A project report on

Underwater Image Enhancement using CLAHE

Submitted in partial fulfillment of the requirement for the award of the degree of

Bachelor of Technology

In

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Bachelor of Technology in DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING to the Jawaharlal Nehru Technological University, Kakinada is a record of bonfide work carried out by them under my guidance and supervision.

To the best of my knowledge, the results embodied in this project report have not been submitted to any other University or Institute for the award of degree.

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ABSTRACT

In recent years, underwater images have been widely used in marine energy exploration, marine environment protection, marine military, marine life research, and other fields. In these applications, image acquisition is carried out at varying depths of water, and artificial light is used to capture the underwater object. The physical properties of the water make light behave differently, changing the appearance of the same object with variations of depth, organic material, currents, temperature, etc. This results in color distorted images and hazy images with very low contrast. Hence, there is a need to enhance the underwater images in light of the above applications.

This project aims to enhance the underwater images which are affected by color distortion, contrast reduction, and haziness. Initially, the original image is pre-processed by the white balance algorithm for color correction. The white balance algorithm involves the process of removing unrealistic color casts in an underwater image. This color-corrected image is treated with a dark channel prior dehazing method to obtain contrast enhancement. These three input images are given to multi-scale fusion. Multiscale fusion strategy entails the image fusion which is based on the weighted maps constructed by combining the features of global contrast, local contrast, saliency, and exposedness. Experimentation is carried out on standard database RUIE of 400 images and U45 dataset to evaluate the performance of this approach in terms of mean square error and peak-signal-to-noise ratio. Further, these enhanced images can be used for various applications such as consumer underwater photography, marine life research, and underwater exploration.

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CLAHE	Contrast Limited Adaptive Histogram Equalization
DCP	Dark Channel Prior
DIP	Digital Image Processing
DWT	Discrete wavelet transform
EMD	Empirical mode decomposition
FB	Fusion Based
GW	Gray World
IEM	Image Enhancement Method
IRM	Image Restoration Method
MSRCR	Multiscale Retinex with Color Restoration**.**
MSE	Mean Square Error
PSNR	Peak Signal-to-noise Ratio
RD	Rayleigh Distribution
RGHS	Relative Global Histogram Stretching
RUIE	Real-world Underwater Image Enhancement
SVD	Singular Value Decomposition
UCM	Unsupervised Colour correction Method
UDCP	Underwater Dark Channel Prior
UICM	Underwater Image Colourfulness Measurement
UIConM	Underwater Image Contrast Measurement
UIEM	Underwater Image Enhancement Methods
UIQM	Underwater Image Quality Measure
UISM	Underwater Image Sharpness Measure

Chapter-1

INTRODUCTION

1.1 Underwater Images

Light undergoes attenuation when it is passed through water. The larger wavelengths are affected more when compared to the shorter wavelengths, thus, images captured underwater appear greenish-blue as they lack certain wavelength components extensively. For instance, an image acquired at a depth of about 4-5m underwater will lack a red wavelength because the longer wavelength components of the visible spectrum are attenuated first (Figure 1.1). With further increase in-depth, other wavelength components also start to lose significance. The images, therefore, suffer from limited visibility range, uneven lighting, presence of bright artifacts. Noise is inevitably a part of any acquired image. Thus a low contrast image with diminished color is obtained. Deep under water, image quality is degraded due to poor illumination conditions that are present underwater, and in deep water, the light properties differ compared to air. The complete study of underwater applications relies on the quality of captured underwater images. Generally, the quality of underwater photos is dependent on numerous aspects, such as limited range of visibility, non-uniform lighting, unwanted signal-like noise, and diminishing color.

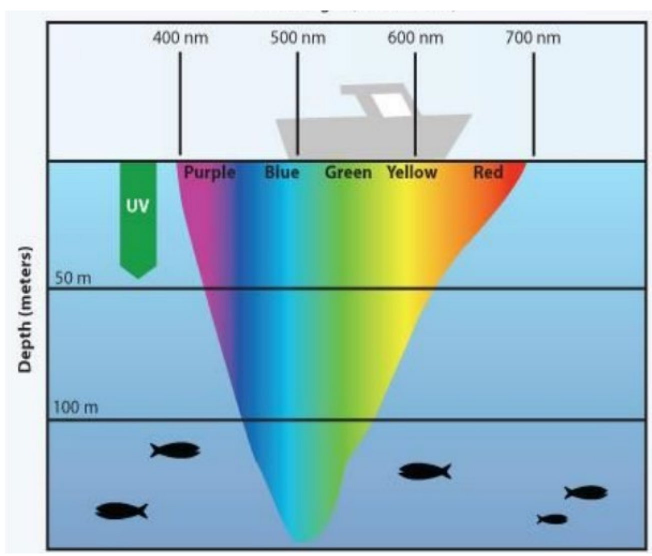


Fig 1.1: Underwater Light Penetration Depth

1.2 Underwater Images Usage

Inspection of underwater infrastructure and detection of any man-made objects.it is also used to understand marine biology research, for environmental evaluation, and the research of monuments submerged in water. The underwater environment offers many rare attractions such as marine animals and fishes, amazing landscapes, and mysterious shipwrecks. Besides underwater photography, underwater imaging has also been an important source of interest in different branches of technology and scientific research, such as inspection of underwater cables, control of underwater vehicles, marine biology research, and archaeology.

1.2.1 Marine Energy Exploration

The exploration of oceans using autonomous underwater vehicles (AUVs) is necessary for activities, such as the sustainable management of fishery resources, extraction of seafloor minerals and energy resources, and inspection of underwater infrastructure. As the next step in ocean exploration, AUVs are expected to employ end-effectors to make physical contact with seafloor creatures and materials. We propose a scenario for realizing a sampling mission using an AUV that is equipped to sample marine life. In this scenario, the sampling AUV observes the seafloor while concurrently transmitting the observed images to a surface vessel for inspection by the AUV operators. If the received images show an object of interest, the object is selected as a candidate for sampling target by the operators, who send a sampling command to the AUV. After receiving the command, the AUV returns to the target area and attempts to sample it.

The process for selecting interesting images selects those that contain interesting objects, such as marine life. The selection process prevents the transmission of meaningless images that contain only flat sand on the seafloor. The image compression method, which is based on color depth compression, reduces the amount of data. The combined process of selecting an interesting image and compressing it reduces various problems in acoustic communication, such as low information density and data loss.

1.2.2 Marine Environment Protection

Recently, Marine bio sphere monitoring has become an important part of the field of marine environment protection. Marine biosphere monitoring is one of the crucial links to the understanding and protection of the marine environment. Moreover, underwater images play an important role in marine biosphere monitoring. Since the capture and transmission conditions are extremely poor in complicated underwater environments, images will suffer typical types of distortions significantly. Pre-evaluation of the image quality to facilitate subsequent processing becomes particularly important. Traditional Image Quality Assessment (IQA) methods are normally developed based on perceptual quality. Nevertheless, images are captured for understanding and analysis to achieve the purpose of intelligent monitoring.

1.2.3 Marine Military & Marine Life research

Underwater imaging has played a crucial role in marine resource exploration, environmental protection, marine defense, military affairs, etc. As random attenuation of light causes the foggy appearance, the image enhancement helps to find the locations and clear visibility to the military over enemy lines. At present, many countries bring underwater ecological protection, rational exploitation, and efficient utilization of underwater resources to the core of scientific and technological development. Capturing images underwater can be a very useful tool for conducting scientific research.

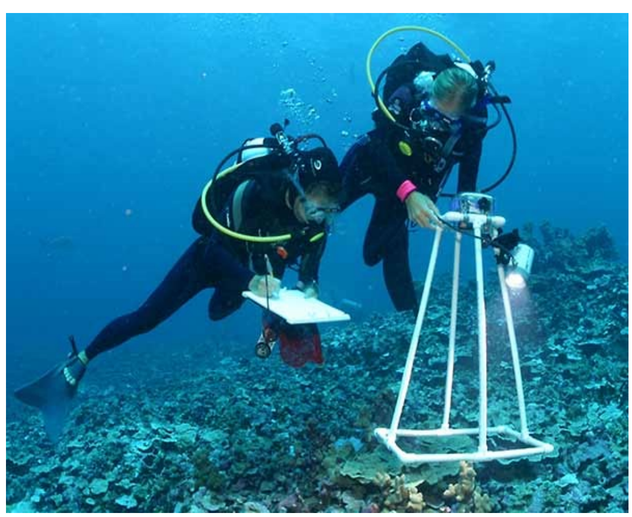


Fig 1.2: Marine Life Research

Underwater photography is very useful when scientists need to examine objects on the seafloor over time. For example, scientists may use underwater photography to take photo quadrats to look at the abundance of coral over time (Fig 1.2) at several reef locations. A photo quadrat is a photograph of a particular habitat within a standardized square area or quadrat.

1.3 Analysis of Underwater Images

With increasing attention being drawn to the underwater observation and utilization of marine resources in recent years, underwater image processing and analysis have become an active research hotspot. Different from the general images, the marine environment is usually faced with some complicated situations such as underwater turbulence and diffusion, severe absorption and scattering of water bodies, various noises, low contrast, uniform illumination, monotonous color, and complex underwater background. In response to these typical challenges, a large body of works in underwater image processing has been exploited in recent years. This survey introduces a review of existing relatively mature and representative underwater image processing models, which are classified into seven categories including enhancement, fog removal, noise reduction, segmentation, salient object detection, color constancy, and restoration. We then objectively evaluate the current situations and future development trends of underwater image processing and provide some insights into the prospective research directions to promote the development of underwater vision and beyond.

1.3.1 Depth of the Water

Underwater depth estimation is an open problem for marine robotics, which is usually used for 3D reconstruction, navigation, and intermediate steps for underwater color correlation. Due to the properties of underwater environments, underwater perception is quite different from in-air perception. Images captured underwater usually look bluish because longer wavelengths of visible sunlight are absorbed earlier than shorter wavelengths. Underwater images may also be more greenish, because of algae in the water. Besides, the underwater images are more blurred than those in-air captured by the same camera, due to turbidity. These reasons increase the difficulty of depth estimation from images. Thus, many researchers put effort into underwater image processing. For example, using dark channel priors is to restore underwater images, inspired by removing haze in the air. The study implemented underwater image stitching based on spectral methods, which are more robust to turbidity than feature-based methods. Besides image enhancement, some work focused on depth estimation. In addition, deep learning was also applied to estimate the depth of underwater images.

