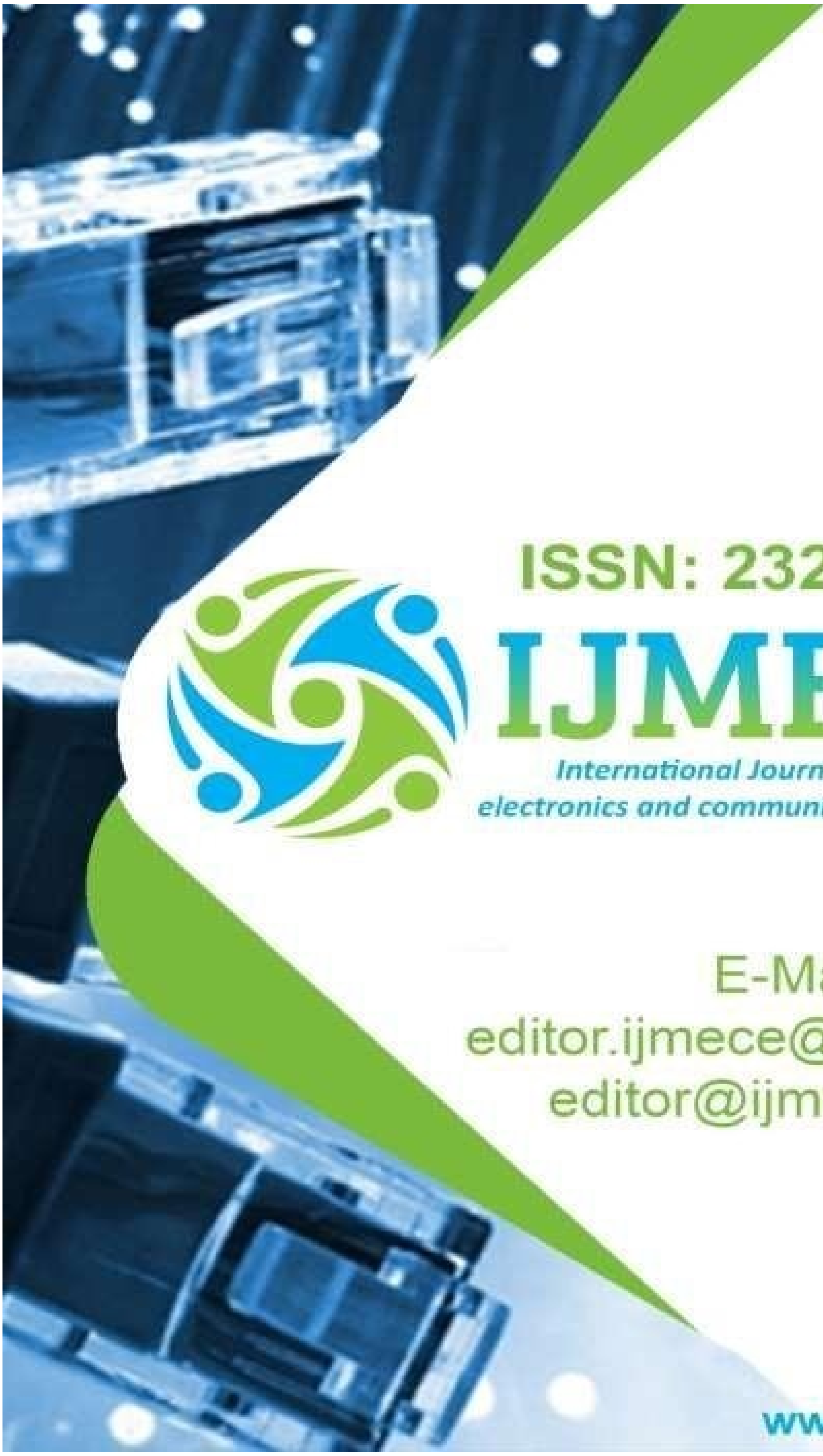

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ESTIMATION OF UNDERWATER IMAGE RESTORATION USING UNSUPERVISED COLOUR CORRECTION METHOD

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Abstract - Improving and reconstructing underwater images is a complex task that has become increasingly important in recent years due to the difficulty humans have in clearly perceiving Underwater photography faces challenges in capturing detailed images at greater depths due to the limitations of image acquisition systems. These systems not only struggle with clarity and detail but are also often quite costly. As a result, image processing algorithms have become essential for enhancing and reconstructing underwater images when reliable and affordable acquisition systems are unavailable. In this context, we examine four different methods for improving and reconstructing underwater images. The first method is Adaptive Histogram Equalization (AHE). The second method involves applying Gamma Correction to the image. The third approach is Brightness Preserving Bi-Histogram Equalization (BBHE). Finally, We utilize Contrast Limited Adaptive Histogram Equalization (CLAHE).

Keywords – Adaptive Histogram Equalization, Brightness-Preserving Bi-Histogram Equalization, Contrast-Limited Adaptive Histogram Equalization, Unsupervised Colour Correction Method, Histogram Equalization.

