

Underwater Image Enhancement using Fusion of Different Techniques

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ABSTRACT

Underwater environment is potentially rich for scientific research and explorations, but it is challenging to capture the image of the underwater environment due to light absorption and scattering effects of water. In this research, white balance algorithm is employed to recover the lost color information and multiscale image fusion is applied to the features of gamma corrected and sharpened image for dehazing the underwater image and improve the contrast. This thesis proposes an approach that enhances color correction with Histogram Equalization (HE) and applies Contrast Limited Adaptive Histogram Equalization (CLAHE) to sharpened image to further improve the details of the underwater image. The UIEB and SQUID datasets are used which include underwater scenery with fish, coral reefs, divers, underwater structures and shipwrecks. The application of the multiscale image fusion with proposed algorithm achieves to balance the distorted colors of underwater image and enhances fine details and contrast to improve image quality.

Keywords: underwater image enhancement, color compensation, multiscale image fusion.

ÖZ

Sualtı çevresi, bilimsel arařtırmalar ve keřifler için potansiyel olarak zengin bir alan olmasına raėmen, suyun ışığı emme ve saçma etkileri nedeniyle sualtı ortamının görüntüsünü yakalamak zor bir süreçtir. Bu arařtırmada, kaybolmuş renkleri kurtarmak için beyaz dengeleme algoritması kullanılmakta ve çok ölçekli görüntü füzyonu, gama düzeltilmiş ve keskinleştirilmiş görüntünün özelliklerine uygulanarak sualtı görüntüsünün sislenme etkisini gidermede ve kontrastı artırmada kullanılmaktadır. Bu tez, renk düzeltmesini Histogram Eşitleme (HE) ile arttıran ve daha sonra keskinleştirilmiş görüntüye Kontrast Sınırlı Adaptif Histogram Eşitleme (CLAHE) uygulayan bir yaklaşım önermektedir, böylece sualtı görüntüsünün detayları daha da belirginleşecektir. UIEB ve SQUID veri setleri, balıklar, mercan resifleri, dalgıçlar, sualtı yapıları ve gemi enkazları gibi sualtı manzaralarını içermektedir. Önerilen algoritma, çok ölçekli görüntü füzyonunun uygulanması, sualtı görüntüsü renklerinin yenilenmesini ve görüntü kalitesini, ince detayları ve kontrastı artırmayı başarmaktadır.

Anahtar Kelimeler: sualtı görüntü geliştirme, renk dengeleme, çok ölçekli görüntü füzyonu.

To My Family and Friends

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LIST OF ABBREVIATIONS

CDF	Cumulative Distribution Function
CLAHE	Contrast Limited Adaptive Histogram Equalization
DCP	Dark Channel Prior
HE	Histogram Equalization
HSV	Hue Saturation Value
IL-NIQE	Integrated Local Natural Image Quality Evaluator
MSE	Mean Squared Error
PSD	Probability Density Function
PSNR	Peak Signal to Noise Ratio
RGB	Red Green Blue
RMSE	Root Mean Square Error
SQUID	Stereo Quantitative Underwater Image Dataset
UDCP	Underwater Dark Channel Prior
UICM	Underwater Image Colorfulness Measure
UIConM	Underwater Image Contrast Measure
UIEB	Underwater Image Enhancement Benchmark
UISM	Underwater Image Sharpness Measure
UIQM	Underwater Image Quality Measure

Chapter 1

INTRODUCTION

Approximately 71% of the Earth's surface is enveloped by the ocean, which is home to numerous aquatic plants and marine animal species. Images taken in underwater can help in different areas of scientific research to discover rich marine life and to explore the depths of underwater environment. However, due to the significant absorption and scattering effect of light in underwater, the images often exhibit low contrast and an imbalanced color scheme. They crucially effect the visibility of the underwater and result in a hazy and contrast degraded image.

The main objective of enhancing the underwater image quality is to restore the colors and remove the foggy appearance from the image while maintaining the original details. However, the underwater de-hazing problem cannot be solved by using image enhancement techniques like gamma correction and histogram equalization alone.

In this thesis, the white balance algorithm is used to enhance the image's color and implements multiscale fusion technique to combine gamma corrected and contrast enhanced sharpened image to increase the underwater image's visibility. Underwater images found in UIEB [1] and SQUID [2] datasets are used as a single input image in the experiments of this thesis.

1.1 Statement of the Problem

Marine ecosystem holds many mysteries since only 5% of the ocean is discovered [3]. One of the main reason is because sunlight approximately enters up to 200 meters (m) below the water surface and makes imaging much harder. When light travels through water, it loses its intensity and the color wavelengths as it goes deeper into the ocean. Figure 1 shows the color spectrum of light from red to blue wavelengths and the depth of underwater is defined as horizontal lines from 0 meters (surface) to 80 meters. Red color, which has the longest wavelength, starts to lose its intensity earlier than the other colors, around 5 m below surface. Then orange, yellow, green and cyan colors fade away as the light goes deeper into the ocean. Lastly, blue color starts to lose its intensity at 80 m.

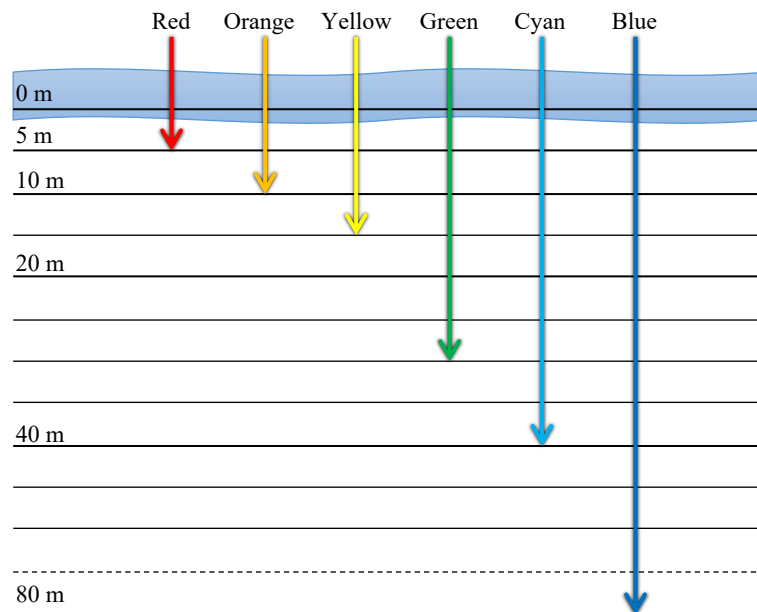


Figure 1: Light Propagation Underwater

Images taken in underwater have low contrast, bluish and greenish color casts, and lack sharp details as a result of the light characteristics of the underwater environment.

This thesis aims to balance the colors of the image in order to make up for the loss of

the red channel and to enhance image clarity by increasing the contrast without losing the general information found in the image which will help to get more accurate answers from scientific researches.

1.2 Significance of the Study

Underwater imaging is essential for scientific research of marine ecosystems and archaeology. Clear representations of underwater environments plays a crucial role for researchers to analyze and document the marine life. This will improve our understanding of marine ecosystem, behavior of marine species and the impacts of environmental changes.

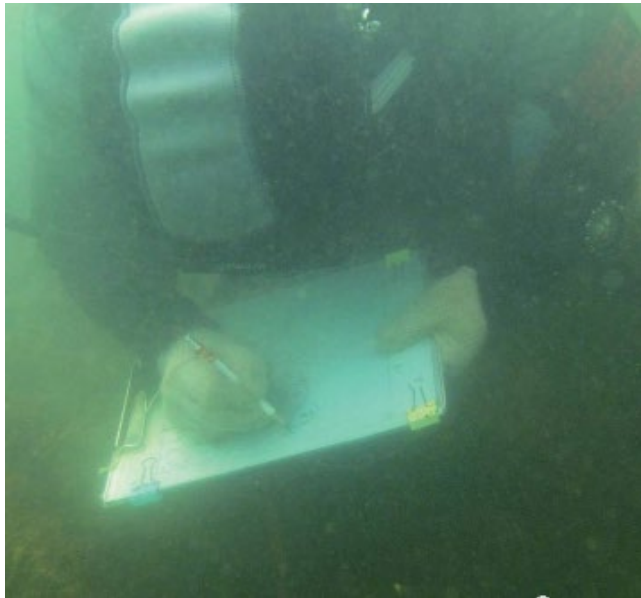
The vivid images of underwater photography attract many people to be interested in underwater environments. These images make marine science and exploration more accessible to the public and inspire the young generations.

1.3 Underwater Image Examples

Hazy images and imbalanced color channels are the main characteristics of the underwater images. Three images from UIEB dataset are shown in Figure 2, which have foggy appearances and color distortions, to better understand the statement of the underwater imaging problems.



(a)



(b)



(c)

Figure 2: Underwater Images: (a) Statue Underwater, (b) Diver, (c) Shipwreck

Figure 2(a) is an example of color imbalance in which the image is in greenish tone which implies the lack of red color. Figure 2(b) is blurry due to illumination and it is hard to identify the scribbles written on white board. On the other hand, Figure 2(c) shows loss of sharpness around edges of the object as it gets far away from the camera.

1.4 Literature Review on Underwater Image Enhancement

There are several algorithms proposed for color balancing and dehazing underwater images. The most common methods include Dark Channel Prior (DCP) algorithm based on He et al. [4]. The algorithm is based on the observation, that at least one color channel has very low intensity values at local pixels. Chosen low intensity area is selected to define the color of the airlight, which is assumed to be the color of the haze. The image is then dehazed by removing the airlight. However, this algorithm fails when the object's color is similar to the atmospheric light. The objects in underwater images appear to be the same color as the haze. Because of this situation, DCP algorithm is not applicable for underwater images and mainly used for outdoor images.

In contrast to DCP, Drews Jr. et al. [5] proposed an Underwater DCP (UDCP) which considers that blue and green channels are the information source of underwater images. Because of this reason, DCP method is only applied for green and blue channels which performs better in the underwater environment. Root Mean Square Error (RMSE) metric is used for the evaluation of that algorithm with different levels of water turbidity. As the level of the turbidity increases, the RMSE metric for UDCP and DCP is plotted and UDCP achieves a higher score with low RMSE value.

On the other hand, Red Channel method is proposed by Galdran et al. [6] as a variant to DCP. That method uses red channel to estimate the haze in underwater scene. As the distance increases in underwater image, the intensity on red channel decays. Based on this fact, the depth in the scene is estimated. According to the coefficient of maximum mutual distances between relative dispersion of RGB channels, the algorithm is able to retrieve the intense colors underwater, while the other methods resulted in retrieving very saturated colors.

Moreover, Ancuti et al. [7] proposed a red channel compensation algorithm, then applied white balance to reduce the color cast in underwater image. Gamma correction and sharpening is applied separately to the white balanced image. Lastly, multiscale fusion is used to combine the features of these two images to remove the underwater haze. Their method is highly effective in removing the illumination and haze in underwater images. The evaluation of that algorithm results in higher values in terms of PCQI, UCIQE and UIQM metrics compared to the previous methods.

1.5 The Work Done in This Study

In this research, underwater image dehazing technique is based on multiscale image fusion algorithm used in the same way as in Ancuti et al. [7]. The experiments are focused on two approaches mainly based on white balancing and multiscale image fusion. White balance method is applied to correct the colors of the image, then to define the edges and enhance the color saturation. The inputs for multiscale image fusion are derived from gamma corrected and contrast enhanced sharpened image.

The algorithms employed in this thesis are red channel compensation, Gray World [8] algorithm and Histogram Equalization (HE) in order to rectify the color equilibrium

of the image. Additionally, gamma correction, normalized unsharp masking and Contrast Limited Adaptive Histogram Equalization (CLAHE) are used to derive inputs for the multiscale fusion.

The structure of the thesis is as follows. The white balance and color adjustment techniques of underwater imaging are introduced in Chapter 2. In Chapter 3, underwater image enhancements are explained in detail and the multiscale fusion process is shown in Chapter 4. The proposed approach is explained in Chapter 5. Chapter 6 is devoted to the experimental analysis and results. Finally, conclusion and future work for underwater image enhancement are presented in Chapter 7.

Chapter 2

UNDERWATER IMAGE WHITE BALANCE AND COLOR ADJUSTMENTS

2.1 Introduction

White balancing is the most crucial preprocessing technique in underwater imagery that aims to reduce imbalanced color distribution. The range of wavelengths within the visible spectrum of light is defined by approximately between 400 and 700 nm which also can be called as color spectrums. When the light enters the water, the red light characterized by its longer wavelength, is absorbed much more quickly than green-blue light, which are characterized by their shorter wavelengths. This phenomenon causes underwater images to often appear as greenish and bluish which lacks the natural colors of the environment. White balancing technique adjusts the histogram of the color channels to make it appealing to human eye. But in underwater imaging, the algorithm is not enough to fully dehaze the underwater image from bluish and greenish mist. Additionally, red channel compensation algorithm is used to recover the red channel from the information preserved in green channel.

RGB color space is used in most of the proposed methods. However, under specific circumstances, the requirement for employing HSV and LAB color spaces becomes an essential need to enhance the images. Their application will be explained in Chapter 3.

2.2 Color Channel Compensation

Underwater images appear to be in different hues due to light attenuation. Greenish image suffers from loss of red light. To compensate the red channel, green channel is used since green channel has the most information in that image. The difference between red and green channel must be proportional to each other and derivation on the new red channel only affects the pixels with lower red values [7]. The red channel compensation formula is depicted as follows:

$$\hat{I}_r(n) = I_r(n) + \alpha(\bar{I}_g - \bar{I}_r)(1 - I_r(n))I_g(n) \quad (1)$$

The terms \bar{I}_r and \bar{I}_g denote the average of the red and green channels. $I_r(n)$ and $I_g(n)$ represent color intensities at n^{th} location for red-green channels, respectively. The optimum value of constant α equals to 1 [9]. Similarly, blue channel compensation can be derived as shown in the following formula:

$$\hat{I}_b(n) = I_b(n) + \alpha(\bar{I}_g - \bar{I}_b)(1 - I_b(n))I_g(n) \quad (2)$$

where $I_b(n)$ is the blue channel pixel intensity at location x and \bar{I}_b is the mean of blue channel. Under special circumstances, for example in a turbid water, underwater scenery appears to be in yellow hue. In this particular case, both the red and blue channels are employed to effectively balance the yellow hue.

