Unsupervised Contrast Correction for Underwater Image Quality Enhancement through Integrated-Intensity Stretched-Rayleigh Histograms

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***Abstract*— The attenuation of light that travels through the water medium results the underwater image to suffer from several problems. Low contrast and color performance are the problems that resulting the image to loss important information. In addition, the objects in the image are hardly differentiated from the background. Consequences from these problems, this paper extend the methods of enhancing the quality of underwater image with the aim of improving the image contrast and increase the color performance. The proposed method consists of two stages. At first stage, contrast correction technique is applied to the image. The image is multiplied with a gain factor. The image histogram is divided into two regions at the mid-point and stretched towards the higher and lower intensity values. The composition of these two different intensities images produces contrast-enhanced image. At the second stage, the image is applied with color correction, where the image is converted into Hue-Saturation-Value (HSV) color model. Dividing and stretching of S and V components increase the image color. By considering the contrast and color performance of the output image, the proposed method outperforms the state-of-the-art methods.**

***Index Terms*— Underwater image; Stretched-Rayleigh histograms; Hue-Saturation-Value (HSV).**

I. INTRODUCTION

Underwater image suffers from several problems such as limited range of visibility, blur, low contrast and color, bright artifacts, noise, and non-uniform lighting [1]. As light travels in water, an exponential loss of light intensity occurs depending on the color spectrum wavelength [2]. Visible light is absorbed at the longest wavelength first [2]. Red, the most affected color, is reduced to one-third of its intensity after 1 m and essentially lost after a distance of 4 m to 5 m underwater [3]. Underwater images normally appear green-blue because these color components are the last to be absorbed. According to [4], light attenuation limits the visibility distance at about 20 m in clear water and 5 m or less in turbid water. In addition, color diminishing problem causes the captured images to have low contrast and color performance, resulting the images to lose important information.

Unsupervised global and local color correction has been proposed by [5]. Authors in [6] and [7] analyzed physical effects of visibility degradation and proposed an image recovery algorithm based on several images. Nevertheless, these physics-based methods have the disadvantages as they require high computing resources and consume long execution time. Bassiou and Kotropoulos demonstrated an increase in entropy and a decrease in Kullback-Liebler divergence by applying probability smoothing in hue-saturation-intensity (HSI) color model [8]. Besides, Bi-Histogram Equalization (BHE) proposed an algorithm to enhance the image contrast while preserving its brightness [9]. Based on the mean value, the histogram is divided into two groups and independently equalized. It has been analyzed both mathematically and experimentally whereby this technique can better preserve the original brightness to a certain extent. Naim and Isa proposed pixel distribution shifting color correction (PDSCC) method for digital color image to correct the white reference point and ensure that the white reference point is achromatic [10]. The method intervenes with the saturation problem of the image and corrects the image color to become more natural. However, it does not significantly increase the underwater image contrast as the blue-green illumination retains in the image.

Iqbal et al. proposed the integrated color model (ICM) [11] and the unsupervised color correction method (UCM) [12]. Through ICM, the output image in red-green-blue (RGB) color model is stretched over the entire dynamic range. The image is then converted into HSI color model. The S and I components are applied with contrast stretching. In UCM, red and green channels are modified based on the Von Kries hypothesis to reduce the color cast. Contrast correction is then applied in RGB color model. The image histograms are stretched at one or both sides based on the minimum and maximum values of each channel taken at 0.2% and 99.8% at the minimum and maximum points of the original histogram, respectively [12]. The image is further converted into HSI color model, whereas the S and I components are stretched at both the lower and upper sides. The overall contrast performances of the output images for both techniques increase. However, these techniques produce high noise and some areas in the output image become darker.

The proposed technique, namely integrated-intensity Stretched-Rayleigh (IISR) extends the method of [11] and UCM [12] for underwater image. Problems of ICM [11] and UCM [12] are addressed in this proposed method. With the aims of increasing the image contrast and reducing the image noise, the proposed technique extends the use of histogram stretching. Moreover, the proposed technique is assumed to significantly reduce the blue-green illumination and over-enhanced areas in underwater images. The detail of the proposed method is explained in details in the next section.

