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An Efficient Preprocessing Methodology for Enhancing Images Captured Underwater

Faizan Shabir[1] and A.A. Mir[2]

[1]*Department of Electronics and Communication*
NIT, Srinagar, India
[2]*Department of Electronics and Communication*
NIT, Srinagar, India
E-mail: [1]zaan1234@gmail.com, [2]aamir@nitsri.net

Abstract—*Underwater images are primarily degraded due to attenuation of light as it travels under water and suffer from issues like noise, improper illumination, single color dominance and low contrast. Due to these issues detection and recognition of underwater images becomes difficult. So, preprocessing of these images becomes essential in order to tackle these issues and produce an enhanced image that can be used for further processing.*

To solve this problem, an efficient preprocessing methodology for underwater image enhancement is proposed. The methodology works in a sequence and begins with noise removal by wavelet denoising, improper illumination correction by homomorphic filtering, color correction by Gray World (GW) algorithm and Equalization of RGB colors, and finally contrast enhancement by the conventional Contrast stretching and Contrast Limited Adaptive Histogram Equalization (CLAHE) on different color spaces. The implementation results show that the proposed methodology improves the quality of underwater images efficiently and produces better quantitative scores when compared to some existing methods.

Keywords*: Wavelet Denoising, Histogram Equalization Color Balancing, Gray World, ROV, AUV, HSV, LAB.*

1. Introduction

Underwater imaging is an unexplored area and has gained importance in the recent years, due to its increased usage in naval and civilian applications. Continuous monitoring of the sea bed is needed, often in the case of coral reef surveys, marine species counting and monitoring, pipeline maintenance, underwater mines, shipwrecks, etc. The census of marine life in 2010 shows that 230,000 rare species are available in oceans, roughly 750,000 are yet to be discovered. The reason is the limited visibility under water and that the sea bed can be reached only after traveling thousands of meters under water. In the recent years (ROV) Remotely Operated Vehicles/ Autonomous Underwater Vehicles (AUV) with inbuilt cameras are used for capturing images deep under the sea.

Underwater image processing is challenging task due to its poor lighting conditions. In normal atmospheric conditions, as light illuminates on an object, based on the light's wavelength, an appropriate color gets reflected. But in case of underwater scene, red color disappears in 3m, followed by orange, yellow and green .Blue color can travel longer than other colors, due to its diminished wavelength and hence underwater images often appear in blue. After 100 m, images appear totally dark and artificial lights are needed. Artificial light attached to the underwater vehicles also leave an imprint of light when capturing images.

The major reason for poor quality images is attenuation and scattering of light. Beer Lambert's Law states that as the distance of the camera to the object of interest increases, the image quality decreases due to the attenuation and scattering of photons in water. In a nut shell, the challenges faced by underwater images are: Reduced lighting/improper illumination. Noise, Color dominance (haziness), Poor contrast. Huge volumes of image data is being captured every day with the help of ROVs and classifying objects in such images has now become challenging. Marine scientists require automated object recognition tools based on image processing techniques. This is because, manual classification is expensive and time consuming. Many image processing techniques are available for real world object classification. But those techniques, might not suit underwater images due to their poor quality. Hence, to achieve a better classification accuracy these images need to be preprocessed before using them for computer vision applications such as object recognition / detection, segmentation etc.

In contrast, this paper introduces an efficient preprocessing methodology that takes care of all the problems faced by underwater images in a sequential manner step by step. These include noise, improper illumination, color correction and contrast enhancement.

The rest of the paper is organized in the following manner, section 2 describes the proposed methodology for enhancement, in section 3 results are discussed and finally the paper is concluded in section 4.

2. PROPOSED METHODOLOGY

In this section, we describe our proposed approach, an efficient preprocessing methodology, which can perform underwater image enhancement. Our proposed approach is based on the following four stages.

A. Noise removal.

B. Improper illumination correction.

C. Contrast correction

D. Color cast removal.

As illustrated in Figure 1.The methodology for underwater image enhancement works in steps, and at each step it addresses a problem faced by the underwater image and attempts to correct it, after correction it moves to next step and the process continues till all the steps are complete. The process begins with noise removal followed improper illumination correction, the third step constitutes color correction and finally contrast enhancement is done and an enhanced image is produced as output.