Red channel has very low intensity in underwater images and the red color fades away as the distance increases as seen in Figure 3. The image becomes less bluish after applying red channel compensation and the red intensity values increases more in the background.



(a)



(b)



(c)



(d)

Figure 3: Results of Red Channel Compensation With Displayed Red Channel: (a) Original Image, (b) Red Channel of Original Image, (c) Red Channel Compensated Image, (d) Red Channel of Red Channel Compensated Image

2.3 Methods of White Balancing

The objective of white balancing is to mitigate the color distortion caused by the scattering of light in underwater, thereby achieving a more precise portrayal of underwater scenery. There are several algorithms that balance colors such as Gray World [8], Max RGB [10], Shades of Grey [11] and Grey Edge [12]. For basic approach, the light source's color is estimated by these algorithms, then each individual color channel is divided by their respective light source to attain normalization of these channels.

The Gray-World method presupposes image's mean color as gray and that the light reflectance from the image is achromatic. Therefore, illumination color cast can be estimated by finding the average of the color channel and then comparing it to gray color. The formula in [13] is expressed in the following manner:

$$\begin{aligned} \bar{R} &= \frac{1}{xy} \sum_{m=1}^x \sum_{n=1}^y R, & \bar{G} &= \frac{1}{xy} \sum_{m=1}^x \sum_{n=1}^y G, & \bar{B} &= \frac{1}{xy} \sum_{m=1}^x \sum_{n=1}^y B \\ m &= \frac{\bar{R} + \bar{G} + \bar{B}}{3}, & \hat{I} &= \left(R \times \frac{m}{\bar{R}}, G \times \frac{m}{\bar{G}}, B \times \frac{m}{\bar{B}} \right) \end{aligned} \quad (3)$$

where image $I = (R, G, B)$ and $\bar{R}, \bar{G}, \bar{B}$ are red, green, and blue channels' average values, respectively. m is the average of the three channels which is multiplied with each channel to form white balanced image \hat{I} .

Color constancy algorithms were simplified in one equation by Van de Weijer et al. [12] and readjusted by Li et al. [14] as follows:

$$\begin{aligned} \left(\int \left| \frac{\partial^n I_{c,\sigma}(x,y)}{\partial x^i \partial y^j} \right|^p dx dy \right)^{\frac{1}{p}} &= k e_c^{n,p,\sigma} \\ \frac{\partial^n I_{c,\sigma}}{\partial x^i \partial y^j} &= I_c * \frac{\partial^n G_\sigma}{\partial x^i \partial y^j} \end{aligned} \quad (4)$$

where ke is the light source color, $I(x, y)$ represents the image pixel intensity at (x, y) , c is a channel list for (R, G, B), n denotes the order of the derivative and p represents the Minkowski-norm which determines weights of the measurements. The derivative of $I_{c,\sigma}$ is calculated by the convolution of the image with the derivative of the Gaussian filter with standard deviation of σ , where σ denoted as the scale of local measurements. Implementation of this algorithm is described in Chapter 6 to speed up the process of the evaluations and the formula constants are shown in Table 1 as an example. There are characteristic properties of each white balance method for this formula which must remain as constant values as shown in bold letters.

Table 1: Color Constancy Parameters

Methods Constants	Gray World	Shades of Grey	Grey Edge	Max RGB
n	0	0	1	0
p	1	5	1	-1
σ	0	0	6	0

The Gray World algorithm is used mostly for the underwater images. However, it results in a reddish image when it is applied to original image because of the low information on red channel as it is shown in Figure 4. For this reason, white balance application is done after color balancing the image to avoid oversaturation on red channel.

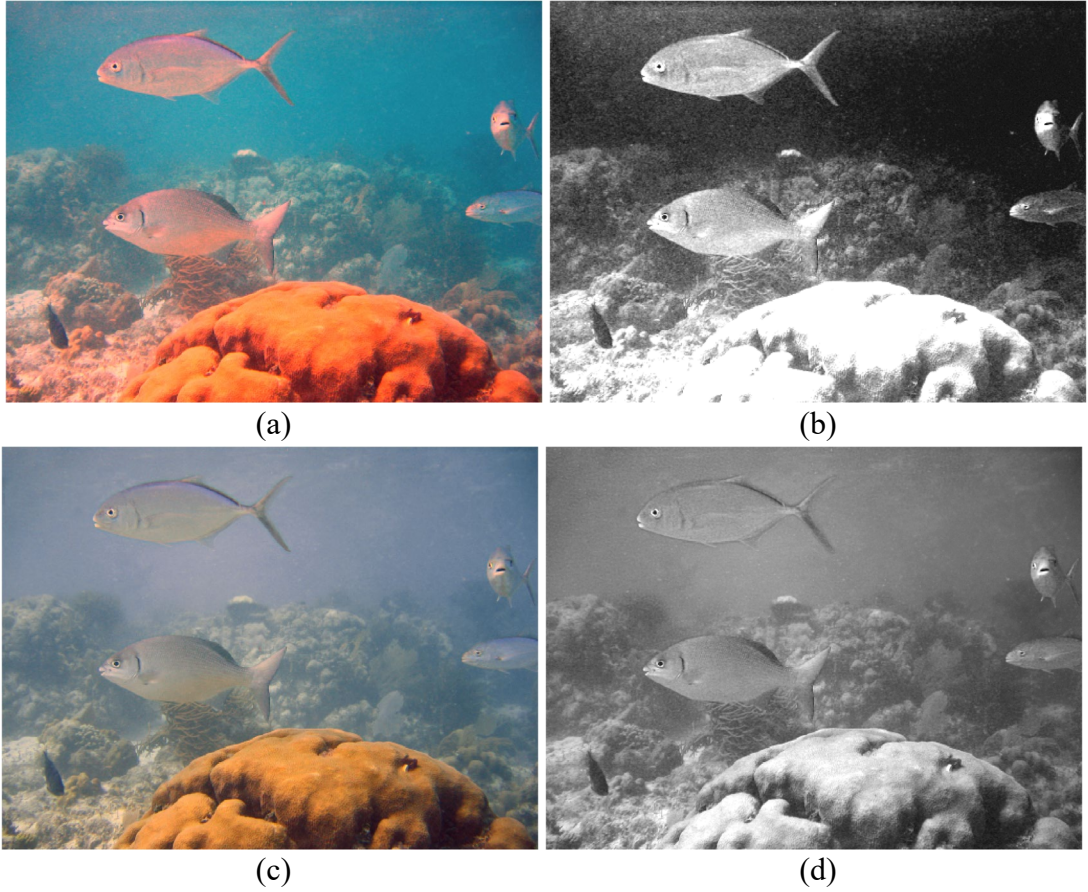


Figure 4: Results of White Balance With Displayed Red Channel: (a) White Balanced Image, (b) Red Channel of White Balanced Image, (c) White Balanced Image After Red Channel Compensation, (d) Red Channel of White Balanced Image After Red Channel Compensation

Chapter 3

UNDERWATER IMAGE ENHANCEMENT TECHNIQUES

The main aim of image enhancement techniques is to enhance the visual quality of an image by improving its colors and contrast. However, there is a notable challenge when it comes to underwater images due to loss of light. Underwater images suffer from loss of sharpness around edges and low contrast. Popular methods to improve the underwater images include contrast enhancement, gamma correction and sharpening techniques. These methods are explained in the following subsections.

3.1 Contrast Enhancement

Contrast enhancement techniques focus on increasing the range between the brightest and darkest regions in an image. Histogram Equalization (HE) and contrast stretching provides a broader spectrum of contrast. These techniques enhance the finer details in image.

The underwater images included in this section are grayscale images converted from the RGB color space, in order to focus on one channel pixel intensities only. But, normally, the RGB color space is transformed into the HSV or LAB color spaces to enhance the contrast of the image without distorting the color channels. This technique focuses on achromatic channels: V (Value) channel for HSV color space and L (Lightness) for LAB color space.

3.1.1 Histogram Equalization

Histogram equalization (HE) is a common way to increase contrast and recover the sharpness around edges. This technique redistributes the values of pixel intensity over the dynamic range. It alternates the cumulative distribution function (CDF) of image channels and equalizes the histogram. Assignment of new intensity values for histogram equalization of gray image with $L = 8$ bits is represented as follows:

$$s_k = T(r_k) = (L - 1) \sum_{k=0}^k \frac{n_k}{n} = (L - 1) \sum_{k=0}^k p_r(r_k), \quad 0 \leq k \leq L - 1 \quad (5)$$

where, $p_r(r_k)$ is the probability density function (PSD) of r_k , in which r_k represent the intensity level of k . n_k is the number of pixels with intensity k and n is the total number of pixels in the image. $T(r_k)$ is the transform function which is the product of CDF. s_k represents the new intensity values, which is obtained by rounding the levels in the transform function. Histogram of the normalized image is then plotted by calculating the PSD of s_k , which is equal to $p_s(s_k)$.

The effects of the HE is shown in Figure 5. The CDF is shown as a curve in the original image, and it is linearized in the HE image which means that the intensity values are distributed evenly.

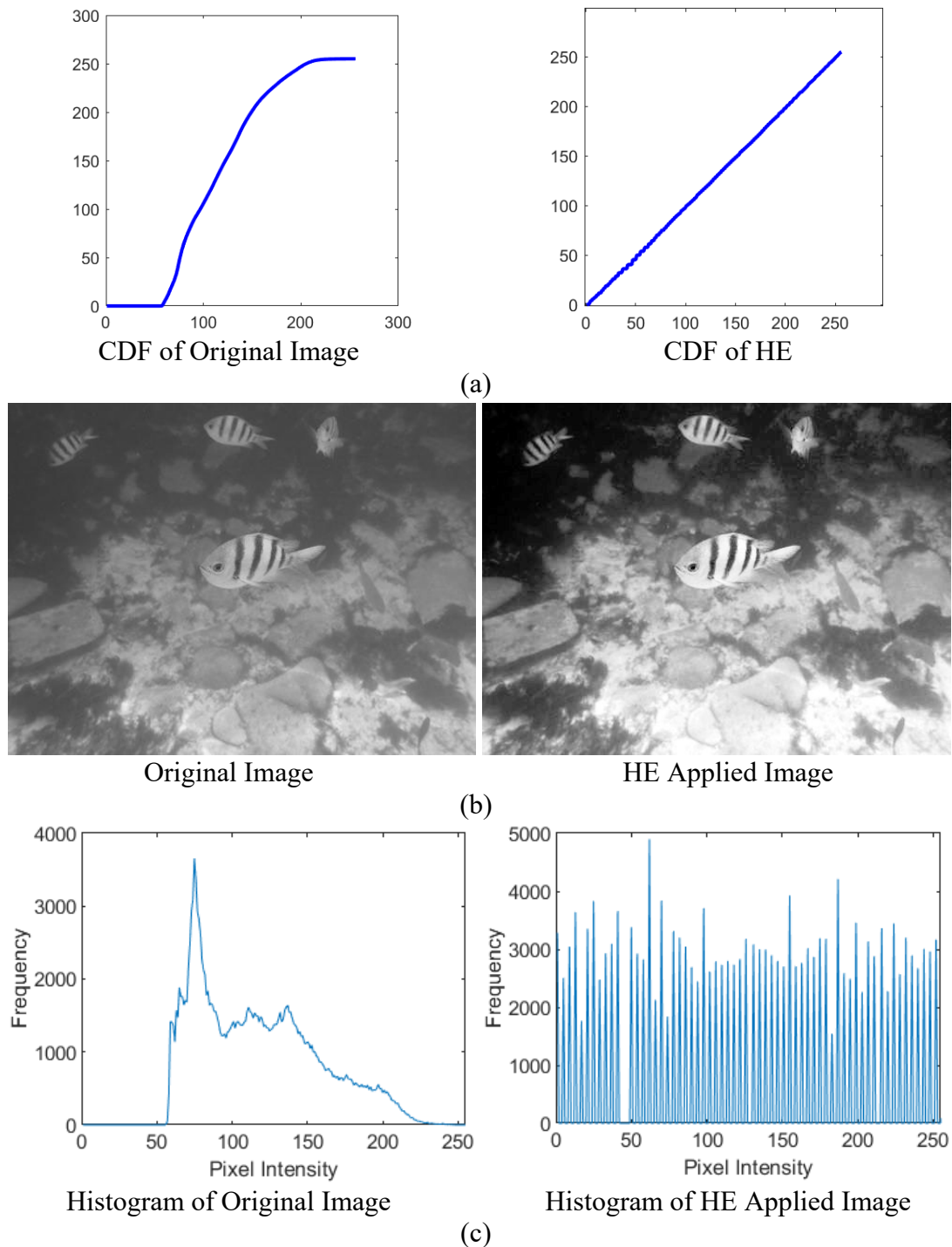


Figure 5: Comparison of Original Image vs HE Applied Image: (a) CDF Graph Comparison, (b) Image Comparison, (c) Histogram Comparison

3.1.2 Contrast Limited Adaptive Histogram Equalization

Contrast Limited Adaptive Histogram Equalization (CLAHE) introduces adaptability and contrast limitation to HE. It enhances the images by dividing the image to sections and then applying HE to each region. CLAHE also prevents excessive contrast

amplification by using special contrast limitation mechanism. CLAHE algorithm is as follows:

1. Input image
2. Divide the image into tiles
3. Compute histogram of each tile
4. Histogram equalization for each each tile
5. Clip excessive pixel values and redistribute to histogram
6. Merge the tiles and use interpolation to smooth the transition between edges
7. Output image

Algorithm 1: CLAHE implementation

If histogram value is higher than the contrast limit, it redistributes this excessive value to the HE. Qualitative implementation result of this approach is shown in Figure 6.