I. INTRODUCTION

The unique physical and chemical properties of underwater settings present obstacles that are not typically encountered in terrestrial imaging and have a significant impact on the quality of underwater photographs. Because red, green, and blue light attenuate at various rates, these images often exhibit a color cast, such as a green or blue tint. Moreover, most of the light energy is absorbed by suspended particles, causing the light to scatter before reaching the camera, producing images that are fuzzy, poor contrast, and foggy. Artificial light sources are frequently utilized to increase the reach of underwater imaging, however, they are also subject to absorption and scattering. This causes uneven illumination, with bright spots in the center and poor lighting towards the edges. Additional issues include shadowing and other forms of quality degradation. Effective methods are necessary to enhance underwater images by correcting color, improving clarity, and addressing issues like blurring and background scattering. To address these objectives, image enhancement, and restoration algorithms must overcome formidable obstacles posed by the complex underwater environment, where water turbidity, light absorption, and scattering all have an impact on picture degradation. We tackle these problems in this work with a thorough overview, an experimental comparison of important techniques, and a discussion of current and upcoming difficulties and trends in the field. It is crucial to stress that the algorithms we are focusing on were developed especially to raise the caliber of individual underwater photos. Our research offers several contributions to enhancing the Underwater image quality. Liu et al. introduced the DSNMF method for maintaining color constancy in underwater images in 2017. This technique, which estimates the illumination in underwater photographs, is called Deep Sparse Non-negative Matrix Factorization (DSNMF). Images are first split up into smaller blocks, and each channel within these blocks is subsequently reconstructed as an [R, G, B] matrix. The DSNMF method applies a sparsity constraint to separate the depth of each input matrix into several layers. The lighting information for the patch is represented in the final layer of the factorization matrix, and the image is modified following these sparse limitations. An improved image is produced by estimating the original image's local block lighting. In May 2015, Charanjeet Kaur and Rachna Rajput emphasized that ordinary histogram equalization applies a uniform transformation to all pixels based on the image histogram. This method is effective when pixel values are uniformly distributed across the image, However, in regions that are noticeably lighter or darker than the rest of the image, it is unable to improve contrast. The goal is to preserve the brightness of underwater photos while enhancing their contrast. According to DITHEE DEV K and S. Natrajan (April 2015), the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique proves effective in enhancing underwater images. This technique involves calculating the dark channel from the underwater input image and processing it through image segmentation. If artificial light affects the image, it is removed using a suitable method before applying CLAHE. Test findings show that by increasing contrast and lowering noise and artifacts, this method greatly improves the visual quality of underwater photos.

For example, methods involving predetermined threshold values have been proposed by [1], and [2]. However, this approach limits its applicability, making it unsuitable for all types of images [1], [2]. Each photograph's uniqueness means these methods may not always be reliable. To address light absorption issues, artificial light-emitting underwater vehicles are used. Nevertheless, this introduces new challenges, such as uneven illumination caused by artificial lighting and shadows cast by moving objects [3]. Some algorithms are also linked to significant computational costs in terms of both time and resources [4], [5]. Furthermore, lens filters have been used in physics-based systems, but these methods have trouble correcting color when shooting in deep water, where red and yellow wavelengths are either almost completely absent or greatly decreased [6], [7]. Developing an image enhancement technique that may enhance underwater photos by lowering color cast and raising contrast is crucial to resolving these problems. Focusing on color balance, contrast adjustment using RGB and HSI color models, along with overall color correction, we provide UCM as a method for improving underwater photos in this work.

II. LITERATURE SURVEY

Red, Green, and Blue color channels' light absorption through water is measured using Beer's Law to rebuild the scene's intensity values [8], [9]. Assuming uniform depth for all objects in the scene, this method uses the scene's depth as its input. The aim is to account for light absorption at each wavelength that corresponds to an RGB channel. When estimating absorption levels using Beer's

Law, the quality of the calibration parameters used determines how efficient this method is. The method's fundamental flaw is its presumption that the medium is uniform and that every component in the scene is at the same depth.

Additionally, because depth, salinity, water composition, and temperature vary, calibration needs to be done again for every image. The primary limitation of this method is its assumption that the medium is uniform and that all elements in the scene are at the same depth. Moreover, the scene's depth, salinity, water composition, and temperature might all change, necessitating calibration with each shot. Prior data is frequently used in statistical methods for picture rectification. One method, for instance, uses a robot to adjust color utilizing the entire spectrum of light in a transparent medium [10], [11].

Due to high energy consumption, the light cannot remain on continuously; instead, the robot periodically pauses to capture still reference images, which provides clearer color accuracy. On the presumption that neighboring frames are similar, a Markov Random Field (MRF) for pixel-by-pixel improvement is subsequently trained using these reference images. However, this method is computationally intensive; in 2005, processing a 400 by 300-pixel image on a normal PC took 40 seconds [11]. Another method, named "AQUA," was introduced by [12].