1.3.2 Colour Distortion

Underwater images are susceptible to various distortions compared to images taken on land, due to the nature of the water environment. These images often suffer from diffraction, polarisation, absorption, scattering, color loss, and attenuation of light as shown in fig 1.3 and fig 1.4. Each part of the ocean will have its sources of distortions, due to flickers caused by direct sunlight, marine snow, the fluorescence of biological objects, the presence of macroscopical organisms, loss of stability in divers, loss of light, artificial lighting, and floating dust particles present in the water. Numerous techniques and algorithms may be used to restore these underwater images.

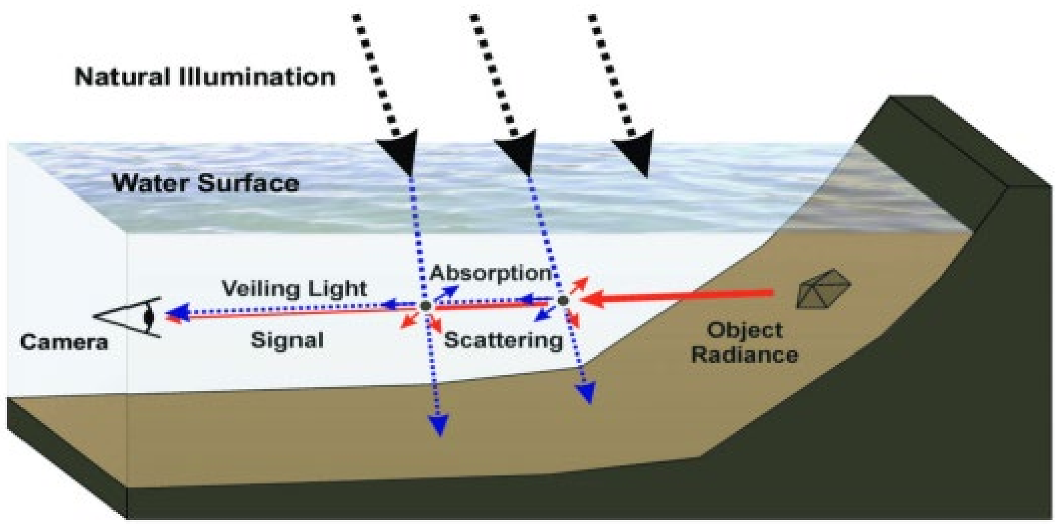


Fig 1.3: Types of Distortion in Underwater Images

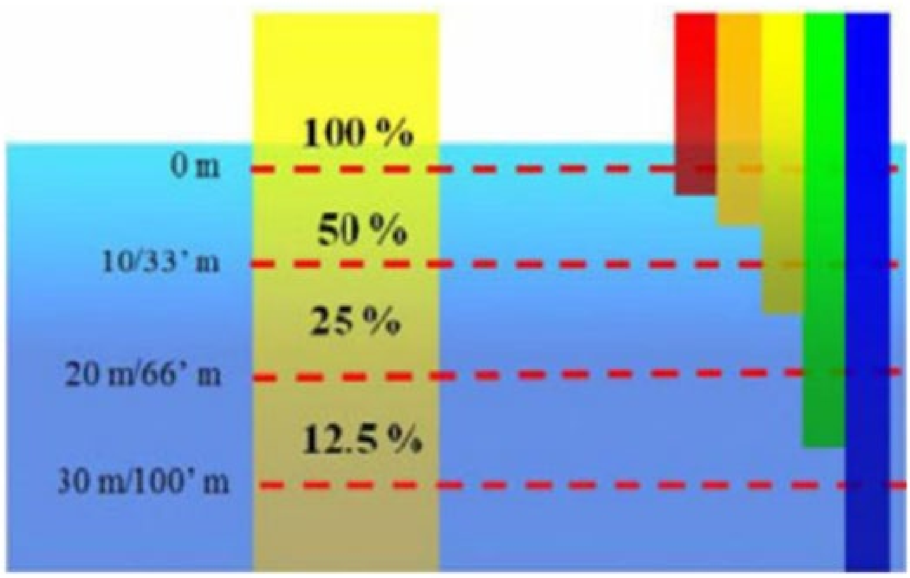


Fig 1.4: Light Absorption in Water

1.3.3 Contrast Reduction

The quality of the underwater image is poor due to the properties of water and its impurities. The properties of water cause attenuation of light travel through the water medium, resulting in low contrast, blur, inhomogeneous lighting, and color diminishing of the underwater images. We have many methods proposed in recent times to enhance the contrast in underwater images.

1.3.4 Haziness

Underwater scenes captured by cameras are plagued with poor contrast and a spectral distortion, which are the result of the scattering and absorptive properties of water. A novel dehazing method is developed that improves visibility in images and videos by detecting and segmenting image regions that contain only water. The color of these regions, which refer to as pure haze regions, is similar to the haze that is removed during the dehazing process. Moreover, a semantic white balancing approach for illuminant estimation uses the dominant color of the water to address the spectral distortion present in underwater scenes.

1.4 Detection of Objects

Image segmentation techniques play a vital role in partitioning the image into segments. These techniques are used for detecting the objects in the images. The real challenge in acoustic image segmentation lies in differentiating the sea floor, sediments, and objects. Due to the typical characteristics and low resolution of the acoustic images, segmentation techniques such as region-based, morphological based and edge-based methods are not suitable. The sediments will also be traced along with the objects which makes the detection process a very difficult one. The edge-based segmentation method that uses morphological operations for identifying the edges followed by an object tracing algorithm is developed. The images used are captured in real-time using Edge tech 4125 Side-scan sonar device. The acoustic images are first pre-processed using Wiener and Median filters and a morphological gradient is obtained by subtracting the morphologically dilated and eroded image. Next, the edge map of the acoustic images is obtained using the binarization method by which the object's boundary is made visible. Finally, Moore's object tracing algorithm is used for detecting the objects in the images.

1.4.1 Sonar Systems

Most of the Earth’s surface is covered with water. These water areas have been used for fishing and transportation by mankind since ancient times but only with the invention of sonar systems, an opportunity was created for in-depth exploration and use of the ocean because the mechanical acoustic waves are the only physical phenomena applicable for underwater sensing.

High-resolution imaging and mapping of the ocean and its floor have been limited to less than 5% of the global waters due to technological barriers. Whereas sonar is the primary contributor to existing underwater imagery, the water-based system is limited in spatial coverage due to its low imaging throughput. On the other hand, aerial synthetic aperture radar systems have provided high-resolution imaging of the entire earth’s landscapes but are incapable of deep penetration into the water.

Sensing and imaging underwater is an extensive field with applications including biological survey, bathymetry, wreckage searching, and defense surveillance, among others. To date, sensing in seawater is performed with sonar systems that use ultrasound to obtain high-resolution subsurface images. Sonar systems are typically hull-mounted or towed by ships that traverse an area of interest.

With this means of operation, imaging throughput is low – leading to costly and time-consuming efforts when covering large areas. In addition, some applications of underwater imaging may prohibit the safe navigation of an in-water sonar system. A more versatile, non-contact or airborne imaging system that is mounted on a moving platform could permit high-throughput sensing of underwater environments.

1.5 Problem Definition

Underwater image enhancement and reconstruction is a challenging task and has gained priority in recent years, as the human eye cannot perceive underwater images. The image acquisition systems fail to capture images with significant detail when used at greater depths underwater, such equipment is also expensive. Thus, with the use of image processing algorithms, it is possible to reconstruct and enhance the image quality in the absence of reliable and costly image acquisition systems.

1.6 Objectives of the work

The main objective of the work is to enhance the quality of the underwater images by using different algorithms. Initially, the original image is pre-processed by the white balance algorithm for color correction. The white balance algorithm involves the process of removing unrealistic color casts in an underwater image. This color-corrected image is treated with a dark channel prior dehazing method to obtain contrast enhancement. These three input images viz., i. Colour corrected ii. Contrast-enhanced and iii. DCP is further processed by a multiscale fusion strategy. Multiscale fusion strategy entails the restoration of the image which is based on the weighted maps constructed by combining the features of global contrast, local contrast, saliency, and exposedness. Experimentation can be carried out on standard database RUIE of 400 images, UIEB of 890 images, and U45 dataset to evaluate the performance of this approach in terms of mean square error, peak-signal-to-noise-ratio. So that it is useful for different applications in marine biology research, and research of monuments submerged in water.

1.7 Organization of the report

The report is further organized into six chapters. Chapter 2 is focusing on a literature survey and reviewing other related models, and shows how our work is distinguished from other works. Chapter 3 provides a brief description of the Materials and Methods that we are using in this project. In Chapter 4, the proposed underwater image enhancement method is elucidated. Experimentation results and discussions are illustrated in chapter 5. Chapter 6 gives the conclusion and future scope of our method.

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE REVIEW:

An approach for underwater image enhancement based on color correction and dehazing. They developed an improved approach for eliminating the local reddish effect and reducing image noise. However, when the image contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced. The objective is to enhance the underwater image contrast while preserving image brightness.

Raimondo Schettini and Silvia Corchs, et al., developed underwater image processing: state of the art of restoration and image enhancement methods. They used the Image Enhancement and Color Correction methods in which they stated that the capacity to image items in the sea is fast improving because of advances in optical imaging technology and the application of advanced sensing techniques. Emerging underwater photography techniques and technologies necessitate the adaption and extension of the methods listed above.

Muhammad Suzuri Hitam, et al. developed mixture contrast limited adaptive histogram equalization for Underwater image enhancement. They used the underwater image, contrast limited adaptive histogram equalization, and color models in which they stated to use a combination of Contrast and Limited Adaptive Histogram Equalization to enhance underwater photos. The enhancement method successfully enhances underwater image visibility while producing the lowest MSE. PSNR values are the highest. As a result, the suggested appears to be promising for classifying coral reefs, particularly when there are visible visual indicators.

Ahmad Shahrizan Abdul Ghani et al. developed underwater image quality enhancement through Rayleigh-stretching and averaging image planes. They used Underwater image processing; Histogram modification; Contrast enhancement; Noise reduction methods in which they successfully improves the contrast and reduces the noise of the original method of the ICM and the UCM previously proposed by Iqbal et al. The combination of the histogram modification in the RGB and the HSV color spaces increases the contrast of the underwater image.