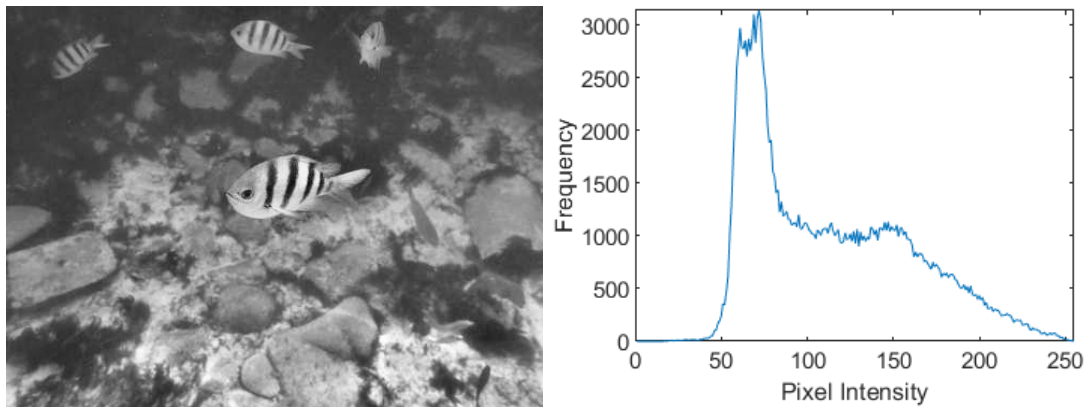


Figure 6: CLAHE Applied Image and Histogram Chart

3.1.3 Contrast Stretching

Contrast stretching technique rearranges pixel intensities to extend the range of contrast values. This function is derived as follows:

$$I_{new} = \left(\frac{I - I_{min}}{I_{max} - I_{min}} \right) \times 255 \quad (6)$$

where, I is the intensity level, I_{min} represents the minimum intensity level of the image and I_{max} represents the maximum intensity level of the image. The image intensity values are adjusted between 0, which represents black, to 255, which represents white. As a result, contrast stretching expands the dynamic range between the brightest and the darkest regions. The effects of this technique are depicted in Figure 7.

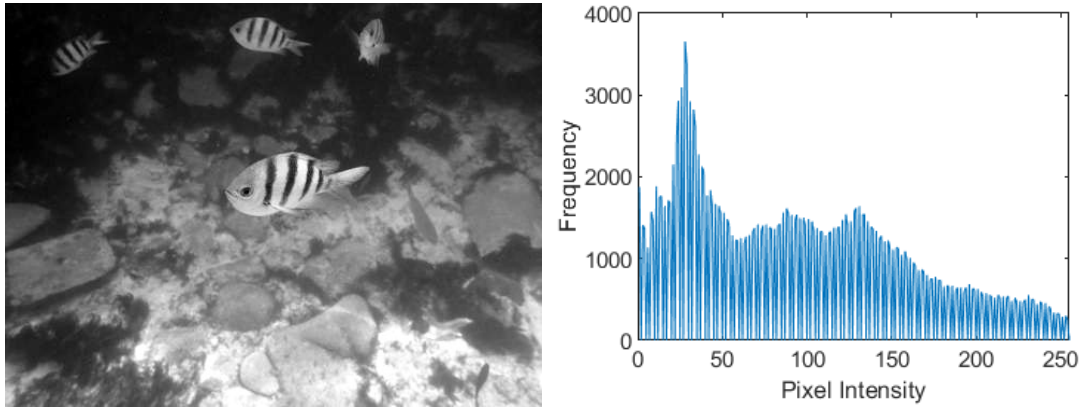


Figure 7: Contrast Stretched Image and Histogram Chart

3.2 Gamma Correction

Gamma correction is a nonlinear operation which can be applied to image to darken or brighten the image. This function is formulated as follows:

$$I_{new} = \alpha I^\gamma \quad (7)$$

where, I is the intensity level, α is set to 1 commonly and γ is the gamma variable. The gamma value which is greater than 1, results in darkening the image, whereas gamma value less than 1 brightens the image. In Figure 8, gamma correction is shown when the gamma value is equal to 2, which results in darkening the image and it is shown when the gamma value is equal to 0.5, which brightens the image.

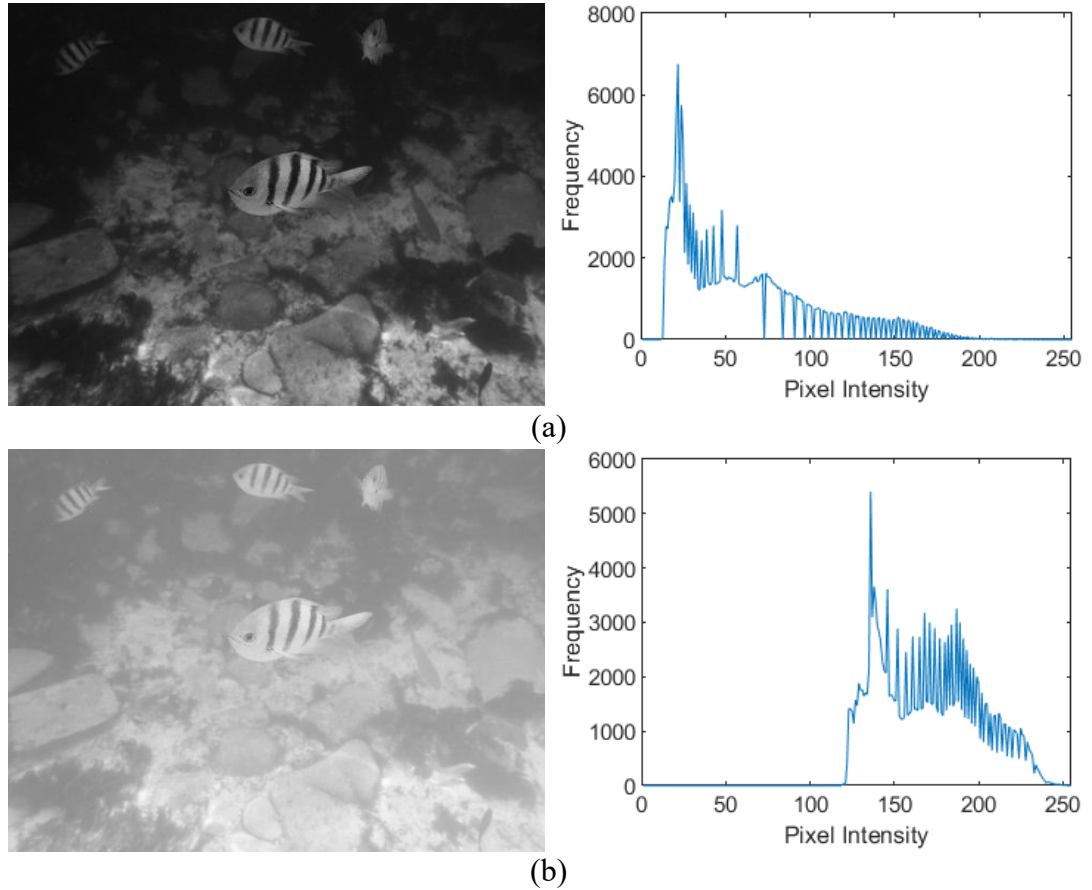


Figure 8: Gamma Corrected Image and Histogram Chart: (a) $\gamma = 2.0$, (b) $\gamma = 0.5$

3.3 Image Sharpening

Image sharpening enhances the clarity, fine details and edges of underwater images. This method can also be referred as high pass filtering since it removes the low frequencies that cause image to be seen as blurry.

Normalized unsharp masking is a commonly used image sharpening technique. It is derived from the idea of subtracting the image from the Gaussian blurred image to get the edges, then adding these well-defined edges to original image to enhance the sharpness effect. However, for the normalized version, defined edges are normalized with histogram stretching operator $N\{\cdot\}$ as it is formulized below:

$$S = (I + N\{I - G * I\})/2 \quad (8)$$

where, I is the original image, G is the Gaussian filter (blur filter) and S is the normalized unsharped image. Firstly, image is applied Gaussian blur, then subtracted from the original image to obtain the image with defined edges only which can also be known as Gaussian high pass filtering. Afterwards, the edges are enhanced with histogram stretching and added to the original image to obtain sharpened image. The results of normalized unsharp masking and the defined edges are shown in Figure 9.

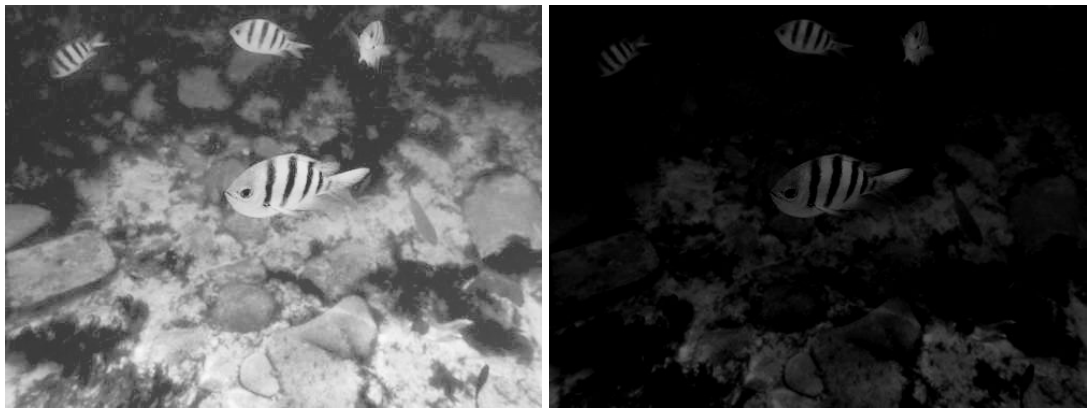


Figure 9: Normalized Sharpened Image (left) and Gaussian Subtracted Image (right)

Chapter 4

UNDERWATER MULTISCALE FUSION

Traditional techniques such as color balancing, contrast enhancement and gamma correction are not enough to remove the foggy appearance of the underwater image. With this extend, multiscale fusion can be used to dehaze the underwater image by enhancing the contrast and edge sharpness while preserving the colors of the single preprocessed image. This technique achieves to enhance the underwater image without losing information from the original image. Gamma corrected and sharpened images are used for this study as the inputs for multiscale image fusion for better representation. Further details related to multiscale fusion are explained in the following subsections.

4.1 Weights of the Multiscale Fusion

Weight mapping is important because pixels with greater weights will have more effect on the output of the multiscale fusion image. Laplacian Contrast Weight (W_L), Saliency Weight (W_S) and Saturation Weight (W_{Sat}) are the three weight metrics used in this process.

Laplacian Contrast Weight concentrates on the input image's luminance channel and it is sensitive to rapid intensity change in pixel values. It is effective to capture edges but it fails at increasing the contrast on flat surfaces.

Saliency Weight aims to highlight the underwater objects to increase their contrast with the background. This procedure is executed within the LAB color space. Its definition is shown as follows:

$$W_S = (L - L_{mean})^2 + (a - a_{mean})^2 + (b - b_{mean})^2 \quad (9)$$

where L , a and b are the three components of the LAB color space. L_{mean} , a_{mean} and b_{mean} represent their mean values, respectively.

Saturation weight enhances the colors of the high saturated regions and its formula is as follows:

$$W_{Sat} = \sqrt{1/3[(R - L)^2 + (G - L)^2 + (B - L)^2]} \quad (10)$$

where R , G and B represents the channels of RGB color space and L is the luminance channel of LAB color space.

For each input of the fusion k , a weight map W_k is obtained by summing up the three weight maps as follows:

$$W_k = W_L + W_S + W_{Sat} \quad (11)$$

Finally, the summed weights in each input k are divided by the sum of all input k weights by using the following equation as shown below:

$$\bar{W}_k = (W_k + \delta) / \left(\sum_{k=1}^K (W_k) + K\delta \right) \quad (12)$$

where \bar{W}_k represents the normalized weight map and K is equal to the number of the inputs. δ is a constant which is set to a low value such as 0.1 to guarantee the contribution of each weight to the output.

4.2 Multiscale Fusion Process

The Multiscale fusion logic is based on applying Gaussian low pass filter to the image, then subtracting it from the input which will enhance the sharpness of the image. This process is equal to Laplacian filtering. Then, it is multiplied by the Gaussian of the corresponding normalized weight for each layer of the pyramid as follows:

$$I_{out} = \sum_{k=1}^K G_l\{\bar{W}_k\} L_l\{I_k\} \quad (13)$$

where l represents the level of the pyramid, K is equal to the number of the inputs of the fusion, $G_l\{\bar{W}_k\}$ is the Gaussian pyramid decomposition for normalized weights and $L_l\{I_k\}$ is the Laplace pyramid decomposition for multiscale fusion inputs.

The representation of Gaussian pyramid is given in Figure 10. Firstly, in level 1, Gaussian filter is applied to the gamma corrected images' normalized weight (first input) and down sampled by factor of two. Then, in level 2, the down sampled image is blurred with Gaussian filter again and down sampled by factor of two. Finally, in the third level, Gaussian filter is applied and the Gaussian pyramid for the first input is created. The same process is repeated for the sharpened images' normalized weight (second input).