Physics-based techniques involving lens filters are used to adjust color temperature by absorbing certain wavelengths of light. These methods help maintain high quality in captured images or videos. To further improve underwater images or videos, contrast enhancement techniques can be combined with lens filters to minimize light scattering [13]. Polarized filters can address issues such as backscatter [14], focusing on recovering objects and mitigating the effects of visibility degradation caused by partial light polarization. While these methods are relatively simple to use, a major drawback is that lens filters absorb some light, leading to darker images. Given the challenges of illumination in underwater photography, these techniques are not ideal for enhancing underwater images or performing color correction and are generally better suited for general or land photography.

Underwater settings often suffer from inadequate lighting, resulting in low energy levels for the RGB components in underwater images. Techniques such as Histogram Equalization (HE), the Gray-World Assumption (GWA), White Balancing (WB), and their variations, when directly applied to enhance these images, can lead to significant artifacts, halos, increased internal noise, and color distortion. Moreover, the low contrast and blurry edges in underwater images often cause the Gray-Edge Assumption (GEA) to be ineffective in achieving meaningful enhancement.

III. METHODOLOGY

To enhance contrast in low-light images, techniques such as Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction, and Generalized Unsharp Masking (GUM) are frequently used. For adjusting the saturation and color of photographs, common color correction methods include the Gray-World Assumption (GWA), White Balancing (WB), and Gray-Edge Assumption (GEA).

Unsupervised Color Correction(UCM):

The term "Unsupervised Color Correction" describes techniques and algorithms that improve or modify an image's colors without the need for manual labeling, oversight, or pre-established ground truth data.

Method for Unsupervised Color Correction (UCM): The UCM method effectively enhances underwater images through three key steps:

1. **Maintaining a Balance:** Underwater images generally exhibit a predominantly blue color. The UCM leverages these high blue values to enhance other colors, thereby achieving a more balanced color representation.
2. **Elimination of color cast:** By extending the blue histogram towards the lower end and the red histogram towards the higher end, contrast correction reduces the blue color cast and increases the red. With this adjustment, the red and blue values are enhanced, producing photographs with excellent quality.
3. **Enhanced Illumination and Enhanced True Color:** Brighter and more vibrant images are the consequence of UCM's adjustment of the Intensity and Saturation parameters in the HSI color model, which enhances brightness and color accuracy.

The effectiveness of the UCM method stems from its ability to adapt to the specific attributes of an image, enhancing it according to its unique features rather than using fixed criteria. It surpasses GW, WP, and APHE, particularly for underwater images with a blue tint. On the other hand, photographs taken on land or without a blue cast could not benefit as much from its performance. These methods use data-driven strategies and statistical models to automatically guarantee color consistency or enhance image quality. Because it can handle a variety of images and applications without the need for human intervention.

This section outlines our proposed method, an Unsupervised Colour Correction Method (UCM), designed to effectively eliminate the bluish color cast and address issues of low red intensity and poor illumination, resulting in high-quality images. Our approach is structured into three key stages:

A. Equalisation of RGB colors
B. Contrast correction, of RGB color model
C. Contrast correction of HSI color model

A. Equalisation of RGB colors

To obtain a high-quality image, it is essential for the RGB components to have balanced color values. However, underwater images are often not properly color-balanced. The first step in the proposed method to equalize the RGB values is to determine the maximum values. Let IR(i,j), IG(i,j), and IB(i,j) represent the red, green, and blue components of an RGB image with dimensions M x N pixels, where i = 1, ..., M and j = 1, ..., N. The maximum pixel values for each color component, Rmax, Gmax, and Bmax, are then calculated [15]:

$$R_{\max} = \max_{i,j} \quad I_R(i,j) \qquad (1)$$

$$G_{\max} = \max_{i,j} \quad I_G(i,j) \qquad (2)$$

$$B_{\max} = \max_{i,j} \quad I_B(i,j) \qquad (3)$$

In the initial step, the dominant color cast channel is identified using the equations above. Afterward, the average values for

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each color component, Ravg, Gavg, and Bavg, are computed [15]:

$$R_{avg} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} I_R(i,j) \quad (4)$$

$$G_{avg} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} I_G(i,j) \quad (5)$$

$$B_{avg} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} I_B(i,j) \quad (6)$$

The proposed method maintains the dominant color cast channel constant, as underwater images typically have a higher blue hue than other colors. To balance the image, higher values are applied to enhance the other colors. Two gain factors are then calculated based on the dominant color cast, as outlined in the following equations. These same equations have also been used to compute the ratio for face detection [16].

$$A = B_{avg} / R_{avg} \quad (7)$$

$$B = B_{avg} / G_{avg} \quad (8)$$

The channel with the highest color value is set as the target mean, while the remaining color channels are adjusted using a multiplier to match this mean and create a balanced image. The proposed method utilizes two color channels to minimize the color cast in the affected image. The adjustments are made according to Von Kries's hypothesis, as outlined below:

$$R' = A \times R \quad (9)$$

$$G' = B \times G \quad (10)$$

Here, R and G represent the original pixel values in the image, while R' and G' denote the adjusted pixel values.