II. UNSUPERVISED CONTRAST CORRECTION: INTEGRATED-INTENSITY STRETCHED - RAYLEIGH HISTOGRAMS

The proposed method applies the idea of histogram stretching in different approach from that used in ICM and UCM. ICM and UCM improve underwater image contrast but produce high noise. Moreover, ICM and UCM could not significantly reduce the under- and over-enhanced areas in the output image. The image also retains more blue-green illumination. Therefore, the proposed method focuses to reduce these problems.

The proposed image enhancement method is based on two main steps: first step is the contrast correction and the second step is the color correction. Figure 1 illustrates the flow of the proposed method. In contrast correction step, image channels are multiplied with a gain factor (G) which is obtained from the median value of channel intensity ratio. The histogram of the image channel is then divided into two regions based on its mid-point. Each region is stretched independently towards upper or lower direction with respect to Rayleigh distribution. This produces two different intensity images. These images are integrated by means of average value to produce an output image. In the second step, the image is converted into Hue-Saturation-Value (HSV) color model. The S and V components are divided at mid-point into two regions and stretched within 1% from the minimum and maximum limits of the output dynamic ranges with respect to Rayleigh distribution. The image is then converted back into RGB color model.

A. *Determination of Gain Factor*

Before applying further processes, image in RGB color model is decomposed into respective channel. These channels are multiplied with the gain factor which is obtained by taking the median value from the channels intensity ratio. For this purpose, the total intensity value is calculated for every channel. Equations (1) to (3) are used to calculate the total intensity value of respective channel; red (R), green (G), and blue (B).

The maximum intensity channel is used as the reference value. The ratio between the channels is obtained by dividing the reference value with the total intensity value for each channel. The gain factor is obtained by means of Equation (4). The gain factor, G is the median value of the ratio of the maximum channel to the respective channel of the image. The gain factor of median value is chosen as it represents the intermediate value between the lowest and the highest average values. Theoretically, by considering the lowest average value as the gain factor, the changes of the intensity values for the image may result in very low changes and thus, the changes of the output image will be hardly seen. On the other hand, if the highest value is chosen, the excessive effect of image intensity could be observed especially for the inferior color channel.

$$R = \sum_{i=1}^{M}\sum_{j=1}^{N} I_R(i,j) \quad (1)$$

$$G = \sum_{i=1}^{M}\sum_{j=1}^{N} I_G(i,j) \quad (2)$$

$$B = \sum_{i=1}^{M}\sum_{j=1}^{N} I_B(i,j) \quad (3)$$

$$G = median\left(\frac{\max(R,G,B)}{R}, \frac{\max(R,G,B)}{G}, \frac{\max(R,G,B)}{B}\right) \quad (4)$$

where M and N indicate the number of rows and columns of the image, respectively and IX(i,j) is the pixel intensity value of respective channel at position (i,j). Each image channel is then multiplied with the gain factor, resulting in an increase of intensity value in each channel. This increasing of intensity value causes the image contrast to slightly improve.

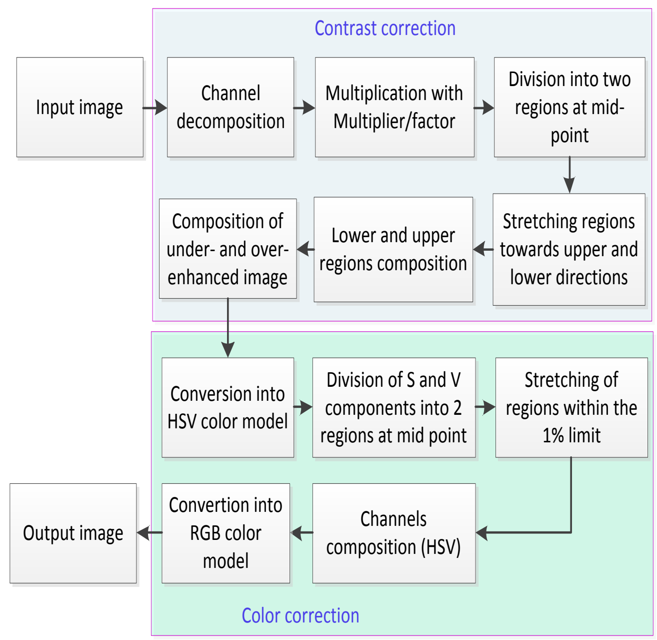

Figure 1: Overall flowchart of the proposed IISR method

Von Kries balancing hypothesis produces sometimes unbalanced image contrast and color, where the image sometime becomes reddish or greenish. In this paper, instead of balancing these three channels by applying Von Kries hypothesis [12], the proposed method multiplies these channels with a multiplier which is equal to the median value obtained from intensity ratio. The median value which lies between maximum and minimum is chosen as gain factors as the middle value could reduce the extreme effect if it is multiplied with dominant and inferior channels.