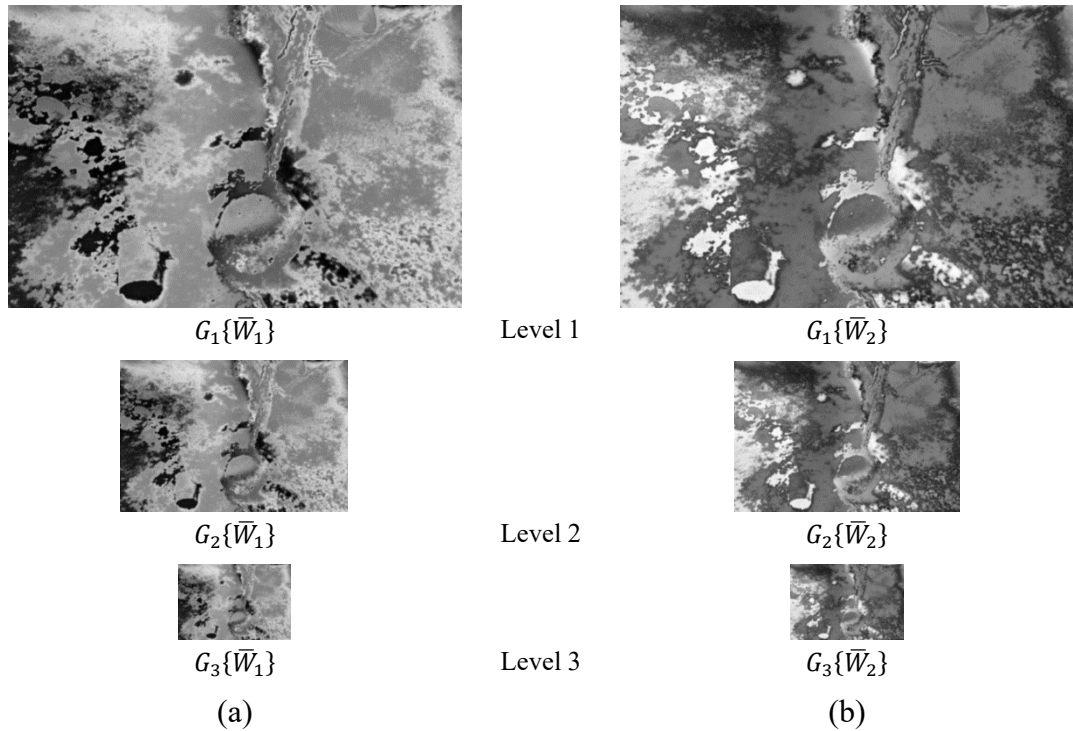


Figure 10: Gaussian Pyramid: (a) Gamma Corrected Images' Normalized Weight, (b) Sharpened Images' Normalized Weight

The representation of Laplacian pyramid is given in Figure 11. Firstly, the first input is directly taken as level 1 and down sampled by factor of two to create level 2 and down sampled again to construct level 3. Then, level 2 is up sampled by factor of two and subtracted from level 1 and assigned as the new level 1 image, which preserves only the edges and details in the image. Lastly, level 3 is up sampled by factor of two and subtracted from level 2 and assigned as the new level 2. The level 3 is left as it is since this example contains only three levels. Same procedure is applied to the second input. The brightness of level 1 and level 2 images are increased by 40% in Figure 11 for better visualization.

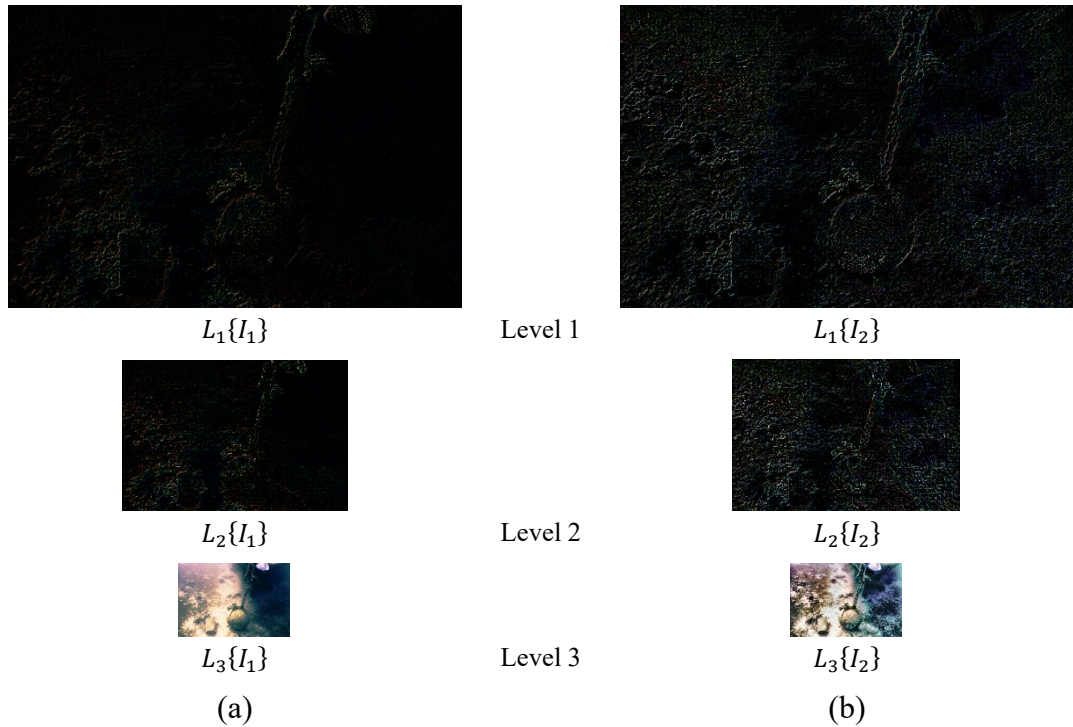


Figure 11: Laplacian Pyramid: (a) Gamma Corrected Image, (b) Sharpened Image

The obtained Laplacian and Gaussian pyramids are then operated as in equation (13). The first and second input's pyramids are multiplied level by level separately as shown in Figure 12.

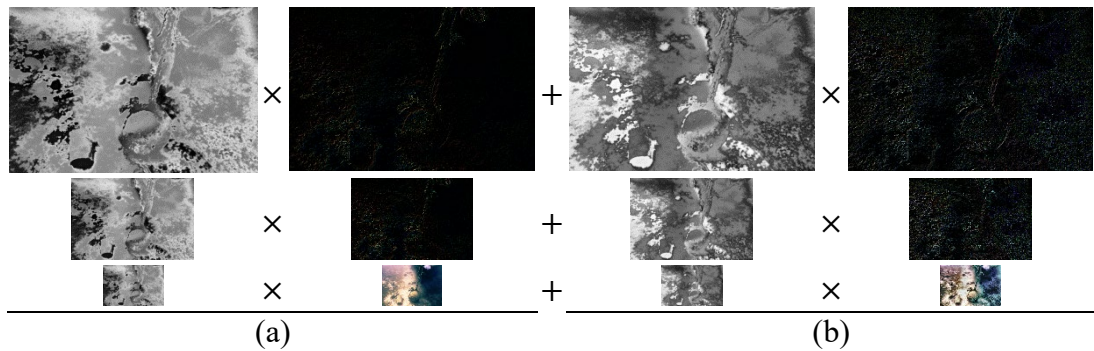


Figure 12: Gaussian and Laplacian Pyramids: (a) Gamma corrected image, (b) Sharpened Image

Two inputs' newly formed pyramids are combined with summation operation and their results are presented in Figure 13. The images are displayed with the same scale

in this example for better visualization, but normally they are scaled as pyramid as shown in Figure 12.

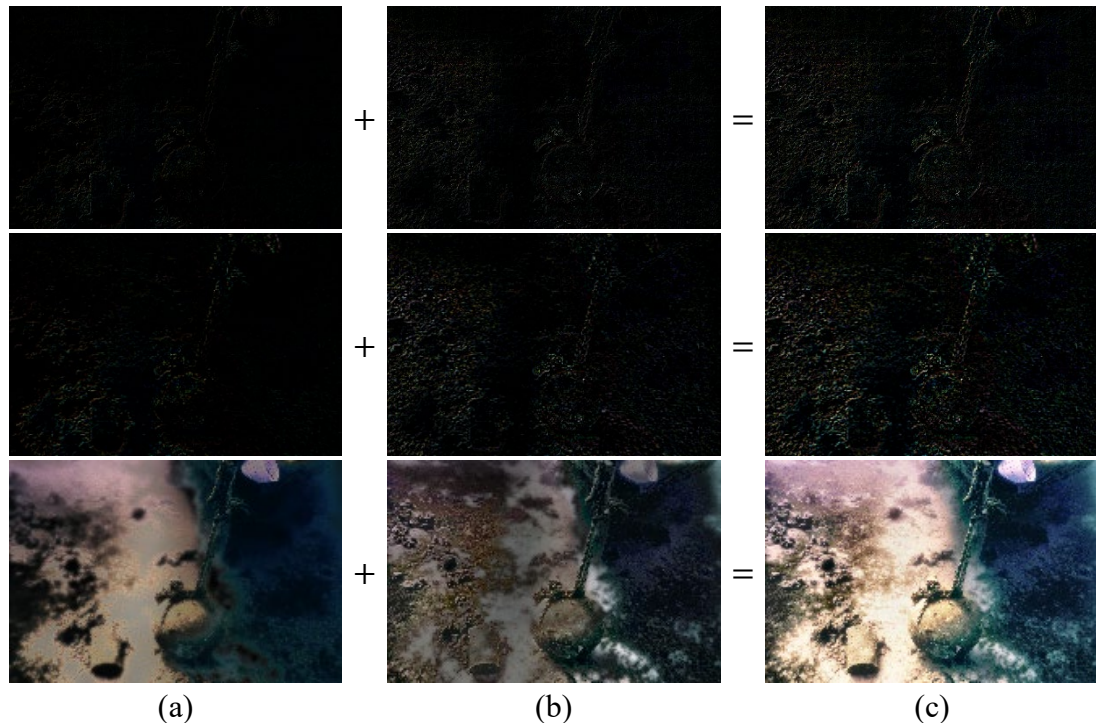


Figure 13: The Summation of Pyramids: (a) Gamma Corrected Image's Pyramid, (b) Sharpened Image's Pyramid, (c) Final Pyramid

After obtaining the last pyramid, some procedures are followed to get the enhanced image as shown in Figure 14. Firstly, level 3 image is up sampled by factor of two, then added to level 2 of the pyramid which added details to up sampled image. Then this process is applied again by upscaling the newly obtained image and adds to the level 1 image. As a results of the last addition operation to level 1, the output of the multiscale image fusion is obtained. Furthermore, the image is also cropped in Figure 14 to focus on the details and enhancement in comparison to resized level 2 image. The output image is further enhanced in details and in contrast by combining the features of input images.

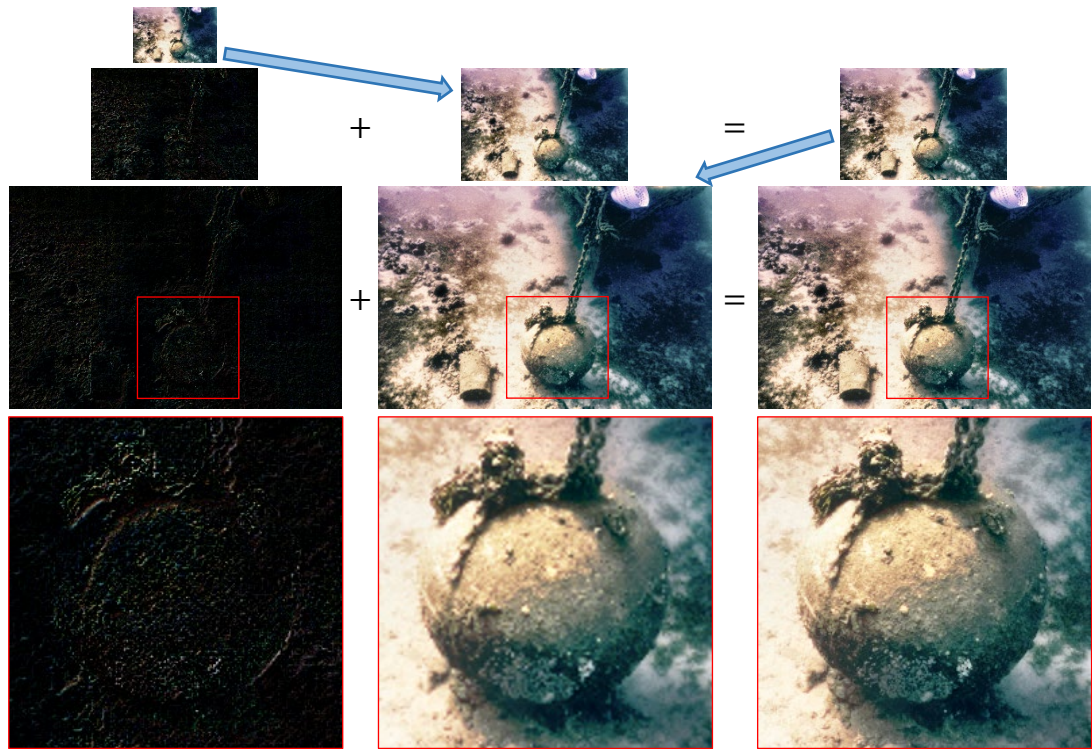


Figure 14: Upscale Process of Final Pyramid

Chapter 5

PROPOSED METHOD

The proposed method aims to improve the quality of underwater images by using various image enhancement algorithms to address common underwater challenges such as poor visibility and color distortion. It restores the color of underwater images and enhances contrast and details in image. This method has wide-ranging applications, from marine biology research to archeology, and has the potential to significantly advance our understanding of underwater scenes.

The proposed approach used in this thesis has two main stages: Preprocessing stage and Multiscale image fusion. Preprocessing stage includes white balancing the image and applying contrast and color enhancement to prepare image for the fusion process. Multiscale image fusion combines two images derived from the preprocessed image to improve the quality of underwater images. Overview of the proposed method is shown in Figure 15. The two stages are explained in the following sections.