Ahmad Shahrizan Abdul Ghani et al., developed the enhancement of low-quality underwater images through integrated global and local contrast correction. They used Underwater image processing Contrast enhancement color improvement Noise reduction Histogram stretching methods in which they stated DIRS-CLAHS method integrates contrast correction and color correction methods. In the contrast correction step, this method incorporates the processes of global and local contrast stretching to enhance image contrast. The color correction step improves the image color performance determined in previous steps.

Chongyi Li et al. developed underwater image enhancement by dehazing with minimum information loss and histogram distribution prior. They used underwater image enhancement, underwater image dehazing, contrast enhancement, and scattering removal methods in which they introduced an underwater image enhancement method that can produce a pair of output versions. The proposed method includes an underwater image dehazing algorithm and a contrast enhancement algorithm.

Codruta O. Ancuti et al. developed color balance and fusion for underwater image enhancement. They used the white-balancing, Gamma Correction, and multi-scale fusion methods in which they studied light propagation in underwater, underwater white balance, and multi-scale fusion and implemented underwater white balance evolution, Underwater Dehazing Evaluation.

The algorithm developed by Erat et al. employs color correction based on histogram equalization methods and contrast enhancement in the frequency domain. The DCT-based approach is used for improving the contrast feature in color images. UIQM measures show that the algorithm plays a crucial role in extracting features of importance from underwater images used for maritime border protection.

Singh and Biswas et al. developed an approach that uses a hazy underwater image to generate a contrast-enhanced input and white balanced input image. The weight maps of chrominance, saliency, and luminance are imposed on the two input images. A multi-scale fusion of all the input images and the weight maps enables in obtaining of the final dehazed image.

Diksha Garg et al. developed underwater image enhancement using the blending of CLAHE and percentile methodologies implemented. They proposed Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Percentile methodologies in which they stated the system has been measured based on two parameters, namely, RMSE (Root Mean Squared Error) and Entropy. The larger the error, the less the accuracy produced better results than the existing techniques.

Omer Deperlioglu et al. developed a practical method for underwater image enhancement with adjusted CLAHE. They used histogram equalization and also contrast-limited adaptive histogram equalization methods. The proposed method has been evaluated by using the entropy value, PSNR (Peak Signal to Noise Ratio), and the MSE (Mean Square Error) considering some existing methods in the literature.

Meng Ge et al. developed a hybrid DCT-CLAHE approach for brightness enhancement of uneven-illumination underwater images with brightness equalization, image enhancement, DCT Coefficient methods used for image brightness equalization by the means of DCT technique, and image contrast enhancement utilizing CLAHE algorithm.

Ashutosh Mishra et al., developed Enhancement of Underwater Images using Improved CLAHE. They used a dynamic histogram equalization technique, in contrast to limited adaptive histogram equalization methods in which the proposed methodology works in two phases. In the first phase. The input image, which is downloaded from the internet, is used as an input in the dynamic histogram equalization technique. And in the second phase, contrast limited adaptive histogram equalization is used for enhancing the underwater image. Dynamic histogram equalization works in three steps. In the first step, it converts the RGB image into a YCbCr image. In the second step, Histogram equalization is used, and finally, in the third step, convert the YCbCr image into RGB image.

Chongyi Li et al. developed An Underwater Image Enhancement Benchmark Dataset and Beyond They used underwater image enhancement, real-world underwater images, comprehensive evaluation, and deep learning methods in which they have constructed an underwater image enhancement benchmark dataset that offers large-scale real underwater images and the corresponding reference images

Chongyi Li, et al., developed an underwater scene inspired by deep underwater images and video enhancement. They used image enhancement, image restoration, and supplementary-information methods in which they stated that an underwater image and video enhancement network based on previous underwater scenes Experiments on synthetic and real-world underwater photos and movies show that our technology is both robust and effective. Our technique has the advantage of just having 10 convolutional layers and 16 feature maps per convolutional layer, allowing for quick training and testing on GPU platforms.

Guzin Ulutas et al. developed Underwater image enhancement using contrast limited adaptive histogram equalization and layered difference representation published[6], in which they used CLAHE, LDR, Contrast correction, and Color correction methods to improve the visual quality of the underwater images. Consists of two modules - Contrast correction and Color Correction.

Somasekar et al. developed a fusion-based approach for quality enhancement Of Underwater Images published [7]. The fast underwater image enhancement for real-time Applications implemented by Aruna Bhat, Aadhar Tyagi, Harsh Vardhan, and Vaibhav Verma [8] in 2021 using histogram equalization techniques for dehazing and automatic white balancing algorithms, UIEB methods to be used for benchmarking and evaluation of our method in considerations of data set and benchmark, Non-reference metrics, and full reference metrics.

Table 1: Summary of Underwater Image Enhancement Methods

S.No	TITILE	YEAR	METHODS	REMARKS
1	Underwater Image Segmentation using CLAHE Enhancement and Thresholding	2012	Contrast Limited Adaptive Histogram Equalization, image segmentation, Global Thresholding, Multi-level Thresholding	It is found that the CLAHE method not only improves the contrast but also equalizes the image histogram efficiently
2	Underwater Image Enhancement by Dehazing with Minimum Information Loss and Histogram Distribution Prior	2016	Contrast enhancement, Underwater Image Dehazing, Global background light estimation, DCP, HE.	HE and the methods with HE post-processing produces many mismatching points because the enlarged noise is treated as a feature point.
3	Underwater image enhancement using a blending of CLAHE and percentile methodology	2016	Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Percentile methodologies	A disadvantage of this method is its high 'instability'
4	Color Balance and Fusion for Underwater Image Enhancement	2017	white-balancing, Gamma Correction, multi-scale fusion	Computationally efficient, single-scale procedure
5	Underwater Image Enhancement via Extended Multi-Scale Retinex	2017	multi-scale retinex, hybrid filter, Bilateral Filter	Suffer graying-out of uniform scenes and tonal rendition is scene dependent and poor.

6	A Hybrid DCT-CLAHE Approach for Brightness Enhancement of Uneven-illumination Underwater Images	2018	Brightness Equalization; Image Enhancement; DCT Coefficient	Our method is used to enhance only the too darkened or overly brightened regions of images by regulating the low-frequency part of image DCT coefficients.
7	An effective underwater image enhancement method based on CLAHE-HF	2019	CLAHE, Homomorphic Filtering	The Independent index of PSNR and MSE is not optimal
8	Underwater Image Enhancement Using White Balance, USM and CLAHE	2019	Colour cast, Contrast Limited Histogram Equalization, Entropy, RMS Contrast, Unsharp masking, White balance	Some blurriness is present in the output image for a few images
9	An Enhancement of Underwater Images using DCP and CLAHE Algorithm	2019	CLAHE, Dark channel prior, Haze, Image Enhancement, RGB	It was also noticed that DCP darkens the image and results in an image of poor contrast
10	Fusion-Based Approach ForQualityEnhancement Of Underwater Images	2021	EMDW, CLAHE, SVD, DWT, WeightedAverage, and Underwater Image Quality Measures	The contrast of the target area cannot be enhanced and there is background noise.

11	Underwater image enhancement using contrast limited adaptive histogram equalization and layered difference representation	2021	CLAHE, LDR, Contrast correction, Color correction	This technique does not consider the spatial relationship between neighboring pixels.
12	Underwater Image Enhancement Based on Local Contrast Correction and Multi-Scale Fusion	2021	underwater image enhancement; local contrast correction; multi-scale fusion; image processing	Performance is not good

2.3 SUMMARY

A detailed review of various UIEMs is conducted to know the state of the art and to understand the challenges involved. The study allowed us to summarize the pros and cons of the different approaches. It is identified that there is still scope for enhancing the underwater images. This motivated us to the problem definition and solution.

CHAPTER 3
MATERIALS AND METHODS

3.1 INTRODUCTION:

Enhancing an image essentially involves improving its interpretability or perception of images that provide information for human viewers and better input for other programs using automated image processing techniques. To enhance the quality of the image, many algorithms and approaches are introduced. To enhance the image quality, the following algorithms were used: White Balancing, Color Correction, Dark Channel Prior Algorithm, Contrast Limited Adaptive Histogram Equalization (CLAHE), Global contrast weight, Saliency weight, Exposedness weight, and Multiscale fusion.

3.1 White Balance Algorithm:

This method is also known as gray World Approach. In this, color constancy is a process of recognition of color independent of light. The White Balance automatically adjusts the colors of the active layer by stretching the Red, Green, and Blue channels separately. To do this, it discards pixel colors at each end of the Red, Green, and Blue histograms which are used by only 0.05% of the pixels in the image and stretches the remaining range as much as possible. The result is that pixel colors which occur very infrequently at the outer edges of the histograms (perhaps bits of dust, etc.) do not negatively influence the minimum and maximum values used for stretching the histograms, in comparison with Stretch Contrast. Like "Stretch Contrast", however, there may be hue shifts in the resulting image.

White balancing is an important processing step that aims to enhance the image's appearance by discarding unwanted color casts, due to various illuminants. In water deeper than 30 ft, white balancing suffers from noticeable effects since the absorbed colors are difficult to be restored. Additionally, underwater scenes present a significant lack of contrast due to the poor light propagation in this type of medium.

Illuminants are the cause of color casts in a captured digital image. To solve this color constancy problem first it has to estimate the color of prevailing light and then remove the unwanted color casts. Gray World(GW) technique is widely used. This algorithm produces an estimate of illumination by calculating the mean of each channel of the image. The average of each channel is used to calculate a separate scaling value for every channel. In this way, the illumination on a different channel is eliminated independently. An image in which many similar colors are present gives a bad result because this method needs a wide range of colors. This algorithm illuminates this dominant color. This algorithm can be executed on every image represented by both one-dimensional and three-dimensional matrices. Below fig(3.1) demonstrates White Balancing.