As next process, the histograms of image channel are then divided into two regions based on their mid-points. This will be explained in details in the next subtopic.

B. *Dividing and Stretching the Histogram*

The histogram is divided at the mid-point, i_{mid} of the original histogram. This will produce two regions: upper and lower regions. To divide the histogram, the minimum and maximum intensity levels are determined. Then, the mid-point of the intensity level is determined using Equation (5). i_{max} and i_{min} are the maximum and minimum intensity values for a certain image channel, respectively.

$$i_{mid} = \frac{i_{max} - i_{min}}{2} + i_{min} \tag{5}$$

The histogram is then stretched as follow: the lower region is stretched towards the upper direction from the minimum intensity value, i_{min} to the maximum dynamic range of the image which is equal to 255; the upper region is stretched towards the lower direction from the maximum intensity value, i_{max} to the minimum dynamic range of the image which is equal to 0. Moreover, the stretching process is mapped to follow the Rayleigh distribution. The Rayleigh distribution is the best distribution for underwater images [3][13]. Figure 2 illustrates the dividing process of the original histogram into two regions and independently stretched into two different histograms. To stretch the histogram to follow the Rayleigh distribution, the stretching formula in Equation (6) is integrated with the probability distribution function of Rayleigh distribution in Equation (7). P_{in} and P_{out} in Equation (6) indicate the input and output pixel values, respectively. i_{min}, i_{max}, o_{min}, and o_{max} are minimum and maximum input and output intensity values for the image channel, respectively. x and α in Equation (7) indicate the input pixel value and distribution parameter for Rayleigh distribution, respectively.

$$P_{out} = (P_{in} - i_{min})\left(\frac{o_{max} - o_{min}}{i_{max} - i_{min}}\right) + o_{min} \tag{6}$$

$$PDF_{Rayleigh} = \left(\frac{x}{\alpha^2}\right) e^{\left(\frac{-x^2}{2\alpha^2}\right)}, \quad for\ x \geq 0, \quad \alpha > 0 \tag{7}$$

This produces a new Stretched-Rayleigh formula as in Equation (8).

$$Rayl.-stretched = \frac{\left[(P_{in} - i_{min})\left(\frac{o_{max} - o_{min}}{i_{max} - i_{min}}\right) + o_{min}\right]}{\alpha^2} \cdot e^{\frac{-\left[(P_{in}-i_{min})\left(\frac{o_{max}-o_{min}}{i_{max}-i_{min}}\right)+o_{min}\right]^2}{2\alpha^2}} \tag{8}$$

For the lower-stretched region, the histogram is stretched towards the upper direction from the minimum intensity level, i_{min}. Therefore, for the lower-stretched region, the value of o_{min} will be substituted with i_{min} in Equation (8). o_{max} is equal to 255 as the histogram is stretched to the maximum intensity value of the dynamic range. Thus, the Equation (8) will become as Equation (9) for the lower-stretched region.