Figure 1: Equalisation of RGB Colors.

The **"Equalization of RGB Colors"** generally refers to the process of modifying the red, green, and blue (RGB) color channels of an image to create a balanced and natural color representation. This technique is especially crucial in situations where images experience color casts due to light absorption in water.

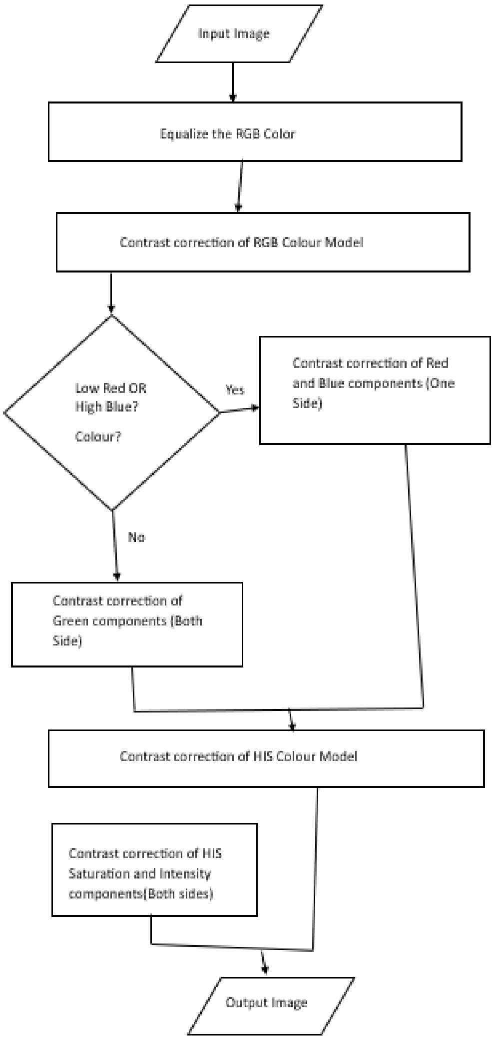

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Figure 2: Flowchart of proposed UCM Algorithm

B. Contrast Correction of RGB Colour Model

Low contrast can make an image unclear and difficult to interpret. As a result, the second step in the proposed method is to apply a contrast correction technique to enhance the image's contrast. This involves stretching the intensity values to cover the desired range. Prior to applying contrast correction, the upper and lower limits of each band in the image are determined. Typically, an 8-bit color channel has a value range of 0-255. A common normalization technique is used to identify the minimum and maximum pixel values in the histogram and stretch them to fit within the specified range. One significant issue with this method is that a single outlier pixel with an excessively high or low value can severely distort the image, leading to inaccurate scaling. This issue can be mitigated by clipping, or removing, a small percentage of pixel values from both extremes of the histogram to produce a clearer image. The proposed approach addresses this problem by generating a histogram of the image and using the 0.2% and 99.8% percentiles as thresholds. This approach enhances the image by disregarding pixel values outside this range and applying the contrast correction only to the pixels within it, as illustrated in Figure 2.

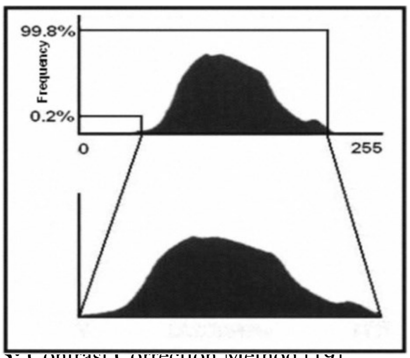

Figure 3: Contrast Correction Method [19]

1) Contrast Correction Method: Three distinct steps are used to apply the contrast correction method, based on the pixel characteristics. The method is applied only to the pixels that fall within the 0.2% to 99.8% range. The contrast correction is performed using the following equation [20].

$$P_o = (P_i - c)\frac{(b-a)}{(d-c)} + a \quad (11)$$

Where:

- Po represents the contrast-corrected pixel value;
- Pi denotes the pixel value being considered;
- a is the lower limit, set to 0;
- b is the upper limit, set to 255 (11);
- c is the current minimum pixel value in the image;
- d is the current maximum pixel value in the image.

For improved results, it is recommended that the contrast correction method be applied to the upper, lower, and both sides of the image, as outlined below.

- **Contrast Correction to Upper Side:** In this case, the color component with the lowest value is selected, typically the red component, as red is the first color to disappear underwater at depths of around 3 meters. Adjustments are then made using the contrast correction method, with the range directed toward the maximum value, as illustrated in Figure 3. The formula (11) is modified to stretch the red color component.