Fig 3.1: White Balance

An image with dimension M x N is represented as I (x, y), where (x, y) denotes the indices of the pixel location. The first step of the GW algorithm is finding the averages of the individual channel as in Eq(3.1).

$$R_{avg} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} I_r(\mathrm{x}, \mathrm{y}) \quad (3.1)$$

$$G_{avg} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} I_g(\mathrm{x}, \mathrm{y}) \quad (3.2)$$

$$B_{avg} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} I_b(\mathrm{x}, \mathrm{y}) \quad (3.3)$$

where, the $I_r(x,y)$, $I_g(x,y)$, and $I_b(x,y)$ are the red, green, and blue channel values of each pixel respectively. T_{avg} is calculated by averaging these three channel averages as in (3.4).

$$T_{avg} = \frac{R_{avg}+G_{avg}+B_{avg}}{3} \tag{3.4}$$

Finally, the color value for each pixel is adjusted by the equation given below(3.5),(3.6), and (3.7) to reach the assumption of GW theory

$$I'_r(x,y) = I_r(\mathrm{x,y}) \times \frac{T_{avg}}{R_{avg}} \tag{3.5}$$

$$I'_g(x,y) = I_g(\mathrm{x,y}) \times \frac{T_{avg}}{G_{avg}} \tag{3.6}$$

$$I'_b(x,y) = I_b(\mathrm{x,y}) \times \frac{T_{avg}}{B_{avg}} \tag{3.7}$$

where, the $I'_r(x,y)$, $I'_g(x,y)$, $I'_b(x,y)$ are the adjusted channel values of each pixel by the gray world method. For the images with a heavy color cast, one color always dominates the whole image. The suitability of GW theory is limited to heavy color cast images. The input image is transformed from the RGB model to the LAB model since the latter describes all the colors visible to the human eye. L, the luminance component closely matches the human perception of lightness, A and B are the green-red and blue-yellow components respectively. In the approach, the formula for normalizing the channels is modified to improve the performance. The color corrections are made by compensating the A and B components using the normalized L channel value. The color value for each pixel is modified by

$$I'_a(x,y) = I_a(\mathrm{x,y}) - \frac{(A_{avg}-128)\times I_1(\mathrm{x,y})}{255} \tag{3.8}$$

$$I'_b(x,y) = I_b(\mathrm{x,y}) - \frac{(B_{avg}-128)\times I_1(\mathrm{x,y})}{255} \tag{3.9}$$

where, the $I'_a(x,y)$, $I'_b(x,y)$ are the adjusted channel values of each pixel by the modified gray world method, $I_l(x,y)$ $I_a(x,y)$, and $I_b(x,y)$ are the respective channel values of each pixel intensity, A_{avg} and B_{avg} are the averages of individual channel calculated using (1). To nullify the chroma distance shift, 128 is subtracted from the averages.

3.2 Color Corrected Image:

Color correction aims at improving the image aspect, primarily by removing the undesired color castings due to various illumination or medium attenuation properties. Underwater, the green-bluish appearance needs to be rectified. However, this correction is not straightforward to implement because the color distortion depends on the scene depth and the light spectrum, as a consequence of the wavelength-dependent light attenuation. Underwater, the color correction should ideally depend on the light attenuation level. However, conventional color correction methods rely on global (and not local) image statistics and are thus missing the capability to tune/adjust the color adjustment locally. To circumvent this limitation, as depicted, a fusion-based approach to adapt the color correction locally. Therefore, we derive inputs (one corresponding to the minimal level of correction, and the second to the maximal level of correction), and blend them in proportion to the desired level of correction, which itself corresponds to the level of light attenuation. An example figure of color correction is below(3.2)

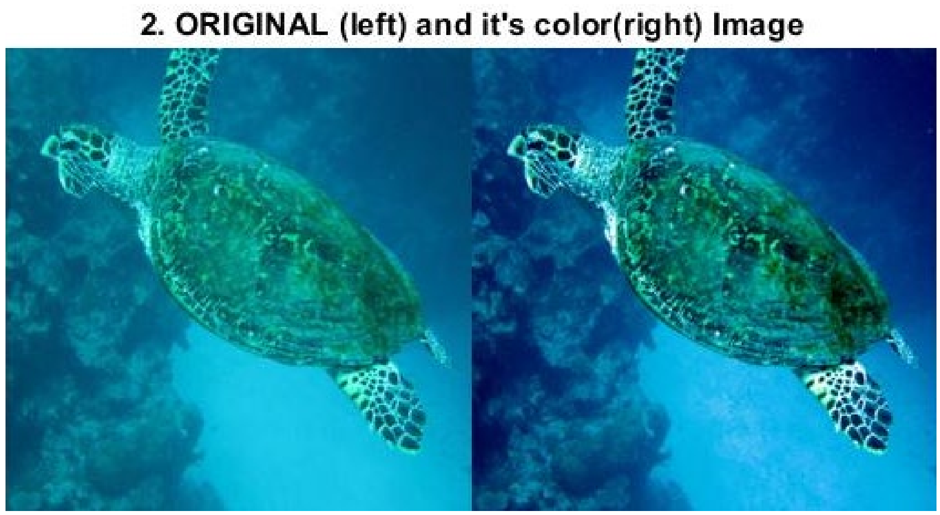


Fig 3.2: Color Corrected

Color correction is the process of adjusting raw image data so the resulting picture looks realistic. It's not a process of making a scientifically accurate picture—our visual system is too non-linear and too mutable. Conceptually, you can break color correction down into three facets: brightness (the overall level of light in an image), contrast (the relative light levels of adjacent areas in an image), and color balancing (adjusting the overall hue of an image). Brightness and contrast together can be considered tonal adjustments. In practice, these three elements are inextricably linked—changes in one facet affect the others. We now explain how the attenuation level is estimated, and how the inputs are derived

In the experiments, the attenuation map A(x) is simply estimated based on the red channel information as:

$$A(x) = 1 - I^{\gamma}x^{\gamma} \quad (3.10)$$

where I^r (x) represents the red channel of the initial underwater image I and γ is the parameter that controls the gamma correction in the form of power-law expression

Second, the color distributions of the source image -which directly determine the global color transfer parameters- should be representative of a scene captured with significant attenuation, so that the associated color transfer parameters become appropriate/relevant to deal with largely attenuated regions. To satisfy those two constraints, we propose to feed the global color transfer procedure with a composite image defined so that the weakly attenuated region's statistics are shifted towards the ones of regions with higher attenuation. Formally, the composite image I ′ is defined by:

$$I'A(x)I(x) \ + [1 - A(x)]I \quad (3.11)$$

where I^- is the mean value of the input image, and A(x) is the attenuation map defined.

Given the color transferred composite image I'_{CT} (x) and the initial image I(x), our final color corrected image I_{CC} (x) is then generated based on a straightforward fusion procedure, using the attenuation map A(x) and it's reciprocal [1 − A(x)] to weight each input:

$$I_{cc}(x) = A(x)I'_{CT}(x) \ + [1 - A(x)]I(x) \quad (3.12)$$

3.3 Dark Channel Prior Algorithm:

In this, we look into the DCP algorithms. First, the image is subjected to a haze removal algorithm which is the DCP, and further is enhanced by the CLAHE technique.

Haze Removal using Dark Channel Prior (DCP). This is used to obtain a natural Haze-free image and is generally used in the process of image enhancement. The haphazard attenuation of light by water particles as we go deeper and deeper into the sea causes a foggy and misty appearance to the image of the scenery. A hazy image can be characterized by using a function S(x) is given by

$$S(x) = Z(x)t(x) + A(1 - t(x)) \tag{3.13}$$

Where S(x) is the haze-containing image, Z(x) is the haze-free image, t(x) is the transmission map and A is the global atmospheric light. The ultimate focus of DCP is to find the haze image Z(x) from the haze containing image S(x). There are 4 steps in the dehazing process which include

(i) estimation of atmospheric light

(ii) Transmission Map Estimation

(iii) Transmission Map Refinement and

(iv) image reconstruction

Most of the local regions in the background of the image often have some pixels which have a very low intensity in one of the three channels of the (RGB). It can be denoted as (x) and it is considered as the dark channel at x can be denoted as

$$Z^{dark}(x) = min_{RGB} min_{\Omega(\mathrm{x})} Z^c(y) \tag{3.14}$$

Where Z^c is one of the channels in Z and (x) is a square region with center x. If the square region does not belong to any local regions, then tends to zero. Hence, it is called the dark channel. S(x) is an image whose intensity is mixed with atmospheric light. So it is usually brighter than Z(x).

So the dark channel of S(x) is brighter than the dark channel of Z(x). This fact serves as a useful result in the estimation of Z(x). Substituting (3.13) in (3.14) we get

$$min_{RGB} min_{\Omega(\mathrm{x})} S^c(y) = min_{RGB} min_{\Omega(\mathrm{x})} Z^c(y)t(x) + A^c(1 - t(x)) \tag{3.15}$$

follow the four steps of estimation in DCP. For computing the value of A, the highest 0.1% of brightest pixels in the dark channel is selected and the color with the highest intensity value among the selected pixels is selected as the value of A. Now dividing both LHS and RHS of (3) by Ac, gives

$$min_{RGB} min_{\Omega(\mathrm{x})} \frac{S^c(y)}{A^c} = min_{RGB} min_{\Omega(\mathrm{x})} \frac{Z^c(y)}{A^c t(x)} + t(x)(1 - t(x)) \tag{3.16}$$

This is the second step in dehazing using DCP. The next step is refining the transmission map t(x). Usually, a Soft mapping is done to refine the transmission map. Finally, the last step is the reconstruction of the haze-free image.

$$Z(x) = \left[S(x) - \frac{A}{\max(t(x), t_0)}\right] + A \tag{3.17}$$

Where t_0 is the threshold value applied to avoid the low value of the denominator.

The below figure(3.3) is an example of a DCP image.

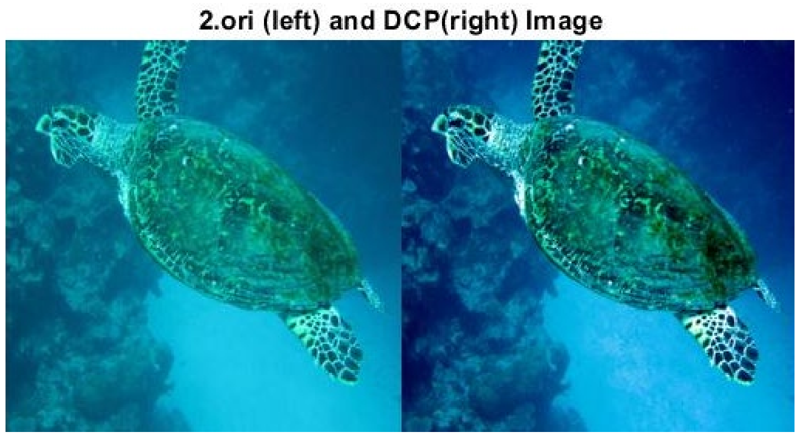


Fig 3.3: Dark Channel Prior

3.4 CLAHE:

CLAHE stands for Contrast Limited Adaptive Histogram Equalization. CLAHE is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definition of edges in each region of an image. CLAHE was originally developed for medical imaging and has proven to be successful in the enhancement of low contrast images such as portal films.