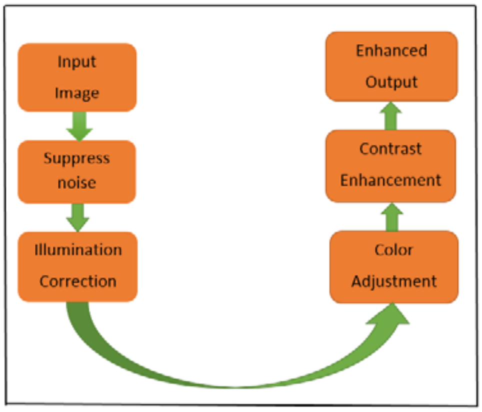

Figure 1: Methodology for Underwater Image Enhancement

2.1. Noise Removal

Image noise may be defined as an undesirable change that occurs in the image pixels. This is usually caused due to the faults that occur during image acquisition and as a result pixels do not represent correct values of the captured scene. While removing the noise, the structures and features of the image must be preserved.

For noise removal we use wavelet denoising as it performs better than other denoising methods such as wiener filter and median filter in terms of PSNR. Wavelet transformation is useful for image processing because it has the capacity of representing the signal's local characteristics in the spatial and temporal domains. Wavelet denoising identifies signals that match from the actual space to wavelet function space in order to get the best restoration of the original signal. Noise commonly manifests itself as fine grained texture in the signal.. A simple filter can be used for eliminating these coefficients and obtaining the original signal on the basis of scale. Since wavelet coefficients can carry edge information at the same scale, a threshold can be set to discard the wavelet coefficients, if their values are below a threshold. These coefficients mostly will correspond to noise, as edge related coefficients of the signal usually have higher threshold values. Since hard thresholding is a keep or kill procedure, it might lose certain signal information, and hence soft thresholding is preferred. Generally, noise is of a lower magnitude and a threshold is introduced such that if the value of coefficients is below the threshold it is taken as noise above it is taken as edge. Wavelet thresholding is performed only on the detail coefficients rather than the approximation coefficients as it contains more important information of the image. Low-Low (LL) region (detail coefficients) of the image represents the significant information compared to other approximation regions namely High-Low (HL), Low-High (LH) and High-High (HH). Therefore, thresholding retains all the significant coefficients greater than a threshold (λ) and eliminates the coefficients less than the threshold considering it as noise. When this kind of hard thresholding is employed it will cause loss of information [**1**].so we have used soft thresholding in order to preserve details.

2.2. Improper Illumination Correction

Illumination problems are caused in underwater images as light attenuates as it travels underwater, and images appear usually dark or improperly illuminated in case an artificial light source is used.

Illumination of an underwater image can be corrected by adding more high frequency elements and reducing the low frequency elements, as low frequency elements represent typically the illumination of the object and high frequency elements represent the object's features typically reflectance components. A high pass filter achieves this by controlling low frequency elements and increasing high frequency components. For improper illumination correction we have used homomorphic filtering.

2.2.1. Homomorphic filtering. Homomorphic filter is a technique that can separate the illumination and reflectance components using log function and process them in frequency domain to achieve an illumination corrected image. Considering the image formation model this filter assumes that, consistent variations in the image corresponds to the illumination component, i.e., low frequencies of an image and abrupt variations in the image corresponds to the reflectance component i.e., high frequencies of an image and is represented as

$$f(x,y) = i(x,y)r(x,y)$$

Where $i(x,y)$ is the illumination component, and $r(x,y)$is the reflectance component. To dynamically improve the intensities of the image, the pixels representing the illumination component $i(x, y)$must be compressed and the pixels representing the reflectance component $r(x, y)$should be amplified. Since Fourier transform cannot be directly applied on the image components, logarithm function is applied to separate illumination and reflectance components [2].

$$g(x, y) = \ln (i(x, y)) + \ln (r(x, y))$$

Followed by Fourier transform on the above equation results in

$$F\{g(x, y)\} = G(u, v) = \mathrm{I}i(i(u, v)) + \mathrm{R}i\ (r(u, v))$$

At last, homomorphic filtering is used for shrinking low frequencies and also enhance the medium and high frequencies.

$$S(u, v) = H(u, v)G(u, v)$$

Where

$$H(u, v) = \frac{1}{1 + e^{-s(\sqrt{u^2+v^2-\omega_0}}} + \mathrm{p}$$

Where ω0 is the corner frequency, s controls the sharpness of the slope and p is an offset term [3].

