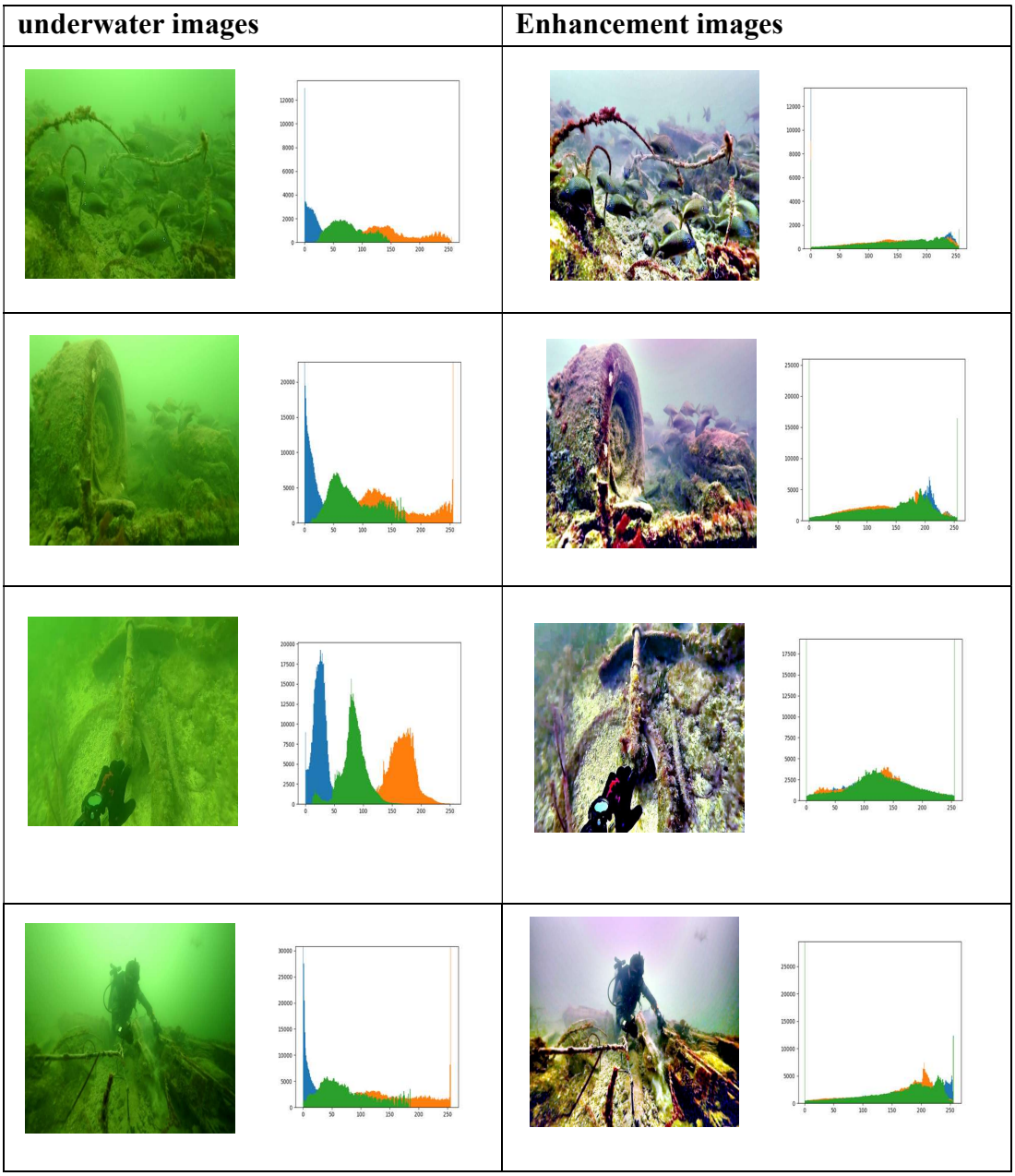

FIGURE 4: LEFT SIDE IS UNDERWATER IMAGES WITH THEIR HISTOGRAM AND THE RIGHT IS ENHANCEMENT IMAGES WITH THEIR HISTOGRAM

The experimental result of our framework is shown in Figure 5 with the images from the **UIEB** dataset[19]. In column c, we can see the enhanced image using AMSR with color constancy to enhance different degraded turbid images.