The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image. Ordinary AHE tends to over-amplify the contrast in near-constant regions of the image. It is originally developed for the enhancement of low contrast images. CLAHE is a variant of adaptive histogram equalization in which contrast amplification is limited, to reduce this problem of noise amplification. To limit the noise amplification we use CLAHE.

In CLAHE, the contrast limited procedure has to be applied for each neighborhood from which a transformation function is derived. Rather than taking the whole image, CLAHE prevents over-amplification by dividing the image into small data regions called tiles, and then it performs contrast enhancement. These tiles are rejoined to get an overall enhanced image. It is applied over both types of images gray scale and color. The expression of modified gray levels for the standard CLAHE method with Uniform Distribution can be given as

$$g = [g_{max} - g_{min}] \times P(f) + g_{min} \tag{3.18}$$

Where g_{max} = Maximum pixel value

g_{min} = Minimum pixel value

g is the computed pixel value P(f) =CPD(Cumulative probability distribution) For exponential distribution gray level can be adapted as

$$g = [g_{max} - \frac{1}{\alpha}] \times \ln[1 - P(f)] \tag{3.19}$$

Where α is the clip parameter, the CLAHE method operates on small regions in the image, called “tiles”, rather than the entire image. Each tile's contrast is enhanced so that the histogram of the output region approximately matches the histogram.

Fig 3.4: CLAHE

3.4.1 Properties of CLAHE

The size of the neighborhood region is a parameter of the method. It constitutes a characteristics length scale: contrast at smaller scales is enhanced, while contrast at larger scales is reduced. Due to the nature of histogram equalization, the result value of a pixel under this is proportional to its rank among the pixels in its neighborhood. This allows an efficient implementation of specialist hardware that can compare the center pixel with all other pixels in the neighborhood. When the image region containing the neighborhood of a pixel is fairly homogeneous, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixels values to the whole range of the resulting image. This causes over amplify a small amount of noise in largely homogeneous regions of the image.

3.4.2 The steps of the CLAHE Method are

Step 1: The original picture should be separated into sub pictures that are continuous and non-overlapping. The dimension of every sub-picture is M×N.

Step 2: The histograms of the sub-pictures are evaluated.

Step 3: The histograms of the sub-pictures are clipped.

3.5 Global contrast weight:

Laplacian contrast weight (WL) deals with global contrast by applying a Laplacian filter on each input luminance channel and computing the absolute value of the filter result. This straightforward indicator was used in different applications such as tone mapping and extending depth of field since it assigns high values to edges and texture.

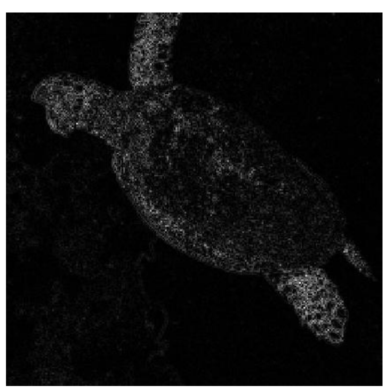


Fig 3.5: Global Contrast

For the underwater restoration task, however, this weight is not sufficient to recover the contrast, mainly because it can not distinguish between a ramp and flat regions. To handle this problem, an additional contrast measurement independently assesses the local distribution.

3.6 Local Contrast Weights:

Local contrast weight (WLC) comprises the relation between each pixel and its neighborhood average. The impact of this measure is to strengthen the local contrast appearance since it advantages the transitions mainly in the highlighted and shadowed parts of the second input. The (WLC) is computed as the standard deviation between pixel luminance level and the local average of its surrounding region.

$$W_{LC} = ||I^k - I^k_{wc}|| \tag{3.20}$$

where I^k represents the luminance channel of the input. I^k_{wc} represents the low-passed version of it. The filtered version I^k_{wc} is obtained by employing a small 5 × 5, ([1, 4, 6, 4, 1]/16) separable binomial kernel with the high-frequency cut-off value $w_{hc} = \pi/2.75$

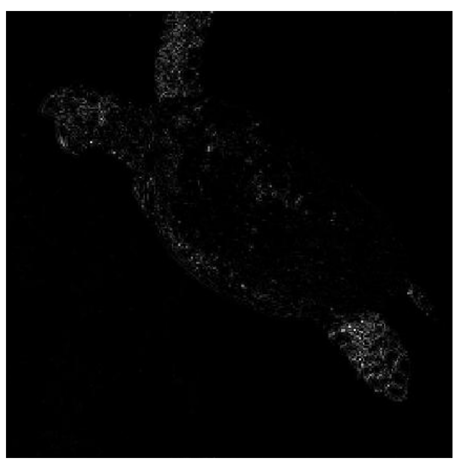


Fig 3.6: Local Contrast

For small kernels, the binomial kernel is a good approximation of its Gaussian counterpart, and it can be computed more effectively.

3.7 Saliency Weight:

Saliency weight (WS) aims to emphasize the discriminating objects that lose their prominence in the underwater scene. To measure this quality, we have employed the saliency algorithm of Achanta et al. This computationally efficient saliency algorithm is straightforward to be implemented being inspired by the biological concept of center-surround contrast. However, the saliency map tends to favor highlighted areas. To increase the accuracy of results, the exposedness map is introduced to protect the mid-tones that might be altered in some specific cases. This method considers global contrast and spatial coherence that can produce a full resolution saliency map. The formulae are shown in Eq (3.21)

$$W_{Sal}(I_p) = \sum_{\forall Ii \in ID}(I_p, I_i) \tag{3.21}$$

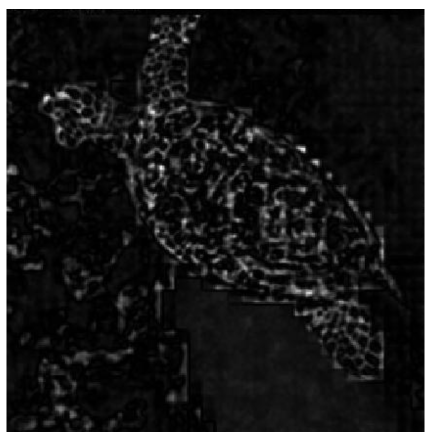


Fig 3.7: Saliency

The algorithm expressed by Equation is the histogram-based contrast method, where $D(I_p, I_i)$ is the Color distance metric between pixels I_p and I_i in the L*a*b* space for perceptual accuracy Saturation weight (W_{Sat}) makes the fusion algorithm adapt to the chromatic information through a high saturation region. For each input I_k, the weight can be calculated as the deviation between the Rk, Gk, Bk color channel and the luminance L_k of the kth input (for each pixel value position)

$$W_{sat} = \frac{\sqrt{(R_k+L_k)^2+(G_k+L_k)^2+(B_k+L_k)^2}}{3} \tag{3.22}$$

After the weight estimates of two different input versions are obtained, the three weight estimates of each input version are combined into one weight in the following way: for each input version *n*, the resulting W_L, W_{Sal}, and W_{Sat} are linearly superimposed to obtain the integrated weight. Then, *N* aggregated maps are normalized on a pixel-per-pixel basis. The weight of each pixel in each map is divided by the overall weight of the same pixels. The normalization method can be expressed by Eq (3.23)

$$W_n^{-} = \frac{W_n}{(\sum_{n=1}^{N} W_n + \delta)} \tag{3.23}$$

Where W^{-}_n is the normalized weight and $N = 2$. δ is the constant coefficient. The denominator is set to 0.001 to prevent it from becoming 0.

3.8 Exposedness Weight:

Exposedness weight (WE) evaluates how well a pixel is exposed. This assessed quality provides an estimator to preserve a constant appearance of the local contrast that ideally is neither exaggerated nor understated. Commonly, the pixels tend to have a higher exposed appearance when their normalized values are close to the average value of 0.5. This weight map is expressed as a Gaussian-modeled distance to the average normalized range value (0.5):

$$W_E(x, y) = \exp\left(-\frac{(Ik(x, y) - 0.5)2}{2\sigma}\right) \tag{3.24}$$

Fig 3.8: Exposedness

Where I^k (x, y) represents the value of the pixel location (x, y) of the input image I^k, while the standard deviation is set to $\boldsymbol{\sigma}$ = 0.25.

3.9 Normalized weights:

To yield consistent results, we employ the normalized weight values W (for an input k the normalized weight is computed as

$$W^k = \frac{w^k}{\sum_{k=1}^{k} w^k} \tag{3.25}$$

By constraining that the sum at each pixel location of the weight maps W equals one.