2.3. Color Cast Correction

Underwater images experience non-uniform color cast as light gets absorbed while propagating in water Color cast depends on the amount attenuation. Different wavelengths of light which include (blue, green, and red) will penetrate water in different degrees, not only the amount of light gets reduces with depth but also the colors disappear one after another depending upon the wavelength of the color. First among the all red color disappears followed by orange, yellow and purple, while colors like green and blue have smaller wavelengths and are able to penetrate deeper so, most underwater images are usually dominated by bluish-green color. Since the colors of underwater images are difficult to recover, conventional color correction algorithms may fail to restore colors. So we have used the following algorithms.

2.3.1. Gray World Algorithm. The first method used is the gray world assumption, which assumes that the average reflectance of a scene is achromatic. In other words, the mean of the red (*R*), green (*G*), and blue (*B*) channels in a given scene should be roughly equal.. Algorithmically, as stated above we can adjust a gain factor to two of the channels so that both their means are now equal to the reference channel, which is often taken to be green. We denote a full-color image of size nxn as *RGB*(*x*, *y*), where *x* and *y* denote the indices of the pixel position. The individual red, green, and blue color components are then *R*(*x*, *y*), G(*x*, *y*), and *B*(*x*, *y*), respectively.

We compute

$$R_{avg} = \frac{1}{n^2} \sum_{y=1}^{n} \sum_{x=1}^{n}\ R(x, y)$$

$$G_{avg} = \frac{1}{n^2} \sum_{y=1}^{n} \sum_{x=1}^{n}\ G(x, y)$$

$$B_{avg} = \frac{1}{n^2} \sum_{y=1}^{n} \sum_{x=1}^{n}\ B(x, y)$$

If all of these values are identical, then the image already satisfies the gray world assumption and no further adjustment is necessary. In general, they may not be. We then compute the gain for the red and blue channels as α and β, where

$\alpha = \frac{Gavg}{Ravg}$ and $\beta = \frac{Gavg}{Bavg}$

The corrected image is formed with *R'*(*x*, *y*), *G'* (*x*, *y*), and *B'*(*x*, *y*), where

$$R'(x, y) = \alpha . R(x, y)$$

$$G'(x, y) = G(x, y)$$

$$B'(x, y) = \beta . B(x, y)$$

This gray world method is quite effective in practice with some exceptions but works quite fairly with the underwater images [4].

2.3.2. Equalization of RGB colors. To achieve a good quality image requires the equal color values of the RGB components. So we have proposed a method which is the modification of the method suggested by Iqbal et al. [4]. Iqbal et al. [4] assumes that images are affected only by blue color cast and attempts to equalize the remaining color channels keeping the blue channel constant. But in practical we have observed the images may also be affected by green color cast instead of blue .So we first check for the dominant color channel and then perform the equalization accordingly by keeping the dominant channel constant. In order to equalize the RGB value, the first step is to calculate the maximum values.

Let $I_R(i, j)$, $I_G(i, j)$ and $I_B(i, j)$ be respectively the red, green and blue components of an RGB image of size M x N pixels, Where i = 1... M; j = 1 ...N. The maximum pixel values of each color component, $R_{\max}$, $B_{\max}$ and $G_{\max}$ are calculated [4]

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

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

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

In the first step, the prominent color cast channel is found using the above equations. Then the average values of each color component R_{avg} , G_{avg} and B_{avg} are calculated [d]

$R_{avg}=\frac{1}{MXN}\sum_{y=1}^{n}\sum_{x=1}^{n} I_R(i,j)$

$G_{avg}=\frac{1}{MXN}\sum_{y=1}^{n}\sum_{x=1}^{n} I_G(i,j)$

$B_{avg}=\frac{1}{MXN}\sum_{y=1}^{n}\sum_{x=1}^{n} I_B(i,j)$

This method keeps the dominant color cast channel same as it was. While high values are used to increase other colors present to make the image balanced. On the basis of dominant color cast, two gain factors are calculated as shown by the following equations.

If the dominant color is mostly blue then gain factors are calculated as

A= $\frac{B_{avg}}{R_{avg}}$ and B= $\frac{B_{avg}}{G_{avg}}$

While if the dominant color is mostly green then the gain factors are calculated as

A= $\frac{G_{avg}}{R_{avg}}$ and B= $\frac{G_{avg}}{B_{avg}}$

The dominant color channel is set as the target mean and other two color channels are multiplied with a multiplier

to produce a balanced image. The proposed method operates on two color channels to correct the color cast of the image. The values are adjusted according to Von Kries hypothesis [5] as given below:

R'= A x R

G'= B x G

Where R and G are original pixels values in the image and R' and G' are the adjusted pixel values. The process is explained by a flowchart.