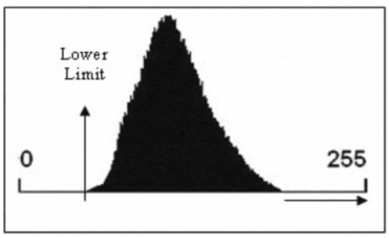

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Figure 4: Contrast Correction to Upper Side

The contrast correction formula (11) is applied, but with a focus on the term (b-a) / (d-c), which is expressed as:

(Upper Limit - Lower Limit) / (Maximum - Minimum)

This is modified to:

(Upper Limit - Minimum of Red) / (Maximum - Minimum)

Here, the lower limit is set to the minimum value of the red component, while the upper limit is 255.

- **Contrast Correction to Lower Side:** In the second step, the dominant color cast component, which typically has a strong color cast, is selected. In underwater images, this is usually the blue color. As a result, underwater images often exhibit a bluish color cast. To correct this, the contrast adjustment method is applied toward the lower end, addressing the bluish color cast, as shown in Figure 4.

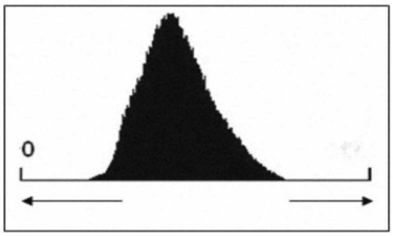

Figure 5: Contrast Correction to Lower Side

The contrast correction formula (11) is applied, with particular focus on the term (b-a) / (d-c), expressed as:

(Upper Limit - Lower Limit) / (Maximum - Minimum)

This is then modified to:

(Maximum of Blue - Lower Limit) / (Maximum - Minimum)

Here, the upper limit and lower limit are both set to 0, with the upper limit being the Maximum of Blue rather than 255.

- **Contrast Correction to Both Sides:** In this step, the proposed approach is used to identify the color component whose value lies between the lower and higher color components. Adjustments are then made in both directions, towards the minimum and maximum, using the contrast correction method. These adjustments help to evenly spread the histogram in both directions, as demonstrated in Figure 5.

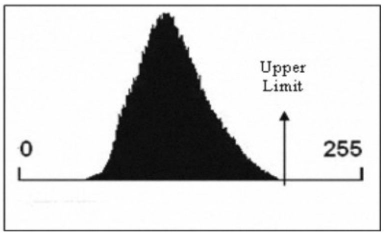

Figure 6: Contrast Correction to Both Sides

The contrast correction formula (11) is applied, with particular focus on the term (b-a) / (d-c), which can be expressed as:

(Upper Limit - Lower Limit) / (Maximum - Minimum)

Here, the Lower Limit is set to 0 and the Upper Limit is set to 255.

Figure 7: Contrast Correction of RGB Colour Model.

The **"Contrast Correction of RGB Color Model"** Usually demonstrates the method of improving an image's contrast by modifying the intensity values of the red, green, and blue (RGB) color channels. This method is crucial for enhancing the visibility and sharpness of images, especially in difficult environments such as underwater photography, where lighting conditions often result in low contrast and degraded image quality.

C. Contrast Correction of HSI Colour Model

This section explains how the quality of an image can be enhanced using the HSI color model. It also covers the process of converting an image from the RGB color model to the HSI model and vice versa. The HSI color model consists of three components: Hue (H), Saturation (S), and Intensity (I). Hue represents the pure color, Saturation indicates the purity of the color, and Intensity corresponds to the brightness or illumination level. The Hue channel is dedicated to pure colors and includes seven colors, similar to the colors of a rainbow. To prevent issues with color gamut, this channel is kept constant. Unlike the Hue component in the HSI model, which represents a range of colors, each component in other color models such as RGB, CMY, and YCrCb corresponds to a single color.

1) Contrast Correction to Both Sides: The Saturation and Intensity components of the HSI color model are utilized in the contrast correction method. In this study, these parameters are integrated with the RGB color model for enhancing underwater images. Adjustments are applied in both directions: downward (towards the darker side) and upward (towards the brighter side) using the contrast correction technique. These modifications assist in spreading the histogram effectively in both directions, as illustrated in Figure 5.

The HSI color model offers a broader color spectrum by adjusting the color properties of the image. The Saturation and Intensity components play a key role in expanding this range. By manipulating the 'S' and 'I' values, the blue color element in the image can be controlled, allowing the creation of a range from pale blue to deep blue. This method enables the control of contrast in underwater images by either increasing or decreasing the values. It works by applying a histogram to the digital values of the image and redistributing the stretching values over the variation in the maximum range of possible values. Additionally, linear stretching of the 'S' value can enhance the strength of each range by focusing on the lower output values. The proposed approach allows for the stretching of both Saturation and Intensity values in the HSI color model. Notably, the use of Saturation parameters helps achieve the true colors of the underwater image, while the Intensity parameter plays a crucial role in adjusting the illumination for underwater images.

Figure 8: Contrast Correction of HSI Model.

The **"Contrast Correction of HSI Color Model"** generally demonstrates the method of improving an image's contrast by applying the HSI (Hue, Saturation, Intensity) color model. This technique is particularly useful for improving the quality of images, especially in scenarios like underwater photography, where color balance and visibility can be significantly affected by lighting conditions.