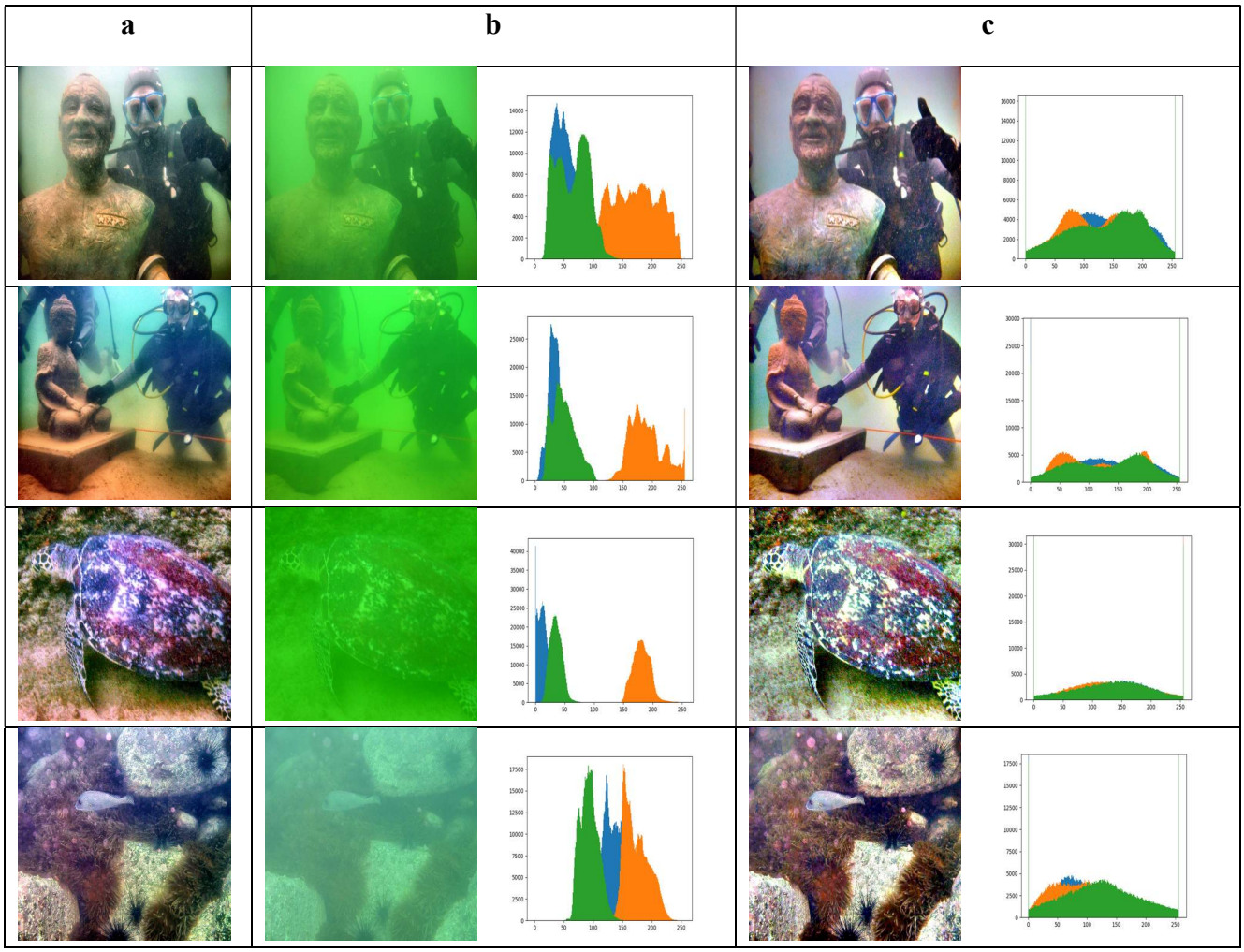

FIGURE 5: (A) IS CORRESPONDING REFERENCE IMAGES, (B)IS UNDERWATER IMAGES WITH THEIR HISTOGRAM, (C) IS ENHANCEMENT IMAGES WITH ITS HISTOGRAM