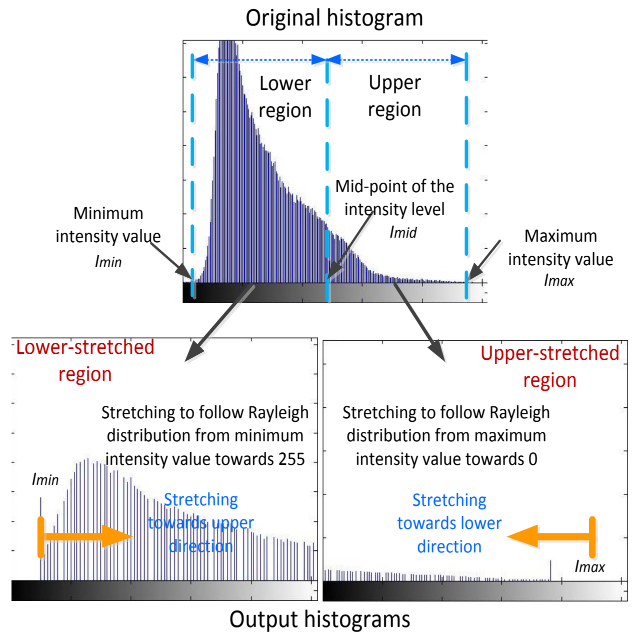

Figure 2: The process of dividing and stretching of original histogram towards upper and lower directions to produce lower and upper regions

$$\mathrm{Rayl.-stretched_L} = \frac{\left[(P_{in} - i_{min})\left(\frac{255 - i_{min}}{i_{max} - i_{min}}\right) + i_{min}\right]}{\alpha^2} \cdot e^{\frac{-\left[(P_{in}-i_{min})\left(\frac{255-i_{min}}{i_{max}-i_{min}}\right)+i_{min}\right]^2}{2\alpha^2}} \tag{9}$$

On the other hand, the value of o_{min} can be substituted with 0 and the value of o_{max} will be substituted with i_{max} if the Equation (8) is applied to the upper-stretched region. Therefore, for the upper-stretched region, the Equation (8) will become as Equation (10).

$$\mathrm{Rayl.-stretched_U} = \frac{\left[(P_{in} - i_{min})\left(\frac{i_{max}}{i_{max} - i_{min}}\right)\right]}{\alpha^2} \cdot e^{\frac{-\left[(P_{in}-i_{min})\left(\frac{i_{max}}{i_{max}-i_{min}}\right)\right]^2}{2\alpha^2}} \tag{10}$$

C. Composition of Lower and Upper Regions

The dividing and stretching processes of the original image histograms are applied to all three channels. Therefore, these processes produce two new histograms for every channel, namely lower-stretched histogram and upper-stretched histogram. A total of six new histograms will be produced for all three image channels. According to Figure 1, the histograms will be composited after the stretching process. Therefore, all lower-stretched histograms are combined to produce a new image and another three upper-stretched histograms are combined to produce another new image. Both under- and upper-enhanced images are composed by means of average value with z-axis as reference to produce a new enhanced-contrast image. As a result, a new contrast-enhanced image will be produced. Figure 3 illustrates the flow chart of the composition image histograms process.

D. Conversion into HSV Color Model: Dividing and Stretching of S and V Components

After the contrast correction process, the image is further processed for color correction where the image is converted into HSV color model. The conversion of image into HSV color model is done in order to correct the image color as the saturation (S) and brightness (V) is directly related to the image color. Therefore, in this step, both values of S and V are modified, where the saturation and brightness of the image are shifted to the middle range between 1% and 99%. These values are set in order to avoid the image from producing more under- and over-enhanced areas, which leads the image to have dark or too bright areas.

If the stretching value is near to 0, the image has a tendency to become under-saturated and has low performance of brightness. On the other hand, if the stretching value near to 100% of the maximum limit, over-enhanced and over-brightness effects may appear in the image. Both of these effects reduce the image details.

In order to divide and stretch S and V components, the identical processes as explained in section B are applied. The differences are, the dividing and stretching processes in this section are applied only to S and V components and the limits of those produced histograms are set between 1% and 99%. Therefore, after stretching these components into two regions (i.e. upper and lower regions), the minimum and maximum stretching limits of both upper and lower regions are set to 1% and 99%. Moreover, the stretching process for both S and V components are also applied to follow bell-shaped Rayleigh distribution.

After stretching, H-S-V components are composed and converted back into RGB color model. Thus, a new contrast- and color-enhanced image is produced. Figure 4 shows the flow chart of the dividing and stretching processes of the S and V components in HSV color model.