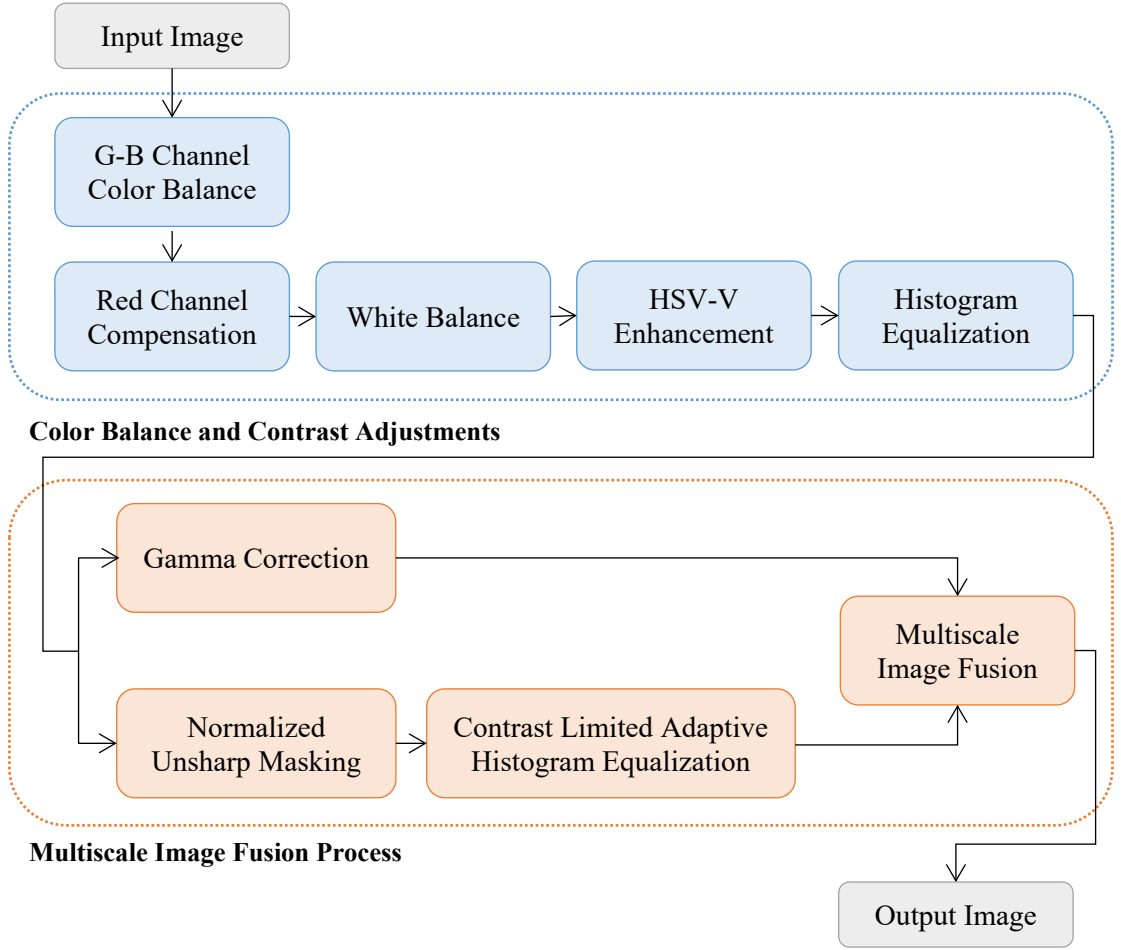


Figure 15: Overview of the Proposed Method

5.1 Color Balancing and Contrast Adjustment

As aforementioned in this thesis, underwater images tend to be blue-greenish, therefore it is essential to balance the colors in order to appeal to human eye. Firstly, blue and green channels (G-B channel) are focused on since they carry the highest information underwater. This channel is equalized based on Gray World algorithm, where the average gray color is assumed to be gray with value 128 in 8-bit image [9]. Then, G-B channel definition is shown below:

$$\begin{aligned}
 k_g &= Gray/\bar{G}, & k_b &= Gray/\bar{B} \\
 \hat{G} &= G * k_g, & \hat{B} &= B * k_b
 \end{aligned} \tag{14}$$

In this context, G and B are green and blue channels of the original image, k_g and k_b symbolize the gain ratios for the newly adjusted \hat{G} - \hat{B} channels.

Red channel color compensation algorithm is applied after G-B channel color balancing since red is the first color to be absorbed in underwater conditions. Then, Gray World white balance algorithm is applied to red channel compensated image to balance red, green and blue channels. The obtained image is then converted into HSV color space, and V value is contrast stretched to enhance the image contrast without losing the original colors [15]. Afterwards, the image is converted back to RGB color space. To further increase the image's vividness, histogram equalization is applied to the image. The color balanced image is then carried into multiscale image fusion process.

5.2 Multiscale Image Fusion

The underwater scene's details and colors are enhanced as a result of the multiscale fusion process. This method relies on the utilization of gamma correction and sharpening techniques, alongside the application of CLAHE to remove haziness within the white-balanced image.

Two inputs are derived from a color-balanced image for the fusion process. Firstly, gamma correction is obtained as the first input to adjust the global contrast of the image. This method might cause loss of details in darker or lighter regions. The second input is used to compensate this loss, which is introduced as normalized unsharp masking that sharpens the fine details of the image. Then CLAHE is applied to further enhance the image's contrast.

Three weights are calculated for each input. Laplacian contrast weight, saliency weight and saturation weight are used for enhancing the edges, defining the objects and increase saturation, respectively. These weights are added with each other, then normalized to create one weight image for both inputs.

Gaussian pyramid with three levels are formed using the normalized weights and Laplacian pyramid is constructed using the two inputs of the fusion. Gaussian pyramid is multiplied with the corresponding Laplacian pyramid, level by level for each input. Then, these newly formed pyramids are combined using summation operation. Starting from the lowest level (level 3) of the finalized pyramid, the image is upscaled one by one and added into corresponding level until the derived image matches the original size. Finally, the output image of this multiscale process is obtained which results in an overall enhancement of the underwater image's quality. The flowchart explaining this multiscale image fusion is shown in Figure 16.

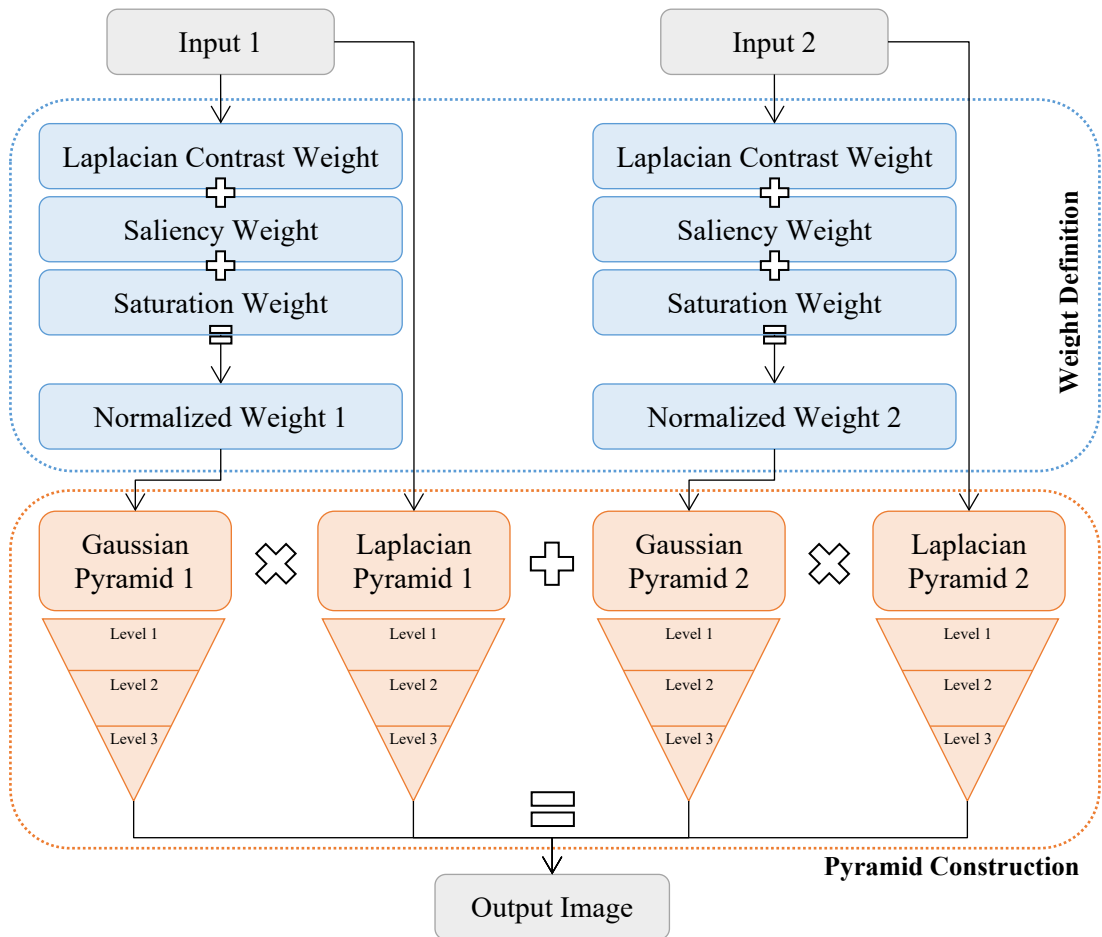


Figure 16: Overview of the Multiscale Image Fusion

Chapter 6

EXPERIMENTS AND RESULTS

The experimental details of the proposed approach are presented in this chapter. Firstly, experimental setup and metrics are explained, then evaluation results are discussed. The evaluation of the experiments are separated into two important sections. The color balancing evaluation is applied to an image, then compared with the other generally known white balance algorithms. In the next step, multiscale image fusion steps are shown with supporting images. Lastly, underwater image dehazing evaluation is presented by comparing the proposed method with previously applied methods.

6.1 Experimental Setup

The images used in these experiments are selected from UIEB and SQUID datasets. Additionally, widely used underwater image dataset provided in Zhang. et al. [16]'s source code is used. Single input image is used for each of the experiments and evaluations.

The proposed method is implemented in MATLAB R2022a on Microsoft Windows 11 with processor of 12th Gen Intel(R) Core(TM) i9-12900H, 2500 Mhz and RAM of 32.0 GB.

6.2 Evaluation Metrics

Evaluation metrics are different for color balance and dehaze removal methods. The color balancing technique is evaluated using two metrics: UICM [17] and IL-NIQE [18]. UICM is a metric specifically designed for measuring underwater image colorfulness that is implemented from UIQM [17] metric, while IL-NIQE uses pre-trained algorithm to compare the image colors with natural outdoor colors. Lower value in IL-NIQE indicates the images' colors are more natural compared to the higher values. The formula of UICM is as follows:

$$\begin{aligned}
 RG &= R - G, & YB &= \frac{R + G}{2} - B \\
 UICM &= -0.0268 \sqrt{\mu_{\alpha, RG}^2 + \mu_{\alpha, YB}^2} + 0.1586 \sqrt{\sigma_{\alpha, RG}^2 + \sigma_{\alpha, YB}^2}
 \end{aligned} \tag{15}$$

where $\mu_{\alpha, RG}^2$ and $\sigma_{\alpha, RG}^2$ are alpha-trimmed mean and variance of RG; $\mu_{\alpha, YB}^2$ and $\sigma_{\alpha, YB}^2$ are alpha-trimmed mean and variance of YB. UICM assigns higher colorfulness value for enhanced images.

Underwater image dehazing is evaluated with three metrics: PCQI [19], UCIQE [20] and UIQM [17]. The UCIQE and UIQM metrics are carefully crafted for the assessment of underwater images, while PCQI metric serves as a general measurement of image contrast. UCIQE measures the color degradation of the image in LAB space and its derivation is as follows:

$$UCIQE = 0.4680 \times \sigma_C + 0.2745 \times con_l + 0.2576 \times \mu_S \tag{16}$$

where σ_C is standard deviation of chroma, con_l represents the difference between top and bottom 1% of values and μ_S is the average of saturation. Greater UCIQE value means better image quality.

PCQI is a metric that requires a reference image while the other metrics are no-reference image quality metrics. The derivation of PCQI evaluation metric is as follows:

$$PCQI(x, y) = q_i(x, y) + q_c(x, y) + q_s(x, y) \quad (17)$$

where x and y are pair of co-located patches in the original image and the test image, respectively. q_i , q_c and q_s represent comparison of the mean intensity, change in contrast and structural distortion, respectively. UIQM evaluates the underwater images based on color, sharpness and contrast. The derivation of UIQM evaluation metric is as follows:

$$UIQM = 0.0282 \times UICM + 0.2953 \times UISM + 3.5753 \times UIConM \quad (18)$$

where $UICM$, $UISM$, and $UIConM$ correspond to evaluating image color, sharpness and contrast. UIQM assigns greater value for enhanced images.

As an addition, in multiscale fusion evaluation section, peak signal-to-noise ratio (PSNR) metric is used to determine the image quality through noise. This algorithm is calculated with mean squared error (MSE) and its equation is as follows:

$$MSE = \frac{1}{M \times N} \sum_{M,N} [I_1(m, n) - I_2(m, n)]^2 \quad (19)$$

$$PSNR = 10 \log_{10} \left(\frac{I_{max}^2}{MSE} \right)$$

where M and N are the number of rows and columns in image, I_1 represents the original image and I_2 represents the derived image, I_{max} is the maximum possible pixel intensity of image which is 255 for 8 bit image.

6.3 Color Balancing Evaluation

The first step in proposed method is balancing the underwater image's colors to obtain natural looking images. Firstly, the image taken underwater is shown in Figure 17. The image is bluish and green-blue (G-B) intensities are higher than the red channel as seen as it is in their histogram plot.