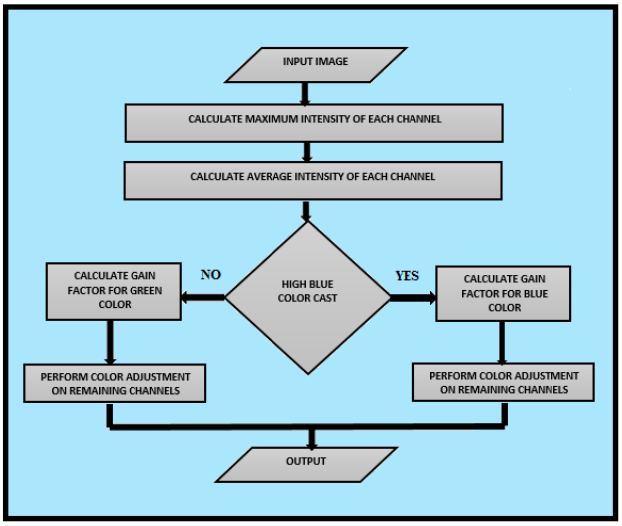

Figure 2:.Flowchart for equalizing RGB colors.

2.4. Contrast Enhancement

As a natural phenomenon, underwater images have low contrast even after color correction, underwater images will still look hazy since the condition underwater is similar to a hazy environment [5]. Contrast should therefore be enhanced in order to highlight objects and details. For contrast enhancement we used two prominent techniques namely Contrast Limited Adaptive Histogram Equalization (CLAHE) and Contrast stretching.

2.4.1. CLAHE. It limits the amplification by clipping the histogram at a certain point known as clip limit. The clip limit determines how much noise in the histogram should be smoothed and hence how much the contrast should be enhanced. In CLAHE an image is partitioned into small data regions, and then equalization is done to each of these regions. These regions are then concatenated by interpolation .This makes the distribution of used gray values even and thus improves the visibility of the image so we can see the hidden features of the image. The CLAHE equation is given by:

$$g = (g_{max} - g_{min}) \ * P(f) - g_{min}$$

Where g is the pixel value, $gmin \ and \ gmax$ are the minimum and maximum pixel values, $p(f)$ is cumulative probability distribution [6]. The procedure adopted for CLAHE operation is shown in Figure 3.

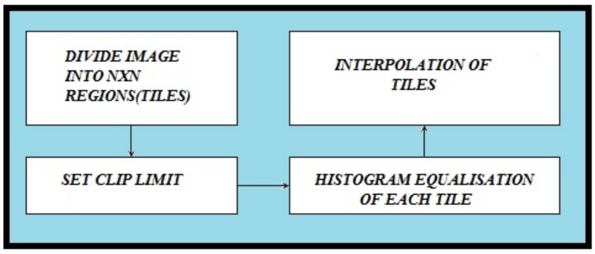

Figure 3: Sequence of Operations in CLAHE

In order to enhance underwater images CLAHE is operated on two different color spaces i.e. HSV color space and LAB color space as the representation of colors in RGB color space is designed for specific display devices and not for human observers. CLAHE on HSV color space: HSV (hue, saturation, value) are alternative representations of the RGB color model, more closely aligns with the way human vision perceives color-making attributes. The HSV representation models the way paints of different colors mix together, with the saturation dimension resembling various shades of brightly colored paint, and the value dimension resembling the mixture of those paints with varying amounts of black or white paint. CLAHE is applied on V and S components.

CLAHE on LAB color space*:* It expresses color as three values: L* for the lightness from black (0) to white (100), a* from green (-) to red (+), and b* from blue (-) to yellow (+). LAB was designed so that the same amount of numerical change in these values corresponds to roughly the same amount of visually perceived change. CLAHE is applied on L channel only. [6]

2.4.2. Contrast stretching. (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, *e.g.* the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the `enhancement' is less harsh. Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example for 8-bit gray level images the lower and upper limits might be 0 and 255. Call the lower and the upper limits a and b respectively. The simplest sort of normalization then scans the image to find the lowest and highest pixel values currently present in the image. Call these c and d. Then each pixel P is scaled using the following function:

$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a$$

Values below 0 are set to 0 and values about 255 are set to 255.In case of color images all the channels will be stretched using the same offset and scaling in order to preserve the correct color ratios [3].