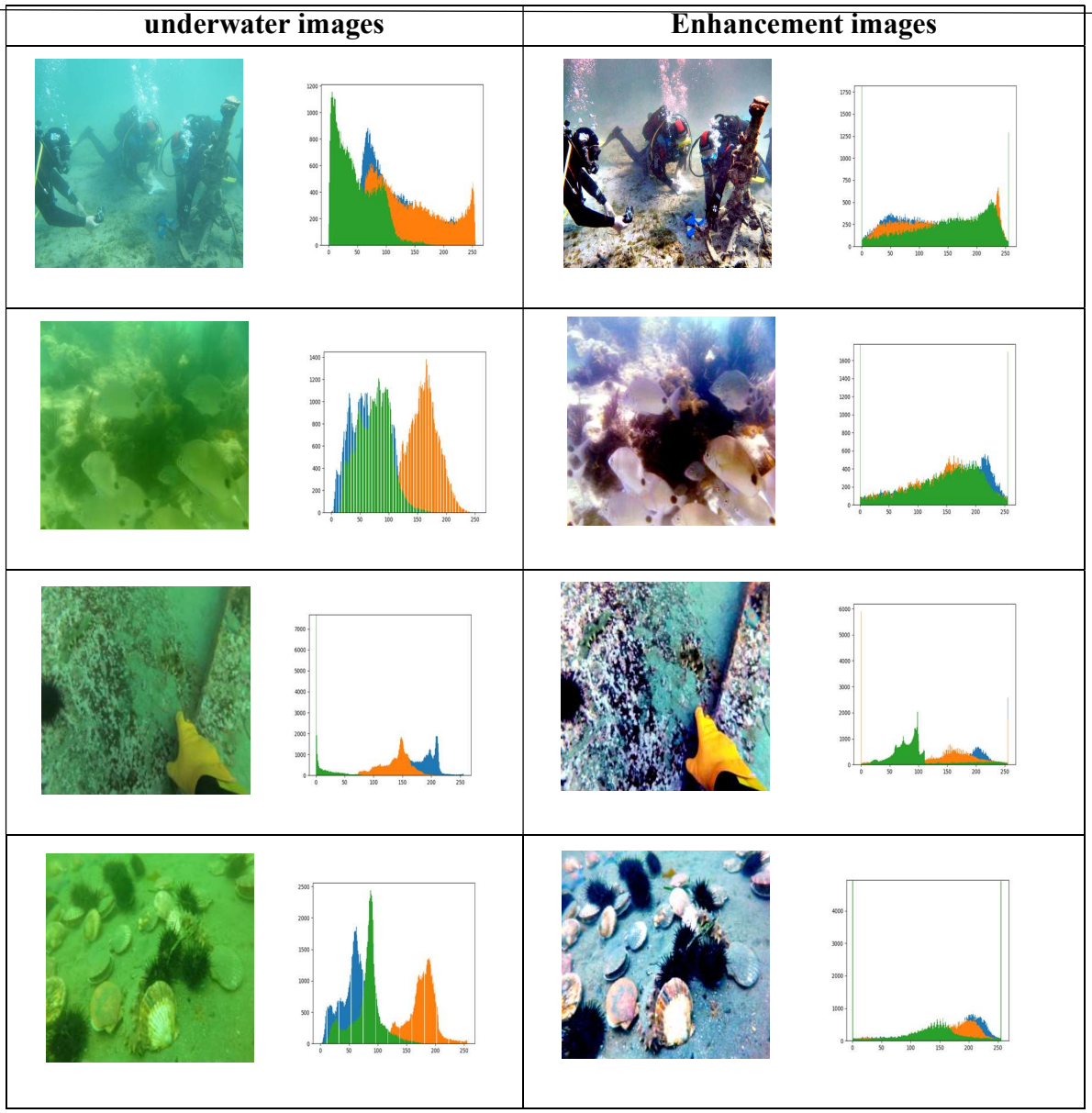

Figure 6: Left side is underwater images with their histogram and the right is Enhancement images with their histogram

Underwater Test Dataset U45(U45) dataset. Which includes underwater degradation's color casts, poor contrast, and haze-like characteristics used in our proposed AMSR technique. Also, we can see how much the output image is enhanced by keeping high quality and color constancy.

From Figures. 3, 4, 5, and Figure 6 of histogram images, the pixel value of the red channel is occupied narrow range, but pixel in the green channel and blue channel shows the opposite case. And from the histogram of the distribution of Enhancement images data, the pixel value of the pixels of three color is convergent in distribution. We compared the experimental results of different researcher techniques with our AMSR techniques. As shown in Figure 7 the best result enhanced underwater image is our AMSR techniques.

(A) (B) (C) (D)

(E)

Figure 7 Comparison of enhancement results of underwater image 'Diver'. (**A)** original underwater and other images are enhanced by: (**B**) by[20]. (**C) by** [21]. (**D)** by[22]. (**E)** by[23]. (**F)** by[24] . (**G)** by[25]. (**H)** by[26] . (**I)** by[27]. (**J)** by [28]. (**K)** by[29]. (**L)** the enhanced image by our proposed AMSR technique

3. Evaluation Functions

This section demonstrates our proposed AMSR technique using various performance quantitative evaluation metrics datasets using PSNR and MSE. PSNR and MSE values are summarized in Table 2 and Table 3.

Table 2: Quantitative performance of proposed AMSR for enhancement

Dataset name	PSNR (dB)	MSE
TURBID	28	0.04
EUVP	28.38	0.11
UIEB	27.8	0.10
U45	28.1	0.10

Table 3: Quantitative performance comparison for enhancement

Method Name	Dataset name	PSNR (dB)	ref
Shallow-water Image Enhancement Using Relative Global Histogram Stretching Based on Adaptive Parameter Acquisition	EUVP	18.643	[30]
Fast Underwater Image Enhancement for Improved Visual Perception	EUVP	21.92	[31]
Simultaneous Enhancement and Super-Resolution of Underwater Imagery for Improved Visual Perception	EUVP	25.25	[32]
Shallow-UWnet: Compressed models for underwater image enhancement	EUVP	27.39	[33]
Our proposed AMSR Technique	EUVP	28.38	

4. Conclusions

In this paper, we explored and successfully implemented novel image enhancement techniques for underwater image processing. Our objective is to develop a universal system that can handle a wide range of underwater photos and convert them to color images. This research proposes an adaptive Retinex-based enhancement approach for underwater images. First, a preprocessing was applied to prepare images to enter the enhancing process. To solve the hazy of the underwater image a new approach from MSR was applied by applying SRR five times. Finally, the AMSR process may produce negative and positive RGB values, to solve this issue a color constancy method is implemented. The results of the experiments show that improved photographs include color correction, brightness, naturalness preservation, and good sharpness.

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