G-B channel color balancing is applied based on Gray World algorithm to equalize the green and the blue channel around pixel intensity of 128 which is assumed to be the Gray color. The results of G-B channel color balancing is shown in Figure 18.

After this correction, red channel is adjusted by using red channel compensation algorithm to restore the absorbed red colors underwater as shown in Figure 19.

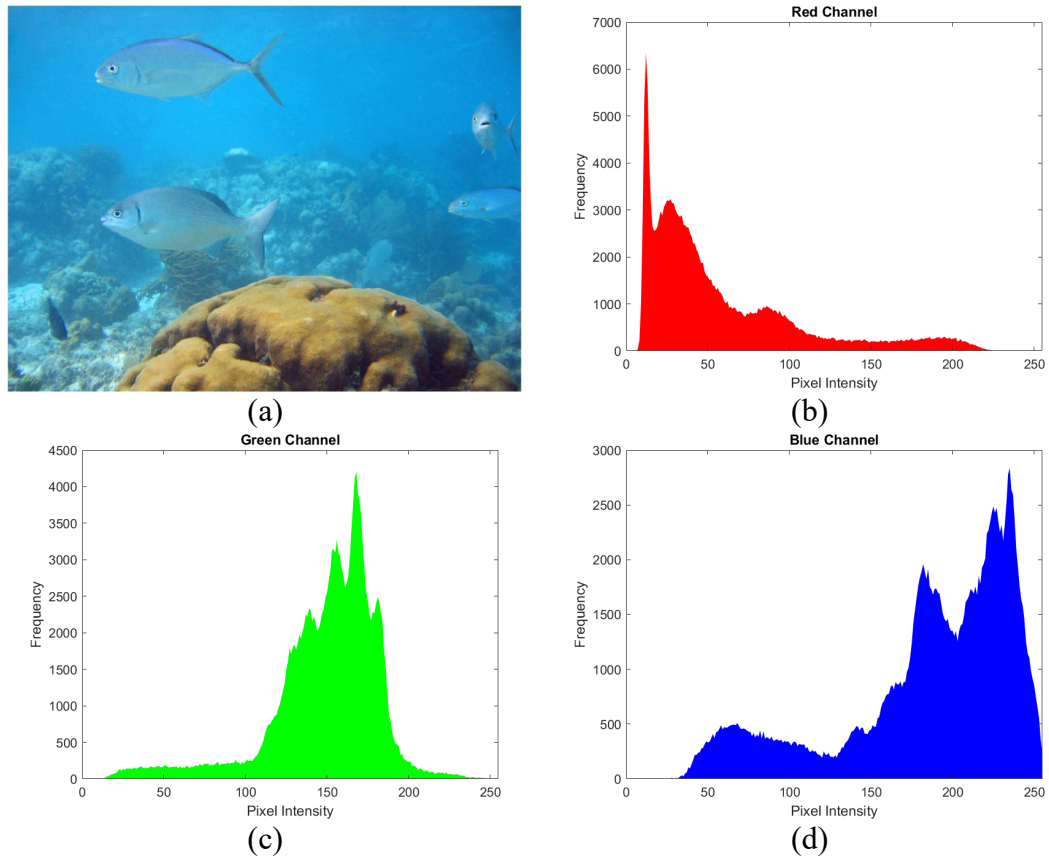


Figure 17: Original Image and Histograms: (a) Original Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

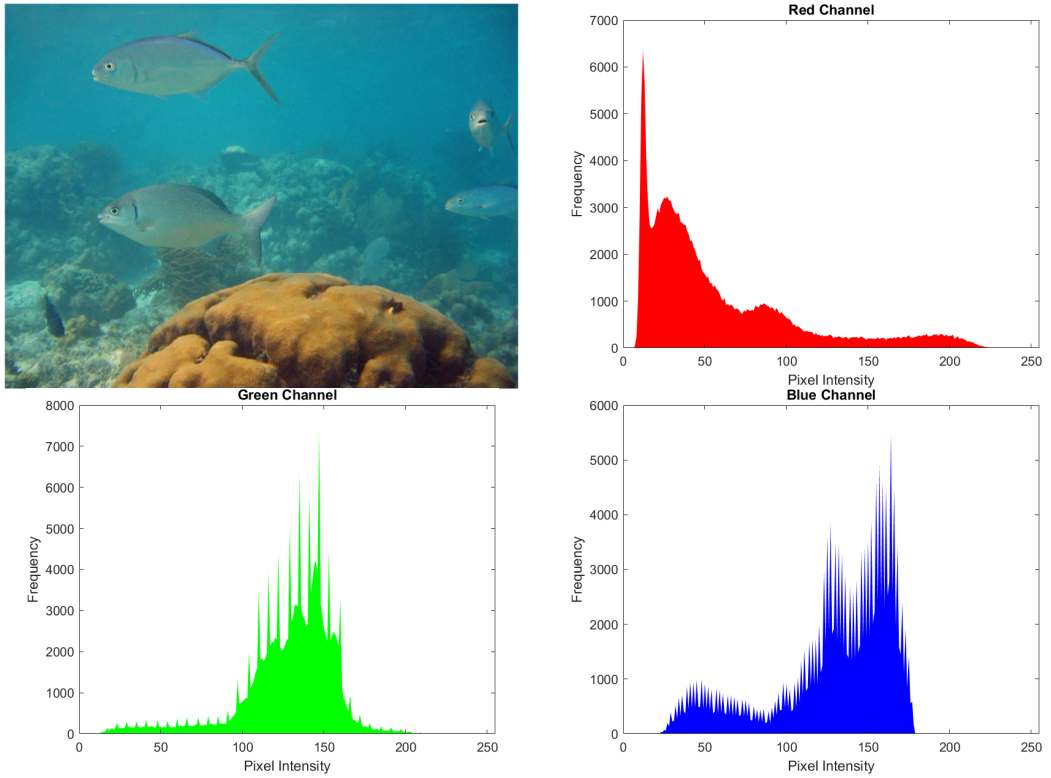


Figure 18: G-B Color Balance and Histogram: (a) G-B Color Balanced Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

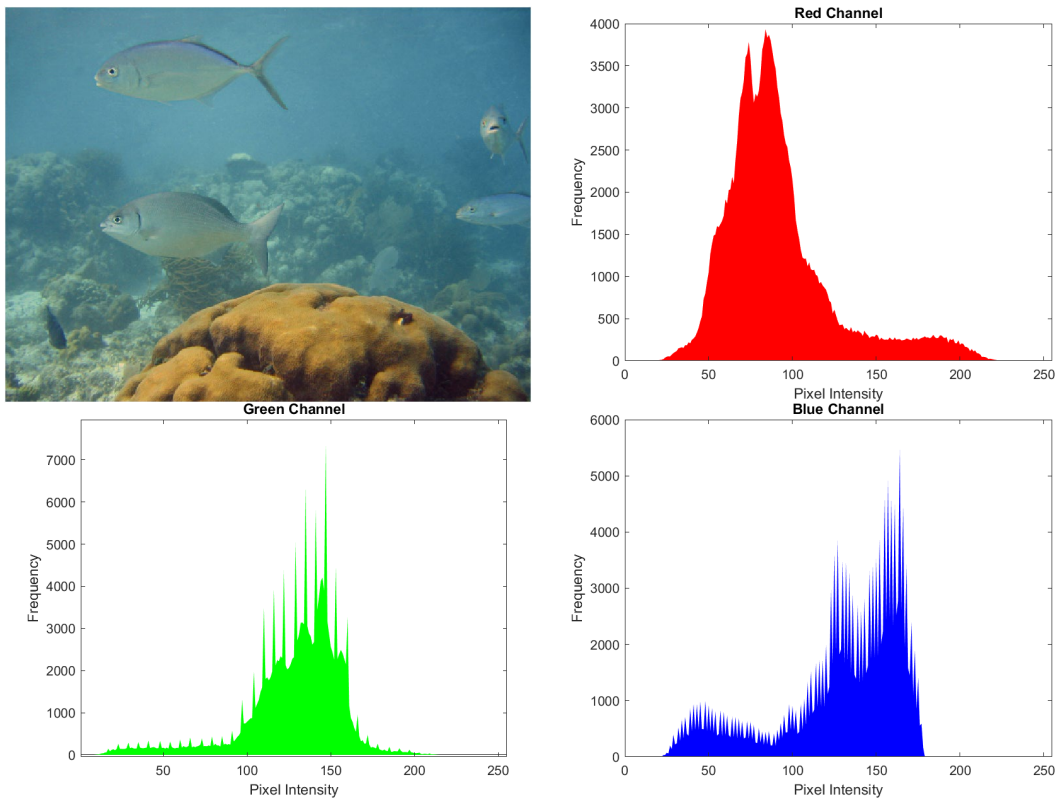


Figure 19: Red Channel Compensation and Histogram: (a) Red Channel Compensated Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

Gray World algorithm is applied to red compensated image. This algorithm balanced all color channels at pixel intensity corresponding to Gray color as shown in Figure 20.

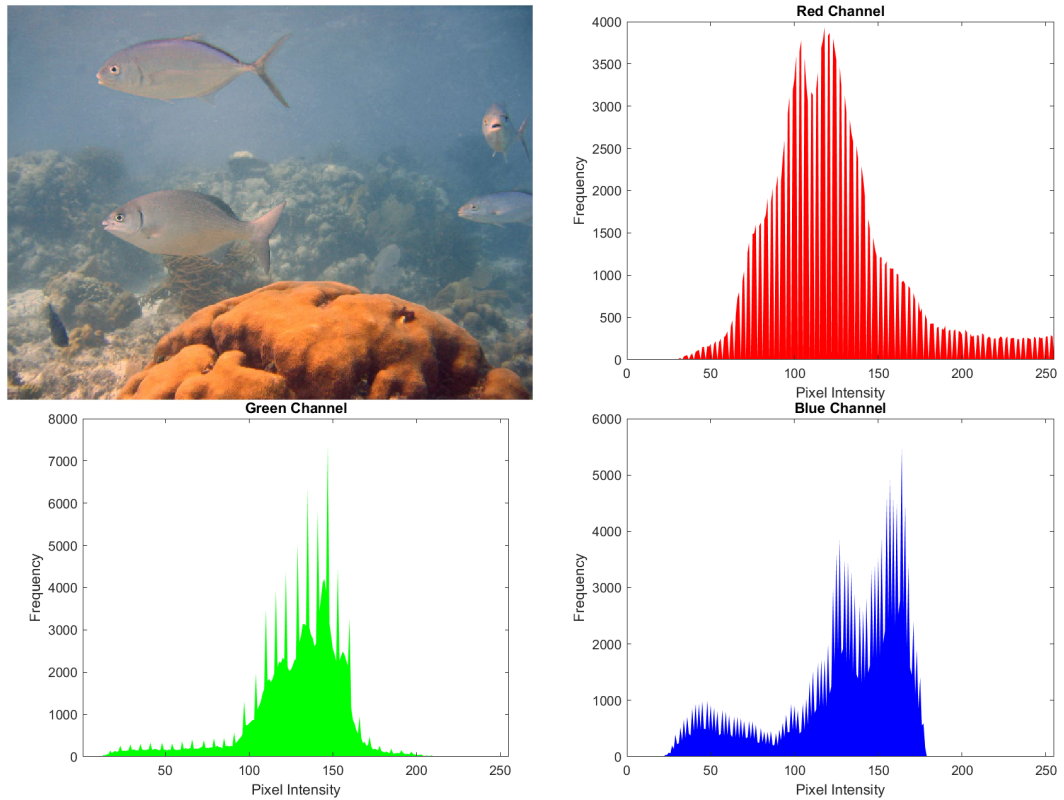


Figure 20: White Balance and Histogram: (a) White Balanced Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

The white-balanced image is transformed to HSV color space and contrast stretching is applied to V value to improve the image's contrast without distorting the colors as shown in Figure 21.

Finally, the image is converted back to RGB color space and its channels are histogram equalized to enhance the color as shown in Figure 22.