Each of the three stages described above is applied to every pixel in the image to determine the correct value for that pixel.

IV. RESULTS AND DISCUSSION

We utilize underwater images processed with the OpenCV library. Various underwater images are used as data for enhancement purposes. In underwater image processing, the pre-processing phase is critical for achieving high-quality images and accurate results in subsequent stages. Underwater images may present issues that can lead to poor visibility and reduced quality. During this phase, we perform background removal, eliminate non-essential features, enhance the image, and reduce noise.

Background Removal: This process involves segmenting and then removing the background of an image to isolate the subject or objects of interest.

Figure 9: Background removal of image.

Eliminating Non-Essential Features: After isolating the main subject, this step removes or diminishes elements that do not contribute to the main focus of the image.

Figure 10: Eliminating Non-Essential Features of Image.

Enhancing the image: Image enhancement involves improving the visual quality of the image to make details more visible or to correct for the degradation caused by underwater conditions like light scattering and absorption.

Figure 11: Enhancing the Image.

Reducing Noise in the image: Noise reduction focuses on minimizing unwanted graininess or speckles in an image, which can be particularly pronounced in underwater photography due to low light conditions.

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Figure 12: Reducing Noise in the Image.

HISTOGRAM EQUALISATION

To evaluate the model's performance on new, untested data and assess its ability to generalize, the dataset is split into training and testing sets.

The next step is model fitting, which is essential for developing the model. We use Adaptive Histogram Equalization (AHE) for this process, which improves contrast locally by computing multiple histograms for different image regions. Although AHE provides better contrast enhancement compared to standard histogram equalization, it can also increase noise in localized areas. Despite this, AHE is favored for its effectiveness in enhancing contrast. To ensure better contrast in the desired areas, it modifies each pixel according to the histogram of the area around it. The transformation function is based on the Cumulative Distribution Function (CDF) of the pixel values within the neighborhood, which is derived from histograms using the same methodology as basic histogram equalization. Special attention is given to pixels near the edges of the image, as their neighborhoods may extend outside the image boundaries. The image is separated into rectangular tiles of the same size, and a transformation function, CDF, and histogram are calculated for each tile. Transformation functions are tailored for the center pixels of each tile. For pixels outside the center, transformations are based on functions from up to four neighboring tiles, with values interpolated accordingly. The image's corner pixels utilize the function from the closest corner tile, while pixels in the image's main area are bi-linearly interpolated and those close to the edges are linearly interpolated. This interpolation method ensures continuity as pixels approach the center of a tile.

Gamma Correction (GC): This technique amplifies image intensities by a gamma factor, enhancing darker tones more than lighter ones. Gamma correction adjusts the non-linear output of CRT monitors to a linear scale, represented as:

$$I_{\text{corrected}} = \left(\frac{I_{\text{input}}}{I_{\text{max}}} \right)^{\gamma} \cdot I_{\text{max}}$$

Where:

- I input: Pixel intensity in the image.
- Imax: The highest possible intensity value (for instance, 255 in an 8-bit image).
- γ: The gamma value.

Bi-Histogram Equalization with Brightness Preservation (BBHE): Brightness Preserving Bi-Histogram Equalization (BBHE) divides the input image into two distinct images, using a selected mean intensity as a reference. Intensities below the mean are present in one image, while intensities above it are present in the other.

Each of these images undergoes histogram equalization individually. The image with intensities below the mean is adjusted to span from 0 to the mean, while the image with intensities above the mean is adjusted to range from the mean to 256 (for an 8-bit depth). Improved contrast results from maintaining the mean brightness throughout the entire intensity range.

Adaptive Histogram Equalization with Contrast Limitation (CLAHE): Although AHE can excessively enhance noise in uniform regions, CLAHE mitigates this issue by limiting amplification. CLAHE operates by dividing the image into smaller segments, known as tiles, and applying contrast enhancement to each tile separately. These tiles are subsequently merged to create the final image with improved contrast.

PERFORMANCE EVALUATION

We assessed the effectiveness of the proposed method by comparing our results with three widely recognized techniques: Gray World (GW), Adobe Photoshop Histogram Equalization (APHE), and White Patch (WP). Histogram analysis and edge detection were used in this assessment.

Edge Detection: Numerous researchers have employed edge detection, which measures the quantity of edges in an image, to assess their methods. Usually, an automatic Sobel edge detector is used for this. The edge detection was carried out with the use of open-source picture software [15]. Pictures with more identified edges are thought to contain more important feature content. To detect edges, an auto-threshold value of 85–175 was used. Our Unsupervised Colour Correction Method (UCM) identified more edges compared to existing methods. In several cases, the APHE method introduced noise, which the edge detector incorrectly classified as objects.