3. RESULTS AND DISCUSSION

The hazy underwater images available for download at [7] are used for enhancement using proposed method. Five images are chosen for evaluation of the proposed method. To evaluate the method quantitatively, four performance metrics are used that include: Root Mean Squared Error (RMSE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Patch based Contrast Quality Index (PCQI) [8]. Generally, MSE and PSNR are utilized in determining image noise. The lower value of MSE and higher value of PSNR values indicates less noise. SSIM measures the impact of three characteristics of an image indicates a high value indicates better result of enhancement. Wang et al. [8] proposed PCQI, and the higher PCQI means that the image has better contrast. TABLE I shows the Average MSE, PSNR, SSIM and PCQI values of enhanced images for different combinations. As we see that the combination of our proposed RGB color balancing with contrast stretching performs better in terms of the metrics used for assessment of quality The comparison of initial and the final enhanced images for RGB color balancing with contrast stretching is shown in Figure. 4. From the results, it can be analyzed that the color, contrast and visibility of the hazy images are enhanced.

TABLE 1: The Average PSNR, SSIM, MSE and PCQI values for set of five images under different combinations.

Method	PSNR	SSIM	RMSE	PCQI
Gray World, CLAHE on HSV	18.163	0.799	0.487	0.998
Gray World, Contrast Stretching,	17.645	0.845	0.017	0.998
RGB Color Balancing, Contrast Stretching	18.706	0.882	.0143	0.999
RGB Color Balancing, CLAHE on HSV	12.67	0.786	.0285	0.998
RGB Color Balancing, CLAHE on Lab	16.171	0.772	0.3114	0.997
Gray World, CLAHE on Lab	18.811	0.806	0.0145	0.998

Figure.4: The comparison of initial and the final enhanced images for RGB color balancing with contrast stretching

4. CONCLUSION

In this paper, an efficient preprocessing methodology has been developed after comparing results for various combinations. It was observed that the combination which includes our proposed RGB color balancing and contrast stretching performs better as compared to other combinations .The initial steps for noise removal and improper illumination correction being same for all combinations. This methodology can enhance underwater images efficiently and these images can directly be used for various computer vision related applications such as object recognition and detection.

REFERENCES

[1] K. Srividhya, M. M. Ramya Performance analysis of preprocessing filters for underwater images In *Robotics, Automation, Control and Embedded Systems (RACE),2015 at the International Conference on... IEEE, 1-7.*

[2] Garcia, Rafael, Tudor Nicosevici, and Xevi Cufi. (2002). "On the way to solve lighting problems in underwater imaging." In OCEANS'02 MTS/IEEE, 2: 1018-1024.

[3] S. Bazeille, I. Quidu, and L. Jaulin. (2006). "Automatic Underwater Image Pre-Processing," *Proceedings of CMM'06*.

[4] Kashif Iqbal, Rosalina Abdul Salam, Azam Osman and Abdullahh Zawawi Talib "Underwater Image Enhancement Using An Integrated Colour Model." IAENG *International Journal of Computer Science 34*.2 (2007): 239-244.

[5] Chong, Hamilton Y., Steven J. Gortler and Todd E. Zickler. "The von Kries Hypothesis and a Basis for Color Constancy." *2007 IEEE 11th International Conference on Computer Vision* (2007): 1-8.

[6] Priyanka P.Mukharjee. *Journal for Research in Applied Science & Engineering Technology (IJRASET)* ISSN: 2321-9653; Volume 5 Issue VIII, August 2017

[7].H.Lu,"Underwater Image Dataset." [Online]. Available:https://sites.google.com/site/kyutech8luhuimin/underwater_image_datasets. [Accessed: 01-may-2019].

[8] S. Wang, K. Ma, H. Yeganeh, Z. Wang, and W. Lin, "A patch structure representation method for quality assessment of contrast changed images," *IEEE Signal Process. Lett. vol. 22, no. 12,* pp. 2387–2390, Dec. 2015.

[9] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer and P. Bekaert, "Color Balance and Fusion for Underwater Image Enhancement," in *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 379-393, Jan. 2018.

[10] X. Ding, Y. Wang, J. Zhang and X. Fu, "Underwater image dehaze using scene depth estimation with adaptive color correction," *OCEANS 2017 - Aberdeen*, Aberdeen, 2017,pp.1-5.doi:10.1109/OCEANSE.2017.8084665