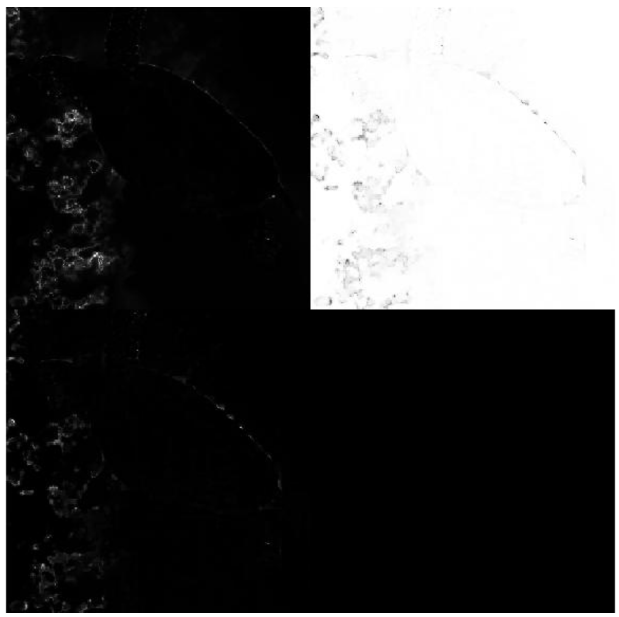


Fig 3.9: Normalized Weight

3.10 Multi-Scale Fusion

Concerning image fusion, Equation (3.10) can be used for the simple processing of the three groups of input images. However, this method will lead to artifacts in the resulting images. Thus, the fusion method based on multi-scale Laplacian pyramid decomposition is adopted in this study to avoid this situation

$$Fusion_{(i,j)} = \sum_{n=1}^{N} W_n(i,j) I_n(i,j) \tag{3.26}$$

The Laplace operator is applied to get the first layer of the pyramid for the input image version. Then, the second layer image is obtained by down sampling the layer, and so on. A three-tier pyramid is set up in this study. Similarly, the normalized weight version $\bar{W}_n$, corresponding to each layer of the Laplacian pyramid, filters the input image using the low-pass Gaussian filter kernel function *G* to obtain the Gaussian pyramid of the normalized weight image. The pyramid of fusion can be expressed as follows

$$pyramid^{l}(i,j) = \sum_{n=1}^{N} G^{1}\{W_n(i,j)\}\, L^{1}\{I_n(i,j) \tag{3.27}$$

Fig 3.10: Multi-Scale Fusion

Where $pyramid^{l}(i,j)$ is the level of the pyramid, *N* is the number of input images, G^{l} is the level *l* of the Gaussian pyramid, and L^{l} is the level *l* of the Laplacian pyramid.

Chapter-4

IMAGE PROCESSING EVALUATION

4.1 Introduction:

Underwater images suffer from blurring effects, low contrast, and grayed-out colors due to the absorption and scattering effects under the water. Few image enhancement algorithms have been developed for underwater images. Unfortunately, no well-accepted mechanism exists that can enhance the underwater images similar to human perception.

The quality and the contrast of the underwater image are poor due to the properties of water and its impurities. Here a method of enhancing the quality of the underwater image is proposed. The proposed method consists of three Normalized Weights.

4.2 Proposed Method:

The flow chart of the proposed approach implementation is shown in Figure(4.1). The proposed approach is composed of three parts, that input images, calculate the weight of input images, and multiscale fusion. First, the first input image (input 1) is obtained by utilizing the WB algorithm to correct the color from the original image, and the second input image (input 2) is obtained by applying the DCP algorithm to input 1 to reduce the degradation due to particle scattering. The third input is obtained by passing it to CLAHE.

Then calculate the global contrast weight, local contrast weight, saliency weight, and exposure weight of input 1, input 2, and input 3, respectively, and normalize the four weights of the two images to obtain the normalized weights W1, W2, and W3. Finally, input 1, input 2, and input 3 are fused according to normalized weights W1, W2, and W3. To avoid undesirable halos in the output image caused by edge mutation, a multiscale fusion strategy is adopted.

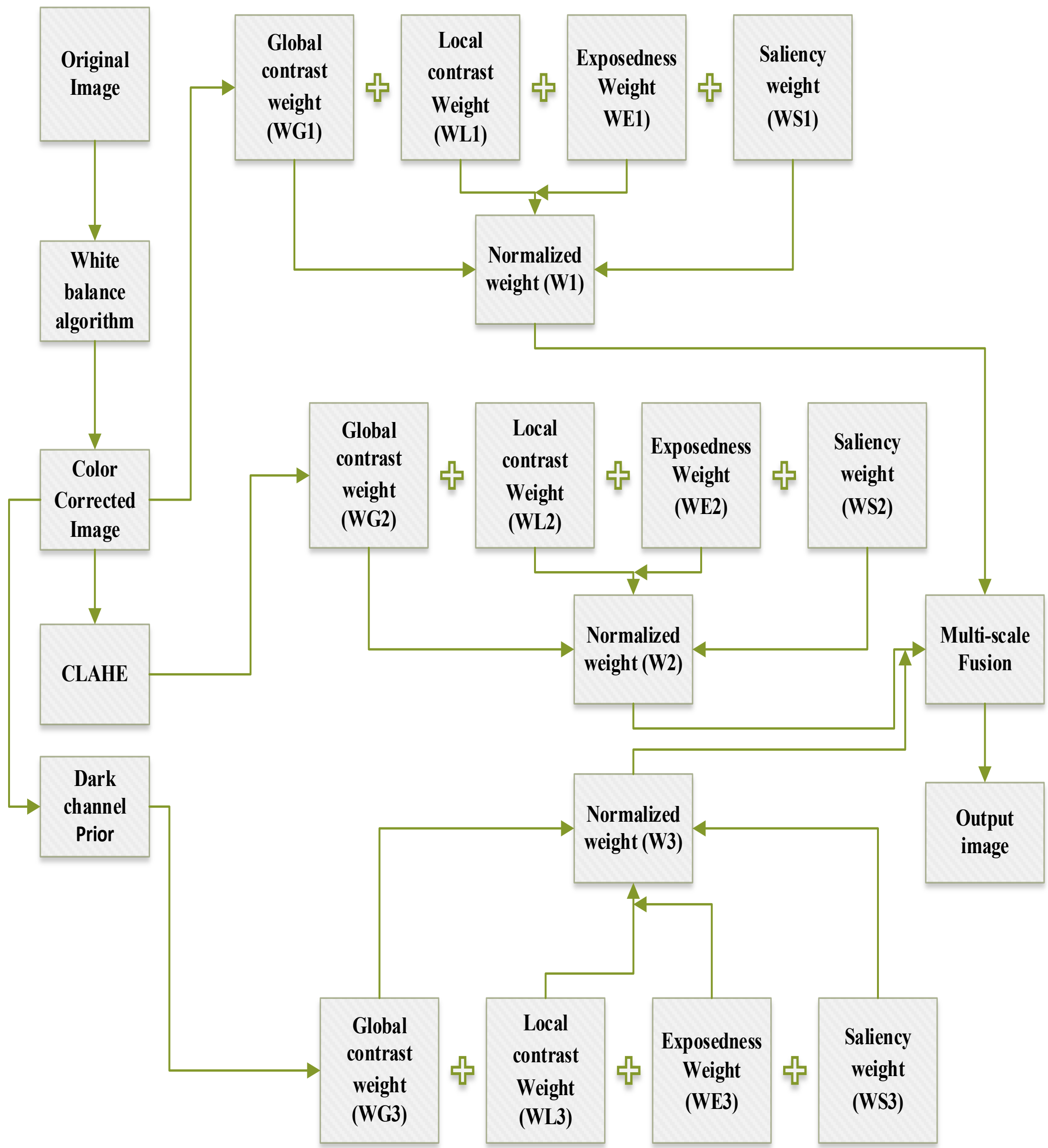


Fig 4.1: Block diagram of Proposed Method.

In our fusion strategy, a well-designed input image is a key to obtaining a high-quality output image. As shown in Figure, the first derived input image (input 1) processed by the WB algorithm is obtained to correct the color deviation of the original image, while the second (input 2) processed by the DCP dehazing and CLAHE (input 3) algorithm is computed to enhance contrast and sharpness of input 1.

4.3 STEPS FOR PROPOSED METHOD:

Step 1: Collect the images from the dataset. The Datasets used are U45, UIEB, and RUIE.

Step 2: Apply the White Balancing Algorithm for all the images in the dataset.

Step 3: Apply Color Correction

Step 4: Pass the color corrected to CLAHE and DCP Algorithm

Step 5: To calculate the Normalized weight(W1), Apply the color corrected to the Global contrast weight, Local contrast weight, Saliency weight, and Exposedness weight.

Step 6: To calculate the Normalized weight of CLAHE(W2) and DCP(W3), Apply the CLAHE and DCP to Global contrast weight, Local contrast weight, Saliency weight, and Exposedness weight.

Step 7: Finally, W1, W2, and W3 are fused by using multi-scale fusion, and the output image is obtained.

CHAPTER 5

EXPERIMENTATION RESULTS & DISCUSSION

5.1 DATASET

There are several image datasets available for various types of underwater image enhancement research. Because underwater data suffer from inherent distortions, such as color loss, poor contrast, and underexposure, as a result of light attenuation, refraction, and scattering, existing open-air trackers don't work as efficiently.

To close this gap, in this project, we considered an Underwater Image Enhancement Benchmark (UIEB) that includes 950 real-world underwater images, 890 of which have the corresponding reference images. We evaluated the performance of this approach on standard databases RUIE of 400 images and U45 dataset in terms of mean square error and peak signal-to-noise ratio.

U45: This dataset is a publicly available underwater test dataset that contains underwater images with degraded color casts, low contrast, and haze effects. This dataset includes green light images, blue light images, and images with haze, respectively. It contains 45 degraded images, and the resolution size of the picture is 256×256.

UIEB: Underwater Image Enhancement Benchmark Dataset includes 950 real-world underwater images, 890 of which have the corresponding reference images where each reference image is selected from 12 enhanced results. The rest 60 underwater images which cannot obtain satisfactory references are treated as challenging data. The UIEBD contains a large range of image resolution and spans diverse scene/main object categories.

RUIE: A real-world underwater enhancement (RUIE) dataset, with over 4000 underwater images captured by a multi-view imaging system under seawater. RUIE consists of three subsets: underwater image quality set (UIQS), underwater color cast set (UCCS), and underwater higher-level task-driven set (UHTS), which are used to validate the capability of UIER algorithms to improve image visibility, correct color cast, and the effectiveness from the aspect of high-level underwater tasks.

5.2 Evaluation metrics:

There are two general classes of evaluations conducted for underwater image enhancement: automatic evaluation metrics and human visual system (HVS). To evaluate the quality of underwater images, the underwater image quality evaluation metric is used Entropy, MSE, PSNR, SSIM, UICM, UISM, UIConM, UIQM, and UICQE.

