

IMAGE RESTORATION USING UNSUPERVISED COLOUR CORRECTION METHOD

Srilakshmi Aouthu

Associate Professor , Vasavi College of Engineering, Hyderabad

Abstract - Enhancing and reconstructing underwater images is a challenging task that has gained increasing significance in recent years due to the difficulties humans face in perceiving underwater environments clearly. Underwater photography, especially at greater depths, encounters obstacles in capturing detailed images due to the limitations of image acquisition systems. These systems often struggle with clarity and detail while also being expensive. Consequently, image processing algorithms have become crucial for enhancing and reconstructing underwater images when reliable and cost-effective acquisition systems are unavailable.

In this context, we explore four distinct methods for underwater image enhancement and reconstruction. The first method is Adaptive Histogram Equalization (AHE), followed by Gamma Correction. The third approach employs Brightness Preserving Bi-Histogram Equalization (BBHE), and finally, we utilize Contrast Limited Adaptive Histogram Equalization (CLAHE).

Keywords – Adaptive Histogram Equalization, Brightness-Preserving Bi-Histogram Equalization, Contrast-Limited Adaptive Histogram Equalization.

I. INTRODUCTION

The distinct physical and chemical characteristics of underwater environments introduce challenges not typically encountered in terrestrial imaging,

significantly impacting the quality of underwater photographs. Because red, green, and blue light attenuate at different rates, underwater images often display a color cast, such as a green or blue tint. Additionally, suspended particles absorb most of the light energy, causing scattering before it reaches the camera. This results in images that appear blurry, low in contrast, and hazy.

To counteract these issues, artificial light sources are commonly used to extend the reach of underwater imaging. However, these sources are also subject to absorption and scattering, leading to uneven illumination—creating bright spots at the center while leaving the edges poorly lit. Additional challenges include shadowing and other forms of image degradation.

Enhancing underwater images requires effective techniques for color correction, clarity improvement, and mitigation of blurring and background scattering. Achieving these objectives necessitates sophisticated image enhancement and restoration algorithms capable of addressing the complex challenges posed by underwater conditions, including water turbidity, light absorption, and scattering.

In this study, we provide a comprehensive analysis, an experimental comparison of key techniques, and a discussion on current and emerging challenges in the field. It is important to highlight that the algorithms we examine are specifically designed to enhance the quality of individual underwater images.

Our research contributes to improving underwater image quality in several ways. In 2017, Liu et al. introduced the Deep Sparse Non-negative Matrix Factorization (DSNMF) method for maintaining color constancy in underwater images. This technique estimates illumination by dividing images into smaller blocks, reconstructing each channel as an [R, G, B] matrix, and applying a sparsity constraint to separate the depth of each input matrix into multiple layers. The final layer of the factorization matrix represents the lighting information for each patch, enabling modifications based on these constraints. As a result, DSNMF enhances image quality by estimating local block illumination.

In May 2015, Charanjeet Kaur and Rachna Rajput highlighted the limitations of traditional histogram equalization, which applies a uniform transformation to all pixels based on the image histogram. While effective for images with a uniform pixel distribution, this approach struggles to enhance contrast in areas that are significantly darker or lighter than the rest of the image. Their research aimed to improve underwater image contrast while preserving brightness.

Similarly, DITHEE DEV K and S. Natrajan (April 2015) demonstrated that Contrast Limited Adaptive Histogram Equalization (CLAHE) is highly effective in enhancing underwater images. This technique involves computing the dark channel of the input image and processing it through image segmentation. If artificial lighting affects the image, it is removed before applying CLAHE. Experimental results indicate that this method significantly enhances visual quality by increasing contrast and reducing noise and artifacts.

II. LITERATURE SURVEY

Beer's Law is used to measure the light absorption of red, green, and blue color channels in water, allowing for the reconstruction of scene intensity values [8], [9]. This method assumes a uniform depth for all objects in the scene, using depth as its primary input to account for light absorption at each wavelength corresponding to the RGB channels. The effectiveness of this approach depends heavily on the accuracy of the calibration parameters used when estimating absorption levels.

However, a major drawback of this method is its assumption that the underwater medium is uniform and that all elements in the scene are at the same depth. In reality, variations in depth, salinity, water composition, and temperature require recalibration for each image. These environmental factors significantly impact image correction, making frequent adjustments necessary.

Statistical methods often rely on prior data for image correction. One such approach involves using a robot to adjust color by utilizing the full spectrum of light in a transparent medium [10], [11]. However, due to high energy consumption, the light cannot remain on continuously. Instead, the robot periodically pauses to capture still reference images, which helps improve color accuracy. Based on the assumption that neighboring frames are similar, a Markov Random Field (MRF) is then trained using these reference images to enhance the image on a pixel-by-pixel basis. Despite its accuracy, this method is computationally demanding; in 2005, processing a 400×300-pixel image on a standard PC took approximately 40 seconds [11].