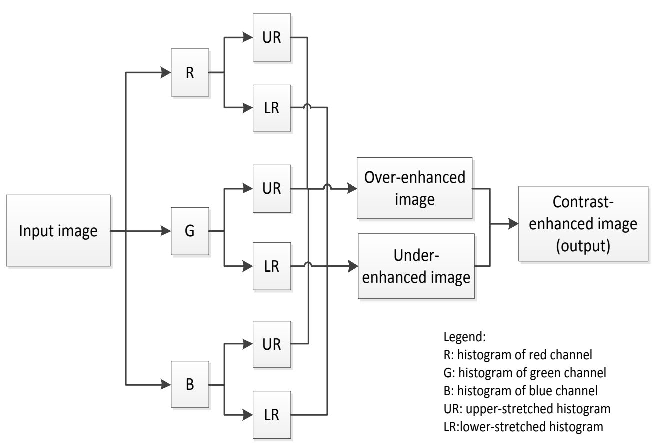

Figure 3: Flow chart of image histogram composition process

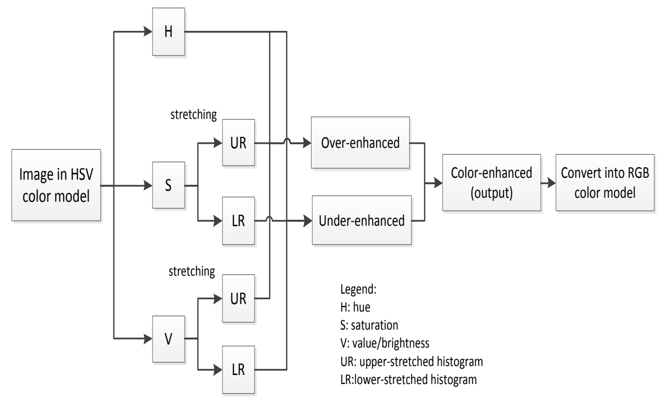

Figure 4: Flow chart of the dividing and stretching processes of HSV color model

III. RESULTS AND DISCUSSION

The proposed technique is present to extend the current underwater image enhancement method of ICM [11] and UCM [12] which are proposed by Iqbal et al. in terms of image contrast, noise, and image details. Therefore, the evaluation will be focused on comparison with these methods. However, two other methods are also used in this comparison, namely conventional histogram equalization (HE) [14] and pixel distribution shifting color correction (PDSCC) [10]. HE is the most commonly used by previous researchers and it is the basic technique in histogram modification. PDSCC is one of the latest contrast enhancement techniques that are designed for underwater image.

A. Qualitative Result

The improvement of output image is described in terms of contrast and color. Two hundred underwater images are tested. Out of 200 images, three underwater images are shown in this paper as samples. Figure 5 to 7 show underwater images that are processed using the proposed methods in comparison with the other methods. For qualitative evaluation, the images are observed in terms of contrast. The proposed method is observed whether it could improve the image contrast compared to the other methods. Moreover, the effect of blue-green illumination is also observed. The proposed method should be able to reduce the blue-green effect. In addition, the production of under- and over-enhanced areas is also observed in the resultant images of the compared images. The proposed method is supposed to minimize under- and over-enhanced areas.

The image of *stone coral* as shown in Figure 5 shows that the HE over-saturates the image contrast as the image become too bright. The methods of Iqbal et al. (i.e. ICM and UCM) could not improve the contrast and color optimally as the coral stone at the left hand side become over brightness. Over-brightness results in loss of image details. Meanwhile, PDSCC increases only a small amount of contrast as the effect of blue-green illumination of water retains in the image. The proposed IISR method increases the contrast and color significantly as the visibility of the coral could be seen. Clear differences of these compared methods can be seen. In addition, the areas of over-brightness are significantly reduced.

Images of *jellyfish* and *coral branch* in Figure 6 and 7 also produce the identical effects as previously mentioned. The effects of dark and too bright areas are identified in the compared methods. However, in the proposed method, these effects are less observed. In addition, the proposed method improves the image visibility by as the different between the objects and background is clearly identified.