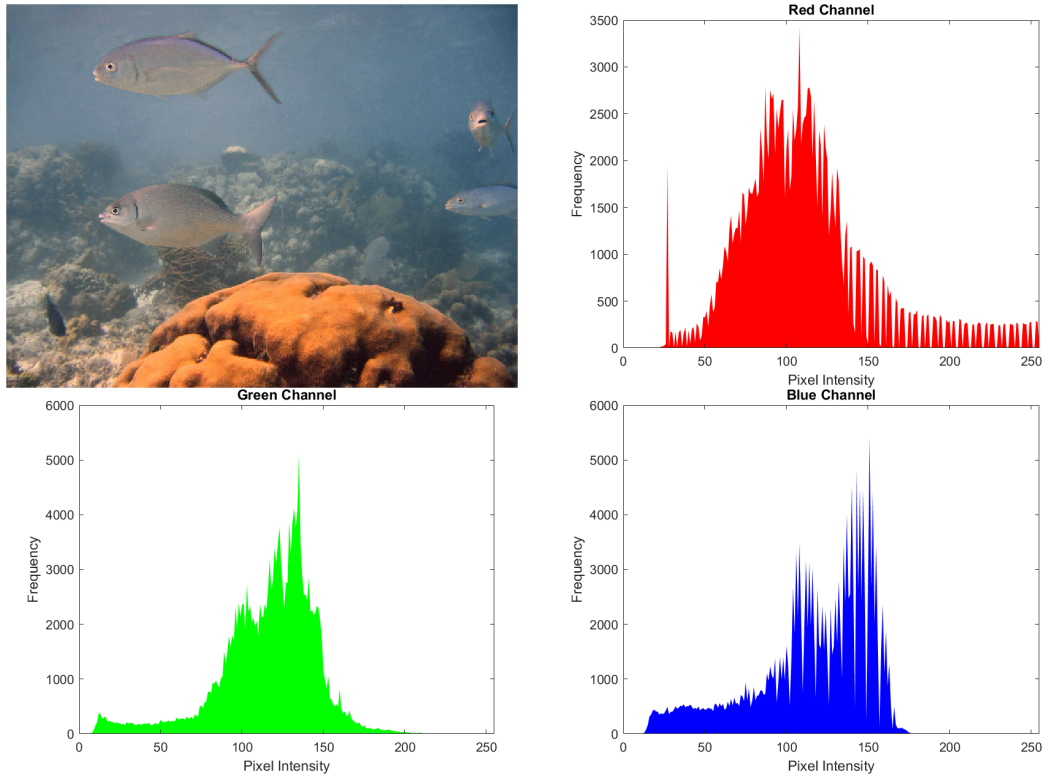


Figure 21: HSV-V Enhanced Image and Histogram: (a) HSV-V Enhanced Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

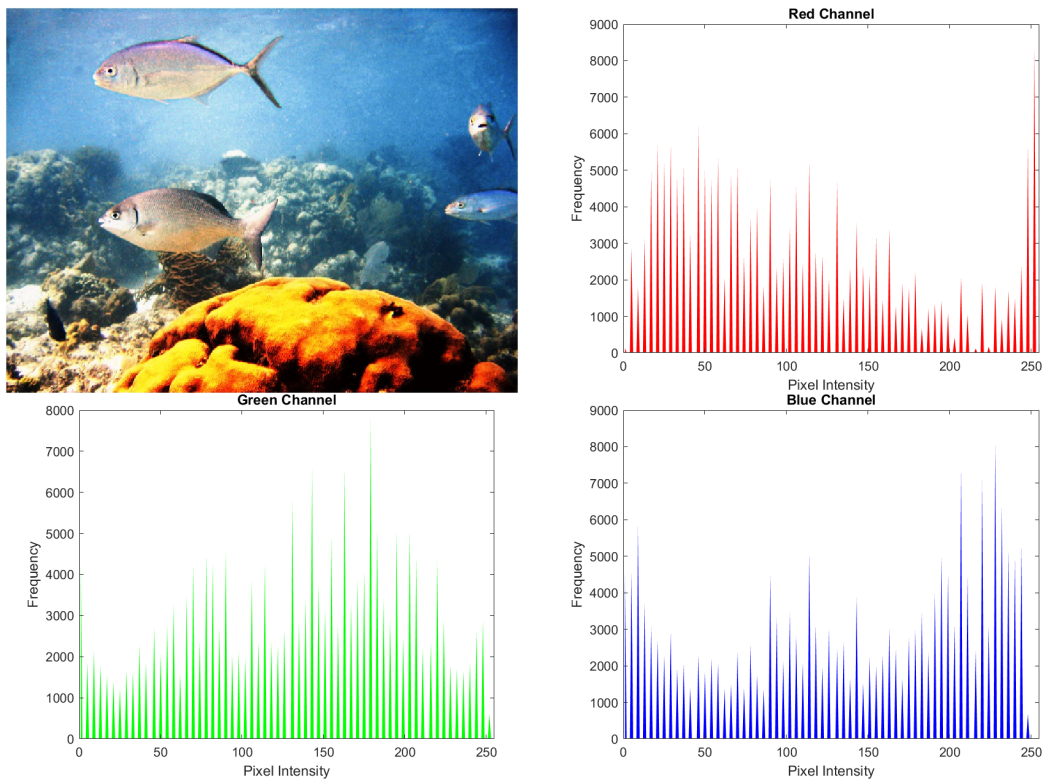


Figure 22: Histogram Equalized Image and Histograms: (a) Histogram Equalized Image, (b) Red Channel Histogram, (c) Green Channel Histogram, (d) Blue Channel Histogram

The results are compared with Ancuti et al. [7]’s method and the white balance algorithms as shown in Figure 23 and color evaluation results are shown in Table 2 with comparison to the contrast stretched white balance of Ancuti et al. [7] and white balance algorithms.

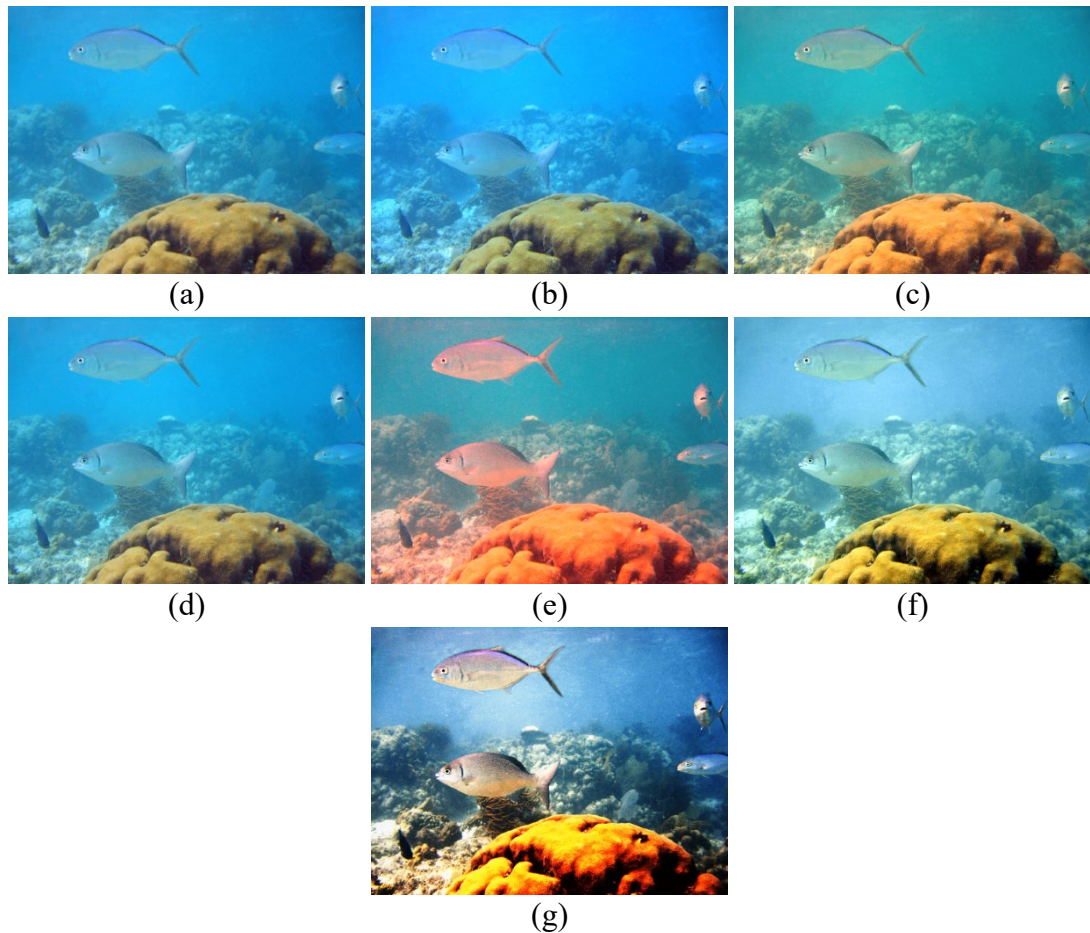


Figure 23: Color balanced images: (a) Original image, (b) Grey Edge, (c) Shades of Grey, (d) Max RGB, (e) Gray World, (f) Ancuti et al. [7], (g) Proposed Method.

The results shown in Table 2 are represented with color metrics based on UICM and IL-NIQE. As shown in the results, Gray World gives the best result in terms of UICM underwater color measurement with the highest value, however Gray World algorithm causes red artifacts due to the loss of information on red, as it can be seen in Figure 23. Because of these reasons IL-NIQE metric is used to measure the image based on the natural colors. The lower value in this metric means better results. This metric

shows that Gray World image has the most unnatural color scheme compared to other images. The results obtained with the proposed method of this thesis reduced this red artifact significantly and achieved the best result in IL-NIQE metric.

Table 2: Underwater Color Balance Evaluation

Methods	Fish	
	UICM	IL-NIQE
Grey Edge [12]	8.15137	28.8553
Shades of Grey [11]	12.6237	27.3935
Max RGB [10]	9.80689	28.1527
Gray World [8]	16.3045	30.0261
Ancuti et al. [7]	9.76932	24.2179
Proposed Method	14.9179	22.0004

6.4 Multiscale Fusion Experiments

Multiscale image fusion aims to increase contrast and details in underwater images. Different values of gamma correction and sharpening parameters are tested in this section to compare their effect in PCQI [19] and UCIQE [20] quality metrics.

After white balancing and adjusting the colors of the image, two inputs are derived for multiscale fusion: gamma corrected image and CLAHE applied sharpened image. These input images are shown in Figure 24. The default parameters for the gamma variable is set to 1.2 and the Gaussian standard deviation for the normalized unsharp mask is set to 20.



Figure 24: Gamma Correction (left), Sharpened Image (middle), CLAHE Applied Sharpened Image (right)

Laplacian, saliency and saturation weight maps are then calculated as shown in Figure 25 based on multiscale image fusion process explained in Chapter 4.

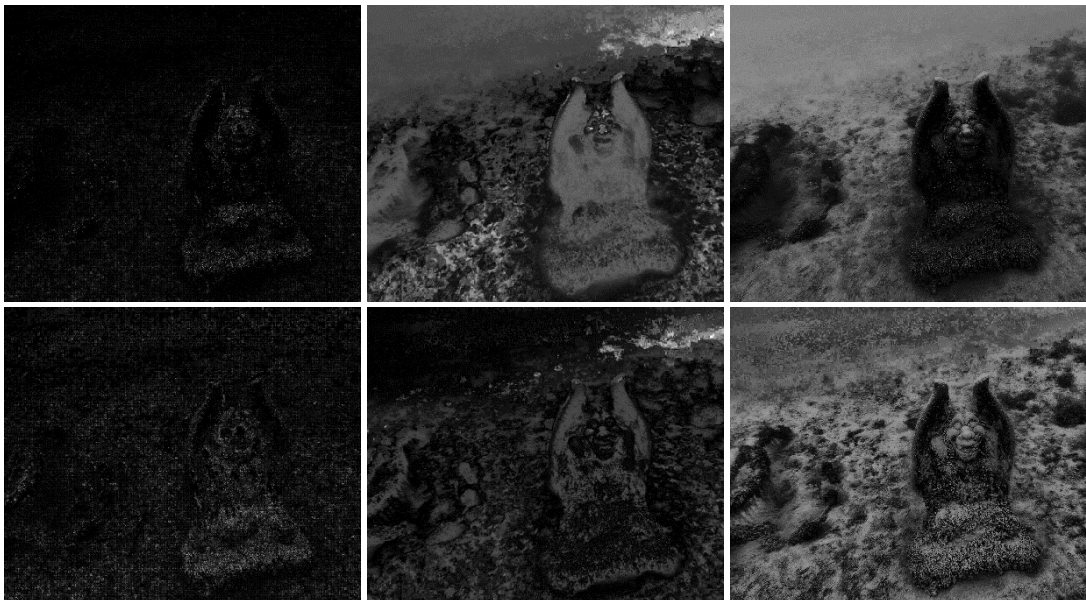


Figure 25: Weight Maps for Gamma Corrected Image (top row) and Sharpened Image (bottom row): Laplacian Contrast Weight, Saliency Weight, Saturation Weight

The aforementioned three weights are then normalized to produce a single weight map as shown in Figure 26. These normalized weights will be used in Gaussian Pyramids.



Figure 26: Normalized Weight Maps (Gamma (left), Sharp (right))

After the multiscale image fusion process, an image with enhanced details and contrast is produced as shown in Figure 27.



Figure 27: Original Image (left) and Fusion Output (right)

The output of the multiscale appears to be in low brightness. The parameters for the Gamma correction input is changed to show the effect of the gamma correction to image quality. The Gamma variable is set to 0.5, 0.8, 1.0 (no Gamma effect), 1.2 (default) and 1.5 as seen in Figure 28. As the Gamma variable decreases, the image gets brighter and when the Gamma variable increases, the image gets darker. This Gamma input affects the brightness of the fusion image directly.

Gamma Corrected Image

Fusion Output



(a) $\Gamma = 0.5$



(b) $\Gamma = 0.8$



(c) $\Gamma = 1.0$



(d) $\Gamma = 1.2$



(e) $\Gamma = 1.5$

Figure 28: Comparison of Gamma Values with Fusion Output - 1

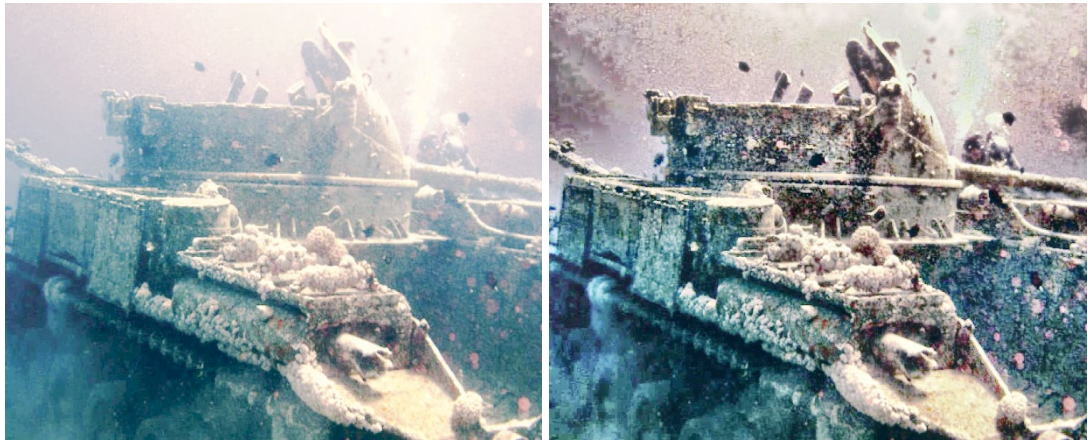
Table 3 shows the PCQI and UCIQE evaluation metric results for Gamma corrected image and the fusion image as the Gamma variable increases from 0.5 to 1.5. Overall, the UCIQE value increases as the Gamma value increases, which results in darker fusion image. For PCQI metric, brighter images give a higher value and it peaks when Gamma variable equals to 0.8 in gamma corrected image, but PCQI metric for the output of the fusion image decreases still when Gamma variable equals to 0.5. Same procedure is then applied to a different underwater image to compare the results as shown in Figure 29.