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 $I_R(i,j)$, $I_G(i,j)$, and $I_B(i,j)$ represent the red, green, and blue components of an RGB image with dimensions $M \times N$ pixels, where $i = 1, \dots, M$ and $j = 1, \dots, N$. The maximum pixel values for each color component, R_{\max} , G_{\max} , and B_{\max} , are then calculated [15]:

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

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

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

In the initial step, the dominant color cast channel is identified using the equations above. Afterward, the average values for each color component, R_{avg} , G_{avg} , and B_{avg} , 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.

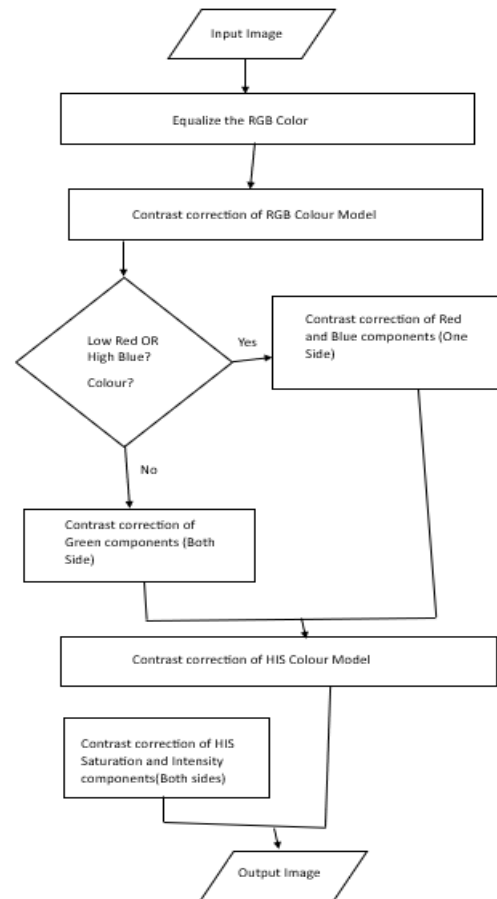


Figure 2: Flowchart of proposed UCM Algorithm

B. Contrast Correction of RGB Colour Model

- Low contrast can make an image appear unclear and difficult to interpret. To address this, the second step in the proposed method involves applying a contrast correction technique to enhance the image. This process stretches the intensity values to span the desired range. Before applying contrast correction, the upper and lower limits of each color band are determined. In an 8-bit color channel, values typically range from 0 to 255.
- A common normalization technique identifies the minimum and maximum pixel values in the histogram and adjusts them to fit within the specified range. However, a significant drawback of this method is its sensitivity to outlier pixels with extremely high or low values, which can distort the image and result in inaccurate scaling.
- To mitigate this issue, a small percentage of pixel values from both extremes of the histogram can be clipped. The proposed approach addresses this problem by generating a histogram and setting the 0.2% and 99.8% percentiles as thresholds. By disregarding pixel values outside this range and applying contrast correction only to those within it, the method enhances the image while preventing distortions, as illustrated in Figure 2.

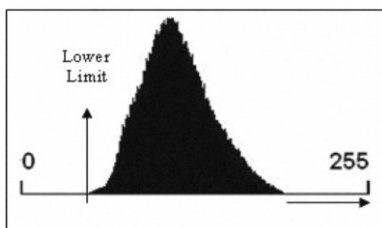


Figure 3: Contrast Correction Method [19]

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:

- P_o represents the contrast-corrected pixel value;
- P_i 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.

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

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



Figure 4: 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.

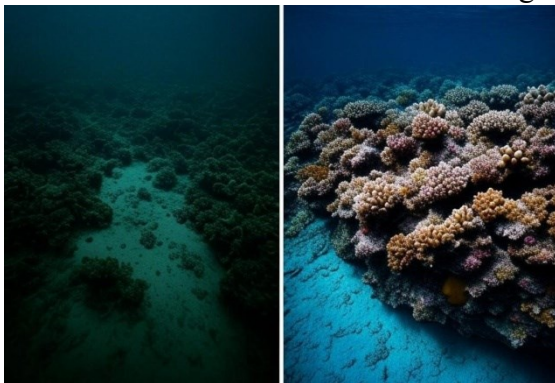


Figure 5: Eliminating Non-Essential Features of Image.

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.

Removal:

Figure 7: 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.

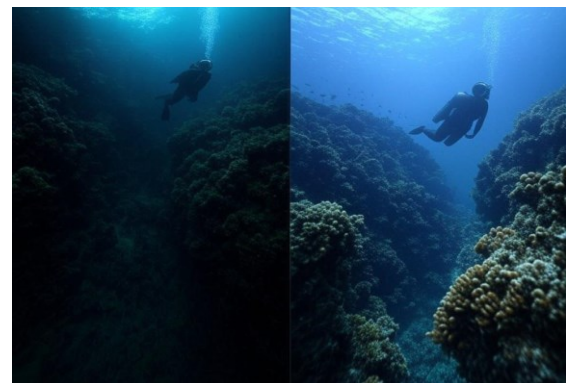


Figure 6: Reducing Noise in the Image.

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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