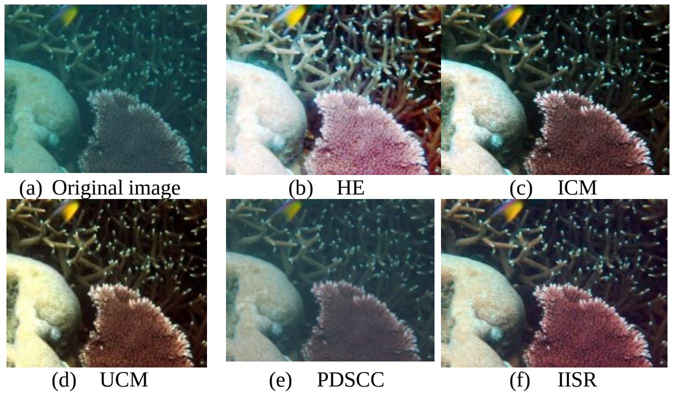

Figure 5: Stone Coral: (a) original image. The rest are images processed using the following methods (b) HE, (c) ICM, (d) UCM, (e) PDSCC, (f) IISR

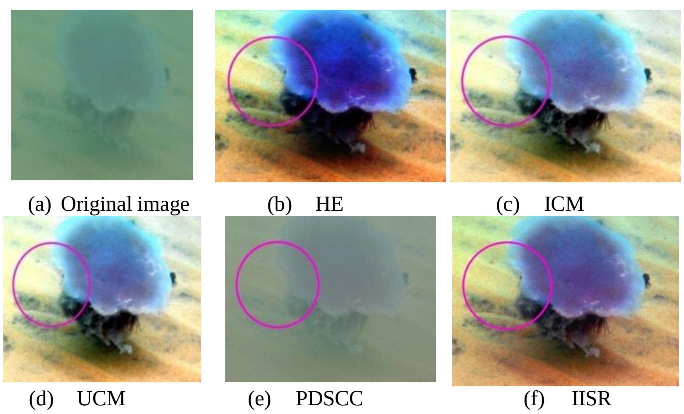

Figure 6: *Jellyfish*: (a) original image. The rest are images processed using the following methods (b) HE, (c) ICM, (d) UCM, (e) PDSCC, (f) IISR

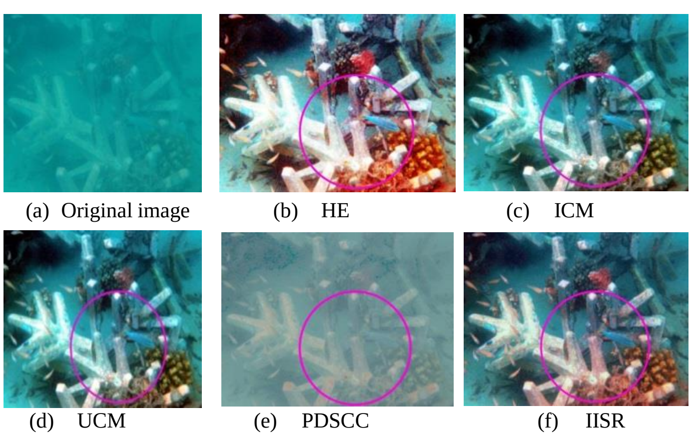

Figure 7: Coral branch: (a) original image. The rest are images processed using the following methods (b) HE, (c) ICM, (d) UCM, (e) PDSCC, (f) IISR

Qualitative results show that there are significant improvements in contrast and color performance of the proposed method. Over-saturated areas are successfully reduced and the objects in the images are better differentiated from the background. Moreover, the effect of blue-green water illumination is significantly reduced.

B. *Quantitative Result*

As the main purposed of the proposed method is to increase the image contrast and reduces the noise that produced by ICM [11] and UCM [12], the output images are evaluated in terms of average gradient, peak signal to noise ratio (PSNR), and entropy. Entropy and PSNR are given by the Equation (11) and (12) [3], respectively:

$$H(X) = -\sum_{x=1}^{k} p(x)\log_2 p(x) \tag{11}$$

where, *p(x)* indicates the probability distribution function of the image at the state *x* (pixel). *k* refers to the number of gray-level.

$$\text{PSNR} = 20Log_{10}\frac{(2^B-1)}{\sqrt{MSE}} \tag{12}$$

where *B* represents the bits per sample. The best resultant image is indicated by low MSE and high PSNR. Entropy is a measurement for image details [15]. The higher value of entropy indicates that the image has more information.