5.2.1 Entropy:

Entropy, which is given in Eq, measures the richness of the details in an image thus we can perceive the information about the quality of the output image. We employed Entropy for, which is given in eq(5.1)

$$Entropy(x) = -\sum_{i=1}^{n} P(x_i) log P(x_i) \qquad (5.1)$$

5.2.2 MSE and PSNR:

Mean Square Error (MSE) as the signal measure. The MSE aims to provide a quantitative score that represents the similarity or distortion between the two signals. Usually, one of the signals is the original signal, and the other one is recovered from some dis- portion or contamination. Mathematically, the MSE between the two signals can be expressed as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2 \qquad (5.2)$$

where x and y are two signals, in this case, images, and x_i and y_i are the pixels at the i^{th} location. Similarly, N is the number of pixels. Furthermore, in the image processing literature, the peak signal to noise ratio (PSNR) measure is computed from MSE as:

$$PSNR = 10\ log_{10}(\frac{L^2}{MSE}) \qquad (5.3)$$

where L is the dynamic range of image pixel intensities (i.e., 255 for image).

5.2.3 SSIM:

The Structural Similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. Let us consider that x and y are the patches taken from the two different images but locations to be compared against each other. Then SSIM takes three measures into account, which are the similarity of the patch 1) luminance l(x; y), 2) contrasts c(x; y), and 3) the local structures s(x; y). these similarities are expressed and computed using simple statistics and are combined to produce local SSIM as:

$$SSIM = l(x;y) * c(x;y) * s(x;y);$$

$$= \frac{2\mu_x\mu_y+C_1}{\mu_x{}^2+\mu_y{}^2+C_1} \times \frac{2\sigma_x\sigma_y+C_2}{\sigma_x{}^2+\sigma_y{}^2+C_2} \times \frac{2\sigma_{xy}+C_3}{\sigma_x{}^2+\sigma_y{}^2+C_3} \tag{5.4}$$

where μ_x and μ_y are means while $\boldsymbol{\sigma}_x$ and $\boldsymbol{\sigma}_y$ are standard deviations of the patches x and y, respectively. Similarly, $\boldsymbol{\sigma}_{xy}$ cross-correlation of the patches after removing their means. The constants C1, C2, and C3 stabilize the terms to avoid near-zero divisions.

5.2.4 Underwater Image Colorfulness Measure (UICM):

Many underwater images suffer from a severe color-casting problem. As the depth of the water increases, colors attenuate one by one depending on their wavelength. The color red disappears first due to it possessing the shortest wavelength. As a result, underwater images usually demonstrate a bluish or greenish appearance. Furthermore, limited lighting conditions also cause severe color de-saturation in underwater images. A good underwater image enhancement algorithm should produce a good color rendition. The HVS captures colors in the opponent's color plane. Therefore, the two opponent color components related to chrominance RG and YB are used in the UICM, as shown in

$$RG = R - G \tag{5.5}$$

$$YB = \frac{R+G}{2} - B \tag{5.6}$$

Underwater images usually suffer from heavy noise. Therefore, instead of using the regular statistical values, the asymmetric alpha-trimmed statistical values are used for measuring underwater image colorfulness. The mean is defined by:

$$\mu_{\alpha,RG} = \frac{1}{K-T_{\alpha l}-T_{\alpha R}} \sum_{i=T_{\alpha l+1}}^{k-T_{\alpha R}} intensity_{RG,i} \quad (5.7)$$

The overall colorfulness metric used for measuring underwater image colorfulness is demonstrated in

$$UICM = -0.0268 \times \sqrt{{\mu_{\alpha,RG}}^2 + {\mu_{\alpha,YB}}^2} + 0158 \quad (5.8)$$

5.2.5 Underwater Image Sharpness Measure (UISM):

Sharpness is the attribute related to the preservation of fine details and edges. For images captured under the water, severe blurring occurs due to the forward scattering. This blurring effect causes degradation of image sharpness. To measure the sharpness on edges, the Sobel edge detector is first applied to each RGB color component. The resultant edge map is then multiplied with the original image to get the grayscale edge map. By doing this, only the pixels on the edges of the original underwater image are preserved. It is known that the enhancement measure estimation (EME) measure is suitable for images with uniform backgrounds and shows non-periodic patterns accordingly; the EME measure is used to measure the sharpness of edges.

The UISM is formulated as shown in

$$UISM = \sum_{c=1}^{3} \lambda \, \text{EME}(\text{grayscale edge}_c) \quad (5.9)$$

$$EME = \frac{2}{k_l k_2} \sum_{l=1}^{k1} \sum_{l=1}^{k2} \log\left(\frac{I_{max,k,l}}{I_{min,k,l}}\right) \quad (5.10)$$

5.2.6 Underwater Image Contrast Measure (UIConM):

Contrast has been shown to correspond to underwater visual performance such as stereoscopic acuity. For underwater images, contrast degradation is usually caused by backward scattering. The contrast is measured by applying the log AMEE measure to the intensity image as shown in

$$\text{UIConM} = \log \text{AMEE}(\text{Intensity}) \quad (5.11)$$

The logAMEE in

$$\log AMEE = \frac{1}{k_1 k_2} \times \sum_{k_2}^{k_1} \sum_{k_1}^{k_2} \log\left(\frac{I_{max,k,l} \times I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}}\right) log\left(\frac{I_{max,k,l} \times I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}}\right) \quad (5.12)$$

5.2.7 UCIQE :

Underwater color image quality evaluation abbreviated as UCIQE, is based on chroma, contrast, and saturation of CIE Lab and is defined as:

$$UCIQE = C_1 \times \sigma_c + C_2 \times \ con_1 + C_3 \times \mu_s \quad (5.13)$$

where $\boldsymbol{\sigma}$ c, conl, and μs are the standard deviation of chroma, the contrast of luminance, and the mean of saturation. It is to be noted here that for underwater images, human perception has a good correlation with the variance of chroma.

5.2.8 UIQM:

UIQM stands for underwater image quality measure and is different from earlier defined evaluation metrics. The UIQ employs the HVS model only, and does not require a reference image; hence, a better candidate for the evaluation of underwater images. UIQM is dependent on three attribute measures of the underwater images, which are 1) image colorfulness measure (UICM), 2) sharpness measure (UISM), and 3) contrast measure (UIConM). Following is the formulation of UIQM:

$$UIQM = C_1 \times UICM + C_2 \times \ UISM + C_3 \times UIConM \quad (5.14)$$

where c1, c2, and c3 are the parameters that are application dependent, e.g., more weight should be given to c1 for underwater color correction while c2 for increasing visibility in the underwater scene.

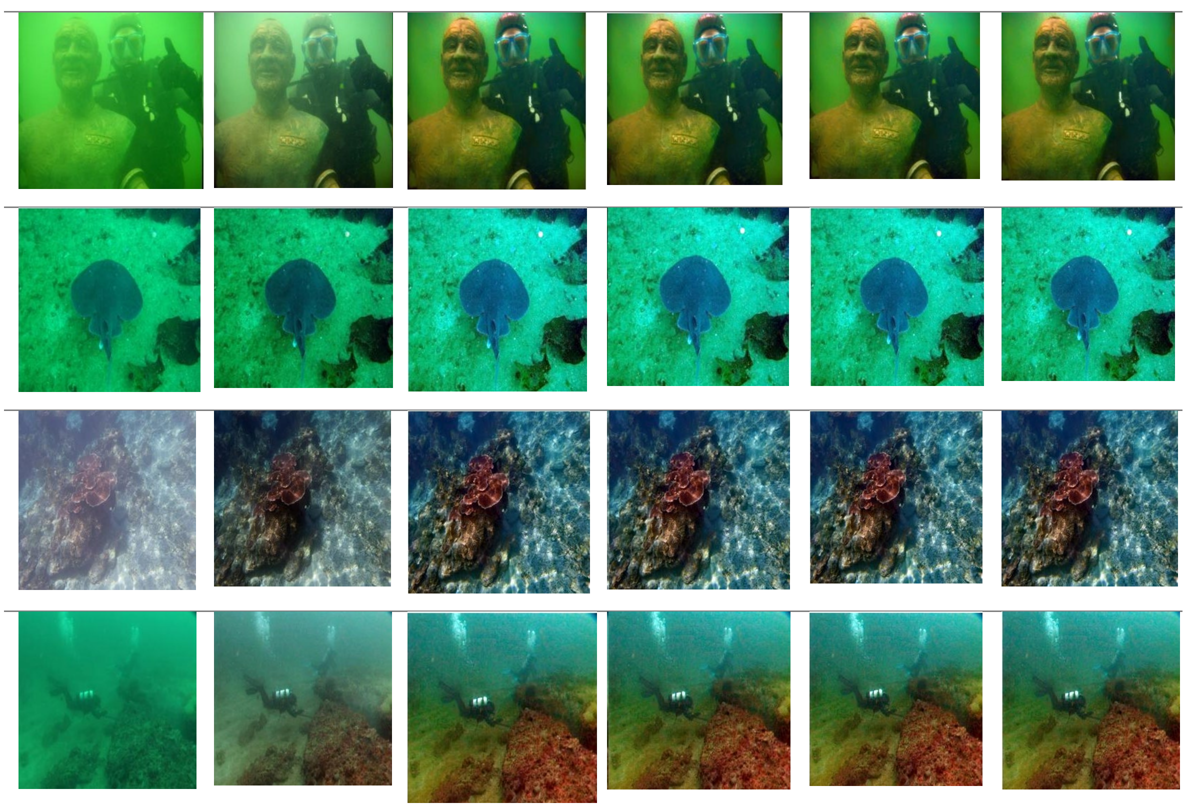
5.3 Human Visual System:

Due to the lack of real ground-truth data, human subjects are used to evaluate the quality of the predicted images in an attempt to incorporate the perceptual measures. These human inputs may either be crowd sourced or specialist persons in different competitions. However, none of these methods have shown any significant advantage over the mathematical measure. In other words, mathematically defined measures are still attractive due to the following reasons. They are simple to calculate and computationally inexpensive normally.

Furthermore, it is thought that viewing conditions play an influential role in the human perception of image quality. However, if there are multiple viewing conditions, a method dependent on viewing conditions may produce different estimations that may be inconvenient to utilize. Moreover, it may also be special to the user observation, and it then becomes the responsibility of each to compute the viewing conditions and provide the output to the measurement systems. On the other hand, a method independent of viewing conditions computes a single quantity that provides a general idea about the image quality. Besides, the experience of volunteers significantly aspects human visual perception. The volunteers who understand what the degrading aspects of attenuation and backscatter are, and what it looks like when either is improperly corrected can provide more reliable subjective scores of image quality.