Histogram: By contrasting the values before and after augmentation, an image histogram can be used as a tool to evaluate the quality of an image. A thorough review must take into account several elements. Histograms have been employed by researchers as analytical instruments to gauge the effectiveness of their methods [4]. Our assessment adheres to the literature's guideline: "A histogram that is more widely spread indicates a more visually appealing image" [16]. The histogram needs to be enlarged to encompass the entire range, from the lowest (0) to the highest (255) value levels, to accomplish this. As shown in Figures 6, 7, and 8, the UCM image histograms are effectively stretched to the minimum (0) and maximum (255) levels. The histograms for the GW, APHE, and WP photos, on the other hand, do not show the same degree of stretching.

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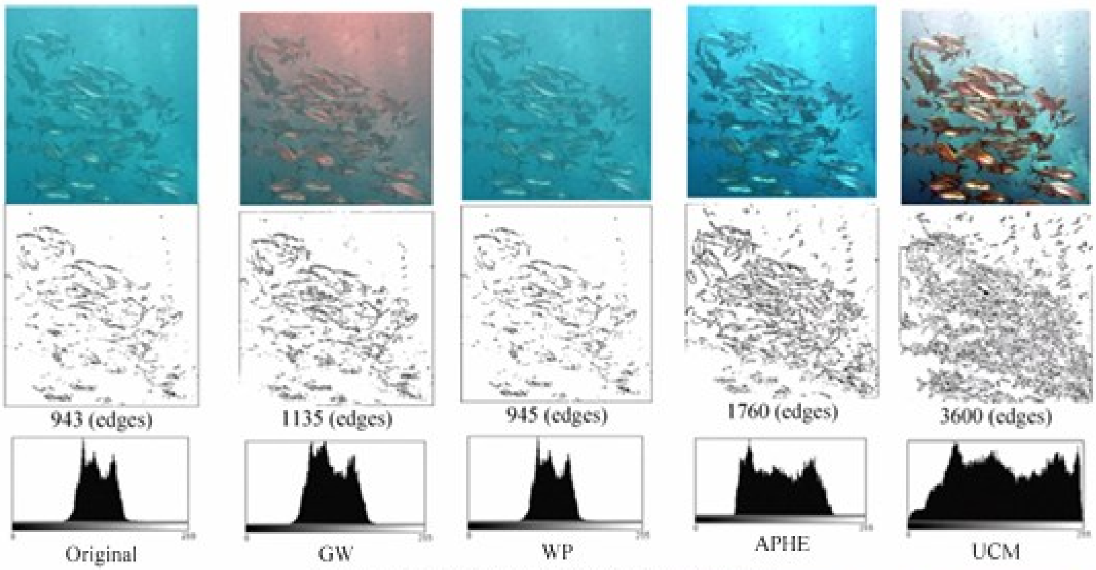