Average gradient shows the fine contrast, texture characteristic, and clarity of an image. The higher value of average gradient indicates that the image has more intensity levels and is clearer [15]. As stated by Wu et al., the average gradient, $\nabla\bar{G}$ can be defined as follows [15]:

$$\nabla\bar{G} = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{\nabla_i^2 f(i,j)+\nabla_j^2 f(i,j)}{2}} \tag{13}$$

where $\nabla_i^2 f(i,j)$ and $\nabla_j^2 f(i,j)$ are the gradients on the row and column direction, respectively. M and N are the numbers of the row and column of the enhanced image, respectively.

Table 1 shows the quantitative results in terms of average gradient, PSNR, and entropy for the images in Figure 5 to 7. HE produces the highest value of average gradient. However, the qualitative result shows that, HE produces over-enhanced image which could reduce the image detail. On the other hand, the results show that the proposed method is only second to PDSCC in terms of PSNR. PDSCC produce the highest PSNR for all sample images. However, visual observation from qualitative results shows that the images produced by PDSCC have very low contrast. The objects in the images are hardly differentiated from the background. Moreover, the effect of blue-green illumination retains more in the output images that produced by PDSCC. In term of entropy, all sample images show that the proposed IISR method successfully improves the image details and outperforms the other state-of-the art methods. Nevertheless, these quantitative results prove that the proposed method successfully reduces the noise and increases the image details unlike the ICM and UCM.

Table 1
Quantitative Results in Terms of Average Gradient, PSNR, and Entropy

Image	Method	Average gradient	PSNR	Entropy
Stone coral	HE	6.822	10.93	5.957
	ICM	5.101	15.21	7.401
	UCM	4.819	14.24	7.368
	PDSCC	2.667	23.93	6.945
	IISR	2.540	16.74	7.411
Jellyfish	HE	5.717	11.57	5.544
	ICM	4.750	6.31	7.086
	UCM	3.856	6.31	6.764
	PDSCC	0.783	25.09	5.469
	IISR	2.157	14.01	7.808
Coral branch	HE	7.046	8.53	5.948
	ICM	5.796	6.57	7.642
	UCM	7.649	6.57	7.682
	PDSCC	6.360	12.53	6.748
	IISR	2.389	11.44	7.880

Note: The values in bold typeface represent the best results obtained in the comparison.

Table 2 shows the average values of average gradient, PSNR, and entropy for 200 tested underwater images. The proposed method is ranked second after PDSCC in terms of PSNR. On the other hand, the proposed IISR method produces the highest value of entropy. However, as mentioned before, the qualitative results prove that the images produced by the proposed method are better than the images produced by PDSCC in terms of contrast and color. The image produced by PDSCC has very low contrast and the objects in the images are hardly differentiated from the background. The effect of blue-green illumination retains more in the resultant images.

These values indicate a degree of improvement in terms noise reduction in the resultant image produced by the proposed method. Visual inspection shows that objects in the image are clear and better differentiated than those obtained using other methods. Moreover, the proposed method has successfully reduced the effect of blue-green illumination. In addition, the under- and over-enhanced areas are also significantly minimized in the output images.

IV. Conclusion

The proposed method that integrates the two images with different intensity according to Rayleigh distribution in RGB and HSV color models produces a better resultant image that outperforms the current state-of-the-art methods. As shown in the results, the proposed method has successfully increased the contrast performance and adequately reduces the image noise. Therefore, the main purposed of lowering the image noise and increasing the contrast have achieved. Even the proposed method ranks second to PDSCC in terms of MSE and PSNR, visual observation shows that the images produced by the proposed method have better contrast and color. The images are clear and the objects in the image are better differentiated. Moreover, the effect of blue-green illumination is significantly reduced. Qualitative and quantitative results show that the proposed method significantly improves the underwater image quality. This shows that, the proposed technique of dividing and stretching the image histogram based on Rayleigh distribution successfully improves the image quality.

Table 2
Average Values of Average Gradient, PSNR, and Entropy for 200 Tested Underwater Images

Method	Average gradient	PSNR	Entropy
HE	10.176	11.78	5.860
ICM	7.221	6.99	7.592
UCM	6.515	6.98	7.575
PDSCC	3.922	21.16	6.846
IISR	3.959	15.00	7.726

Note: The values in bold typeface represent the best results obtained in the comparison

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