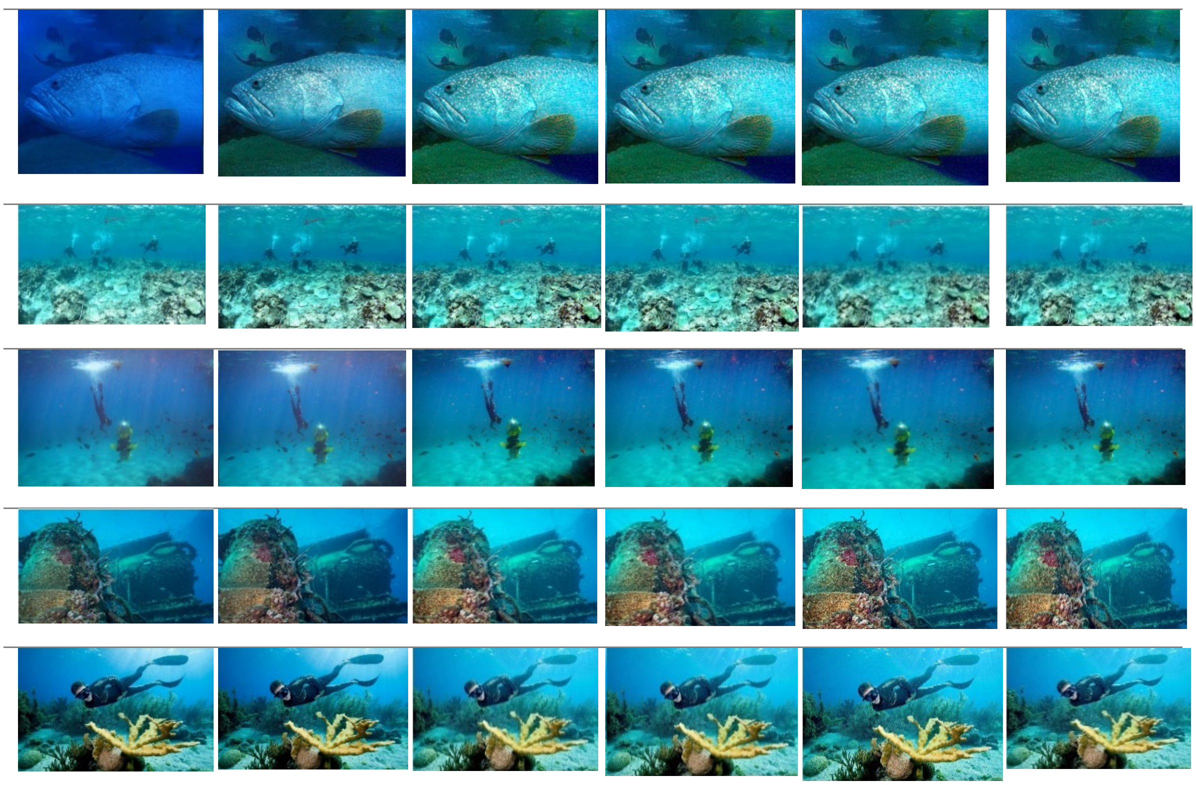
5.4 Qualitative Results

The following images are from different datasets like U45, RUIE, and UIEB. Each block is the output of the images of different algorithms like White Balance, Color Correction, DCP, CLAHE, and finally, the fused Output image.



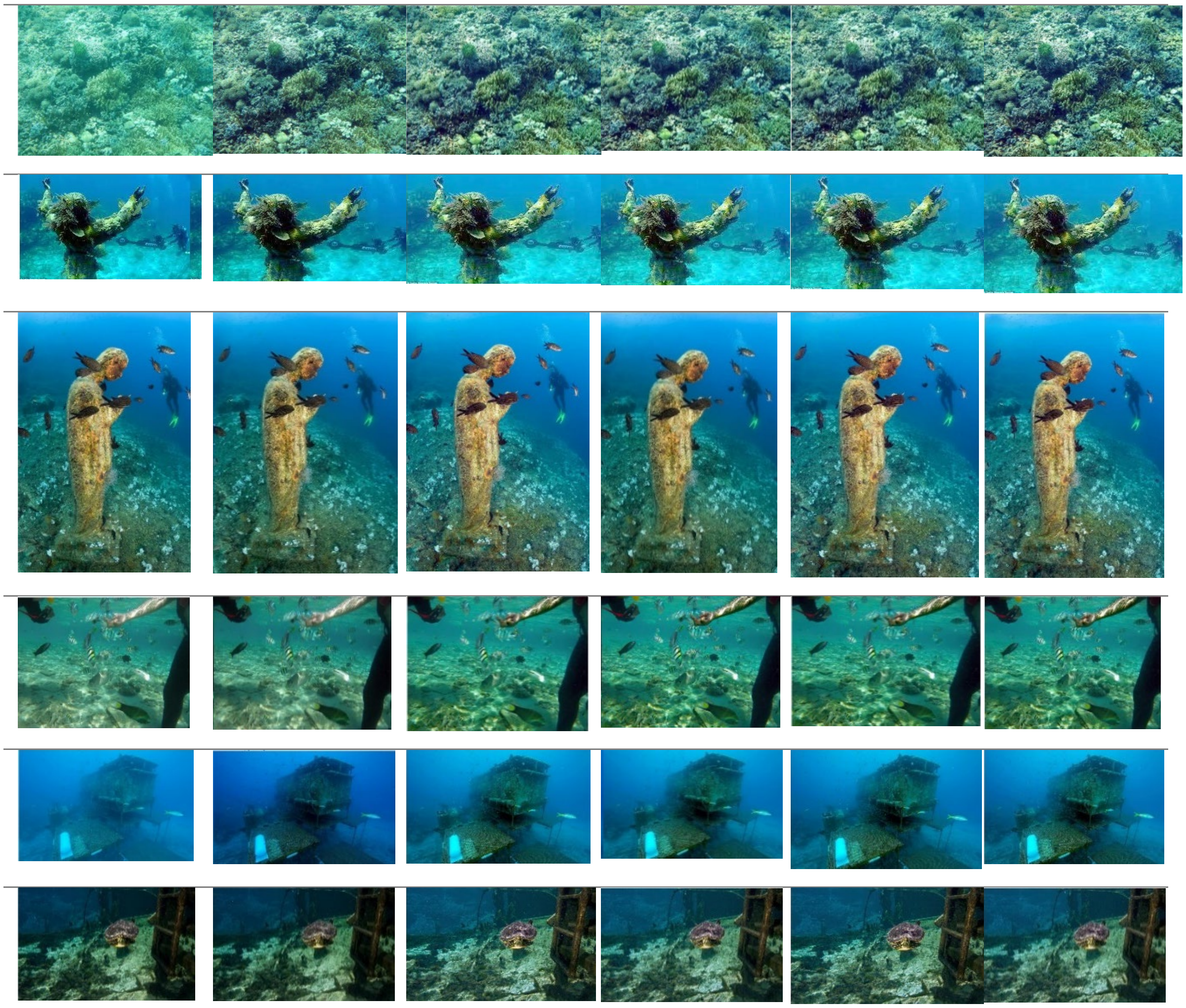
Original Image	**White Balancing**	**Color Correction**	**DCP**	**CLAHE**	**Output Image**

Fig 5.1: U45 Dataset



Original Image	**White Balancing**	**Color Correction**	**DCP**	**CLAHE**	**Output Image**

Fig 5.2: RIUE Dataset



Original Image	**White Balancing**	**Color Correction**	**DCP**	**CLAHE**	**Output Image**

Fig 5.3: UIEB Dataset

5.5 Quantitative Results

Metric	Results of U45 Dataset	Results of RUIE Dataset	Results of UIEB Dataset
Entropy	7.43	7.59	7.40
MSE	2216.48	2076.78	1407.55
PSNR	16.55	16.17	18.60
SSIM	0.69	0.42	0.78
UICM	-59.55	-30.24	-49.33

UISM	7.19	4.31	5.17
UIConM	0.78	0.80	1.36
UIQM	3.14	3.21	5.05
UICQE	0.58	0.56	0.57

5.6 Comparative Analysis

Our project has improved underwater image quality metrics. The following table compares some of the metrics. Several approaches and methodologies are discussed for improving underwater images.

Qualitative results for U45 dataset

Metric	Results from [21] reference	Proposed Method
Entropy	7.41	7.43
MSE	2199.96	2216.48
PSNR	16.467	16.55
SSIM	0.68	0.69
UICM	-60.50	-59.55
UISM	7.13	7.20
UIConM	0.75	0.78
UIQM	3.07	3.14
UICQE	0.57	0.58

Qualitative results for RUIE dataset

Metric	Results from [21] reference	Proposed Method
Entropy	7.53	7.59
MSE	2078.62	2076.77
PSNR	15.94	16.17
SSIM	0.40	0.42
UICM	-33.60	-30.24
UISM	4.48	4.30
UIConM	0.78	0.80
UIQM	3.18	3.21
UICQE	0.55	0.56

Qualitative results for UIEB dataset

Metric	Results from [21] reference	Proposed Method
Entropy	7.35	7.40
MSE	1554.49	1407.55
PSNR	17.88	18.59
SSIM	0.76	0.77
UICM	-51.02	-49.33
UISM	5.28	5.17
UIConM	1.34	1.36
UIQM	4.90	5.05
UICQE	0.56	0.57

CHAPTER-6

CONCLUSIONS & FUTURE SCOPE

6.1 CONCLUSION:

We proposed a new method to enhance the underwater images, by using the CLAHE algorithm in this project to achieve better contrast in images. We used MSE, PSNR, SSIM, UICM, UISM, UIConM, UIQM, and UICQE metrics to measure image contrast. This approach has successfully corrected the color cast and removed the haze of the underwater image, based on the qualitative results obtained. In addition to achieving the highest average UIQM value compared to those of the advanced methods, the quantitative results demonstrate that the proposed approach also maintains an excellent performance on different levels of distorted and hazy images. As a result of the experimental findings, it was found that the proposed technique outperforms classical HE by a wide margin and offers better preservation of local features, including contours and textures.

6.2 FUTURE SCOPE:

An underwater image enhancement algorithm is essential for computer vision tasks. In this project, we proposed a method which is suitable for real-time data to understand marine biology research, environmental evaluation. In the future, the performance and effect of the method need to be evaluated for algorithms such as optimal CLAHE and also implement this techniques in hardware model so that the images that are capured under the water are enhanced properly.

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