Figure 6: Results comparison before and after enhancement

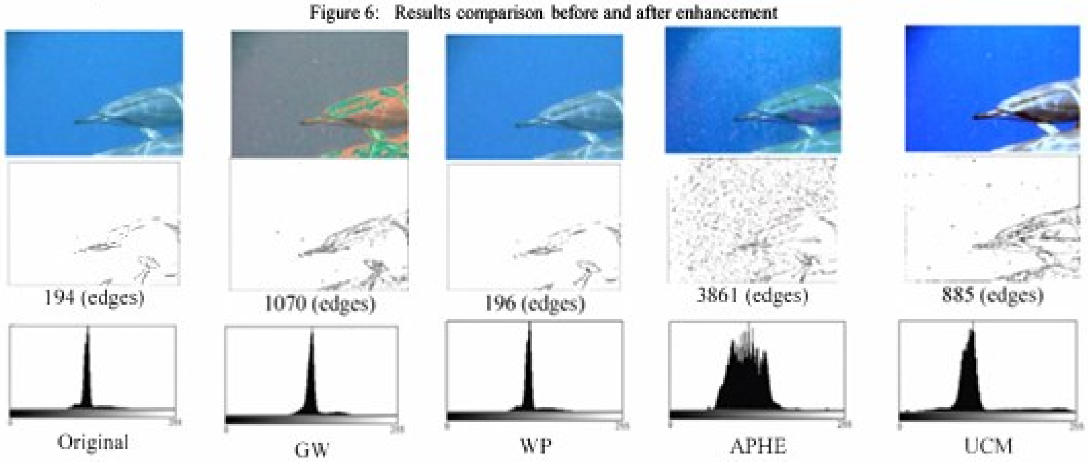

Figure 7: Results comparison before and after enhancement

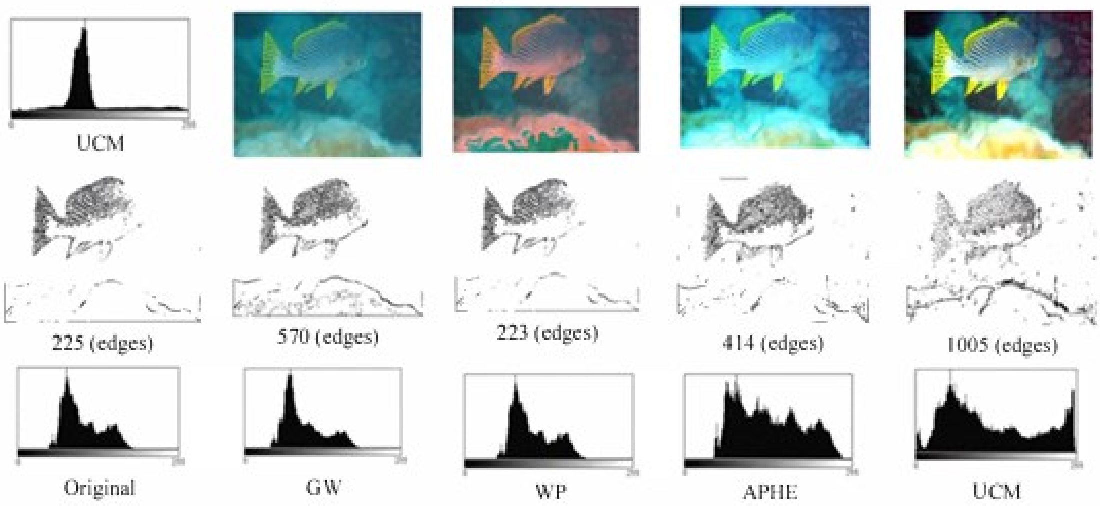

Figure 8: Results comparison before and after enhancement

RESULTS

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Results Table: Comparison of Underwater Image Enhancement Methods

Figure	Method	Edges Detected	Histogram Observation	Remarks
Figure 6	**Original**	943	Low contrast	Baseline image without enhancement
	Gray World (GW)	1135	Slight improvement	Improved edges with minimal contrast changes
	White Patch (WP)	945	Similar to original	No significant enhancement observed
	Adaptive HE (APHE)	1760	Improved contrast	Significant enhancement with well-defined edges
	UCM Method	3600	High contrast	Best enhancement with the highest edge count
Figure 7	**Original**	194	Low contrast	Baseline image without enhancement
	Gray World (GW)	1070	Slight improvement	Enhanced details with moderate contrast changes
	White Patch (WP)	196	Similar to original	No significant enhancement observed
	Adaptive HE (APHE)	3861	Improved contrast	Best enhancement with sharp edges
	UCM Method	885	High contrast	Good enhancement with noticeable improvements

Figure 8	**Original**	225	Low contrast	Baseline image without enhancement
	Gray World (GW)	570	Slight improvement	Enhanced details with better edge detection
	White Patch (WP)	223	Similar to original	Minimal or no enhancement
	Adaptive HE (APHE)	414	Improved contrast	Moderate enhancement in edges
	UCM Method	1005	High contrast	Best results with improved edge clarity

DISCUSSION

This section contrasts the results of our proposed Unsupervised Color Correction Method (UCM) with those of Adobe Photoshop Histogram Equalization (APHE), Gray World (GW), and White Patch (WP). It explains why our method produces better outcomes by outlining the main features of each approach and their effects on image quality.

Gray World (GW): The GW method is effective only when an image has a balanced distribution of all color components; otherwise, it can cause distortions. This technique can only fix photos where all pixel values are evenly balanced because it is dependent on the average values of the colors in the image. In underwater environments, where one color often predominates, GW is not ideal for improving images with strong color casts. While it works well in cases with minimal color cast, it does not address issues related to brightness or contrast.

White Patch (WP): The WP method utilizes these values to estimate the illuminant, based on the assumption that the maximum values of each color component represent full illumination. Nevertheless, WP frequently produces little discernible effect because it uses the brightest pixel to determine the hue of the illuminant, which does not work well in photos with strong color casts.

Histogram Equalization (APHE) in Adobe Photoshop: The APHE method enhances images but with limitations. It distributes intensity values evenly across the range, focusing on brightness. This approach often results in overly bright images, especially if they contain dark or shadowed regions, making them unrealistic. APHE does not address color cast issues, equalizing values without considering the image's nature.

V. CONCLUSION

Improving underwater photos is difficult because there are a lot of variables that affect the photos that are taken. Techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Brightness Preserving Bi-

Histogram Equalization (BBHE), Gamma Correction (GC), and Adaptive Histogram Equalization (AHE) can significantly improve the visual quality of these images. Selecting the appropriate technique is crucial for successful enhancement, as it helps mitigate issues like noise, blurring, and limited visibility. Our findings suggest that AHE and CLAHE deliver superior results compared to Gamma Correction and BBHE. Moving forward, we aim to develop algorithms capable of reconstructing images taken in different liquids, considering their unique wavelength absorption properties.

Advancements in underwater robotics have simplified underwater exploration, but the high cost of sophisticated cameras remains a challenge. Future research should focus on creating robust, camera-independent algorithms that could enhance the quality of underwater images. Integrating these algorithms into underwater robots could significantly reduce costs while improving the quality of images obtained during exploration.

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