Table 3: Evaluation of Gamma Correction - 1

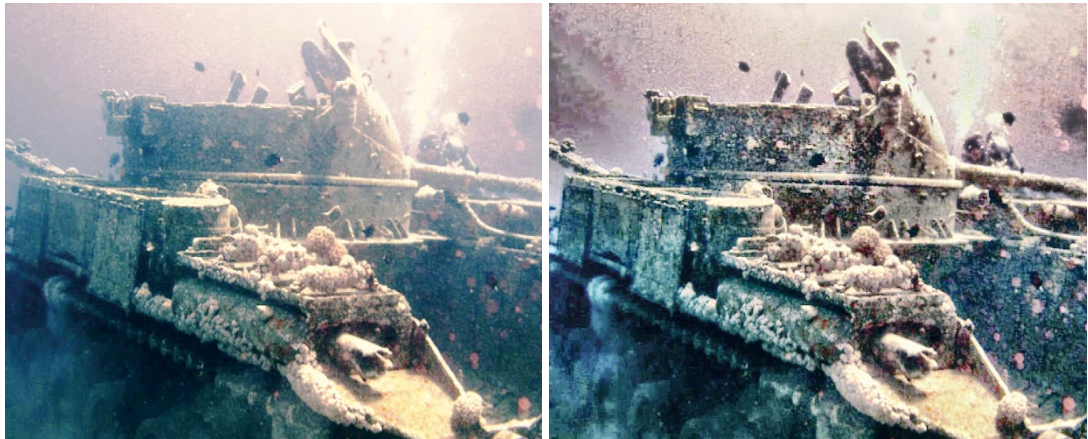
Image	Metrics	$\Gamma = 0.5$	$\Gamma = 0.8$	$\Gamma = 1.0$	$\Gamma = 1.2$	$\Gamma = 1.5$
Gamma	PCQI	1.1544	1.2071	1.2069	1.1950	1.1678
Image	UCIQE	0.5964	0.6306	0.6415	0.6495	0.6555
Fusion	PCQI	1.3058	1.2886	1.2782	1.2718	1.2668
Image	UCIQE	0.6125	0.6296	0.6367	0.6420	0.6477

Gamma Corrected Image

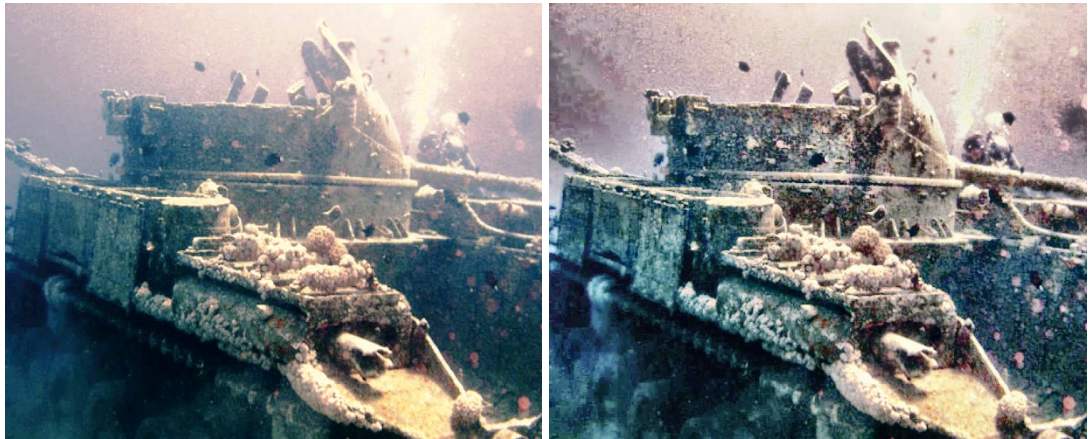
Fusion Output



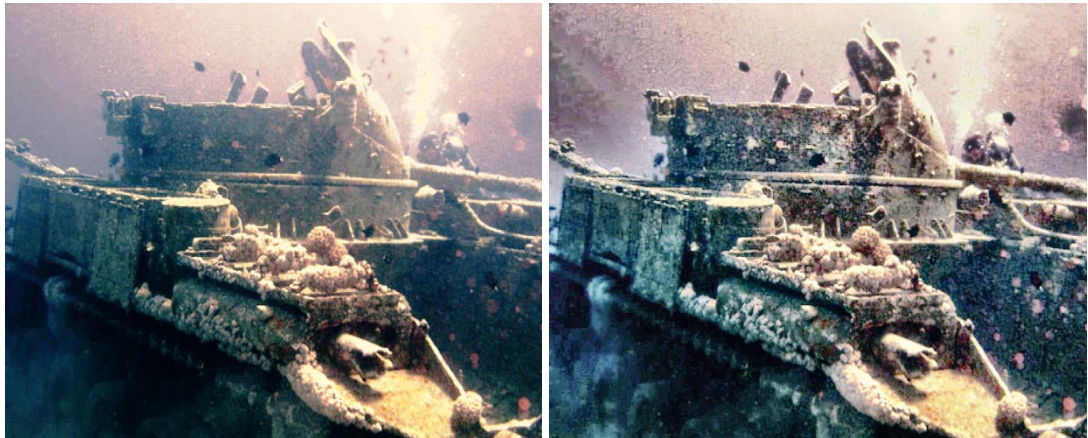
(a) $\Gamma = 0.5$



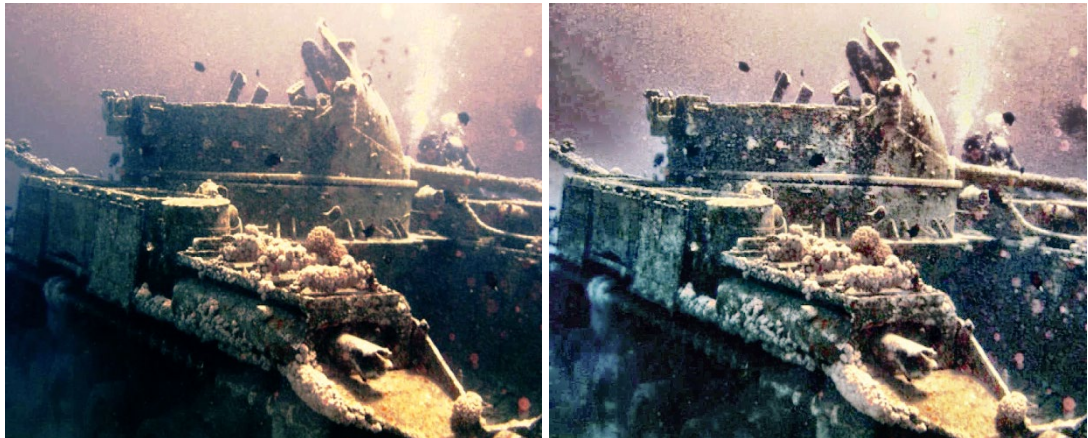
(b) $\Gamma = 0.8$



(c) $\Gamma = 1.0$



(d) $\Gamma = 1.2$



(e) $\Gamma = 1.5$

Figure 29: Comparison of Gamma Values with Fusion Output - 2

According to Table 4, UCIQE increases as Gamma variable value increases. PCQI metric is the best when gamma equals to 1.2 for the Gamma corrected image but it is not the highest value for the fusion output. PCQI increases as the Gamma variable increases in fusion image which makes the image to appear darker. UCIQE metric

increases as the Gamma value increases but darkening the image costs the loss of details. Gamma value is set to 1.5 in the following section.

Table 4: Evaluation of Gamma Correction - 2

Image	Metrics	<i>Gamma</i> = 0.5	<i>Gamma</i> = 0.8	<i>Gamma</i> = 1.0	<i>Gamma</i> = 1.2	<i>Gamma</i> = 1.5
Gamma	PCQI	0.8428	0.9819	1.0209	1.0346	1.0268
Image	UCIQE	0.5639	0.6172	0.6327	0.6392	0.6450
Fusion	PCQI	1.1159	1.1435	1.1576	1.1670	1.1763
Image	UCIQE	0.5992	0.6181	0.6247	0.6277	0.6311

Normalized unsharp masking and CLAHE is applied to color balanced image as the second input. The parameters for the normalized unsharp masking Gaussian standard deviation (σ) input is changed to show the effect of the sharpening to image quality. CLAHE parameters are set to default by 8×8 number of tiles with a clip limit at 0.005. The standard deviation variable is set to 10, 15, 20, 25 and 30 as seen in Figure 30. As the Sigma variable decreases, the image gets sharper and when the sigma variable increases, the image sharpening effect decreases. The focus on these images are the faint white edges around the shipwreck which defines the object edges.



Figure 30: Comparison of Sigma Values with Input 2 and Fusion Output

In Table 5, it evaluates sharpened image, CLAHE applied image and fusion image based on PCQI and UCIQE metrics. PCQI is as its peak when sigma equals to 10 in all images. In sharpened and CLAHE applied image, UCIQE metric is the highest when Sigma is equal to 25 but it is the highest at Sigma which equals to 15 in fusion image. If overall changes are observed in fusion image for all metrics, the Sigma variable values has very little effect on UCIQE. PSNR is measured for fusion to compare the quality of the image based on noise. Sharpening the image causes fusion output to be more noisy compared to original image. Overall, the sharper image has the best PCQI value.

Table 5: Evaluation of Sharpening

Image	Metrics	$\sigma = 10$	$\sigma = 15$	$\sigma = 20$	$\sigma = 25$	$\sigma = 30$
Sharp Image	PCQI	1.1887	1.1717	1.1569	1.1460	1.1358
	UCIQE	0.6098	0.6137	0.6146	0.6157	0.6150
CLAHE Image	PCQI	1.2368	1.2264	1.2205	1.2187	1.2162
	UCIQE	0.6182	0.6211	0.6206	0.6215	0.6208
Fusion Image	PCQI	1.1934	1.1834	1.1763	1.1717	1.1671
	UCIQE	0.6313	0.6320	0.6311	0.6315	0.6316
	PSNR	12.6340	12.6424	12.6659	12.7035	12.7437

In conclusion, changing parameters for Gamma correction directly affects the brightness of the output image and its colorfulness measure; and sharpened input affects the contrast of the image.

6.5 Underwater Dehazing Evaluation

Three images are dehazed to evaluate the underwater image quality, in which the images are named as Galdran 1, Ancuti 1 and Ancuti 3. He et al. [4], Drews Jr. et al. [5], Galdran et al. [6], Ancuti et al. [7] and proposed method are applied to these images and their results are shown in Figure 31.



Figure 31: Dehaze Evaluation Results of the Proposed Method and the State-of-the-art

Table 6 shows the comparison between the proposed method used in this thesis and the state-of-the-art methods for evaluating underwater image dehazing. The method used in Ancuti et al. [7] performs better in terms of color quality. According to Table 6 results, the proposed approach in this thesis achieves high results with PCQI and UIQM metrics; and has considerable score with UCIQE metric. To conclude, according to the quality metrics, the proposed method in this thesis performs better in complex structural images and preserves considerable amount of vibrant colors compared to the state-of-the-art approaches.

Table 6: State-of-the-art Comparison for Underwater Image Dehazing Evaluation

Methods	Galdran 1			Ancuti 1			Ancuti 3		
	PCQI	UCIQE	UIQM	PCQI	UCIQE	UIQM	PCQI	UCIQE	UIQM
He et al. [4]	1.056	0.593	0.578	0.860	0.485	0.353	1.071	0.577	0.596
Drewno Jr. et al. [5]	0.749	0.544	0.519	0.909	0.499	0.383	0.973	0.535	0.492
Galdran et al. [6]	0.507	0.529	0.569	0.962	0.641	0.458	1.021	0.614	0.646
Ancuti et al. [7]	1.152	0.659	0.680	1.022	0.594	0.507	1.207	0.664	0.651
Proposed Method	1.305	0.654	0.844	1.226	0.587	0.731	1.165	0.644	0.788

On the other hand, execution time of the proposed method is calculated and presented in Table 7. Execution time of proposed method is directly related to resolution of the image. Real time applications are not possible for higher resolutions, but it is possible to use it on 512x384 or lower resolutions with at least 1.74 seconds of delay.

Table 7: Execution Time of the Proposed Method

Resolution of Image	512 × 384	1024 × 768	2737 × 1827
Execution Time	1.740469 s	5.114554 s	30.412016 s

Chapter 7

CONCLUSION

In this thesis, underwater image enhancement algorithms are used on hazy and imbalanced color underwater images to amplify the valuable information hidden in the image. White balance and histogram equalization is used to recover the lost red channel. Two inputs are derived from the recovered image. Firstly, Gamma correction is applied to correct the contrast. Then, contrast enhanced sharpening effect is applied to define the fine details. Evaluations of color balanced image show that proposed approach performs better at preserving the natural colors of underwater image compared to the state-of-the-art with the IL-NIQE metric. Underwater image dehazing evaluation results in higher UIQM and PCQI values overall which shows improved contrast and quality. These evaluations conclude that, proposed approach enhances the underwater images with high contrast and recovers important faded features and edges better than the state-of-the-art. The method used in this thesis can easily be deployed for underwater imaging and exploration purposes to document the marine life and biology and further for the discovery of the underwater environment. For further research, investigating various input models for multiscale image fusion could provide a more comprehensive understanding of underwater scenes.

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