ADVANCING UNDERWATER IMAGE ENHANCEMENT THROUGH FUSION TECHNIQUE

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ABSTRACT
Enhancing images poses a lot of challenging areas, such as low-light image enhancement, deraining, dehazing, deghosting, and many more. One of the challenging areas is enhancing images from underwater conditions. This type of enhancement itself has a lot of challenges. The underwater images have low contrast and sustain haziness. Wavelength absorption can cause a significant color deviation in captured images. Due to technological breakthroughs enhancing underwater images has gained much popularity and importance in the past few decades. Although tedious, enhancing an underwater image is important in scientific exploration and computational applications. Hence, removing haze and color casting in underwater images is the primary step for many computer vision tasks. Considering all the shortcomings, like limited visibility, non-uniform illumination, and diminished contrast, an underwater image enhancement algorithm based on the fusion principle is proposed. It focuses on two color-balanced input images compared to the source underwater image. Four weight maps are used to gain the details of the distant objects degraded due to scattering and absorption. After extensive experiments, the simulation result shows that our proposed approach performs superior to the state-ofthe- art methods.

Index Terms – Scattering illumination, color balance, contrast enhancement, fusion.

1. INTRODUCTION

A large part of our earth's surface is covered by the ocean, and those water resources govern the health of our planet. Research into ocean habitats is a critical component of marine science. Underwater surveys are required in various scientific studies like archaeology and geology [1], underwater environmental assessment [2], gas pipelines, and fiber optics line laying to connect landmasses [3]. Another study that is done underwater is the tracking of ancient ship wreckages. Besides all these, underwater vision is another application used in underwater photography, ocean basement mapping, marine biology, submerged robots, nuclear reactor, and mine detection. Thus, underwater imaging has gained importance and has become a challenging area in research. Limited parts of Earth's ocean have been explored till now. This is because the poor vision and the sea bed can only be reached after hundreds of meters underwater. Several kinds of ocean science research have been done worldwide in recent years with the help of Remotely Operated Vehicles/ Autonomous Underwater Vehicles (ROV/AUV) deep under the sea [4]. ROVs acquire massive amounts of image data every day. Almost every time, the specifications, like the color and contrast of the images taken, vary with the medium's initial conditions [5].

Fig. 1: Degraded image in the left vs our enhanced image in the right

Depending on the wavelength of the light, an appropriate color is reflected when it hits an object in normal atmospheric conditions. Color cast is found due to this reason. Two main factors are responsible for the light attenuation process: 1) absorption and 2) scattering. Light absorption is the absorption resulting in reduced light energy, whereas light scattering pertains to the deflection of the trajectory of light from its initial course. These phenomena arise due to the arrangement of the aqueous medium itself and supplementary constituents such as dispersed biological detritus or diminutive non-soluble suspended particles. Water's absorption of light exhibits its distinctive features for various wavelengths of light. Water's density is 800 times more than air's, making it denser. As the depth of water increases, the energy of light decreases.

In the meantime, a water particle has the ability to assimilate a certain amount of light energy. Color is determined by the wavelength of light; as wavelengths become shorter, color diminishes. At 40 meters, water absorbs nearly all the red visible light. However, because of the shorter wavelength, blue light can still penetrate beyond these depths, causing a bluish appearance in underwater images. As a result of this phenomenon, the original color of any object under water is impacted. There are two forms of scattering: 1) forward scattering and 2) backward scattering. The light randomly deviated while traveling from an object to the capturing device (e.g., camera) is called " forward scattering." This effect usually results in the blurring of an image feature. Conversely, Backward scattering represents a portion of the light projected onto the water surface that is rebounded by the water in the direction of the imaging apparatus before reaching the objects within the scene. Backward scattering typically hides the object scene and reduces image contrast.

Another issue arises from the widespread use of artificial lighting for underwater photography, which creates vignetting in obtained photographs. The flickering effect exists during sunshine days. These include limited visibility, blurring, non-uniform lighting, noise, low contrast, floating particles, bright artifacts, and diminishing true color [6]. Therefore, image processing applications are necessary to restore details and reduce underwater image problems.

The paper is arranged in an ensuing manner; Section 2 elaborates on the literature associated with the methodologies utilized for enhancing underwater Images. Section 3 gives an insight into the methodology used and explains the proposed work in more detail. It is followed by section 4, which shows our simulation and results. At last, section 5 shows the concluding remarks following future works in section 6.

2. RELATED WORKS

Considering the issues mentioned above, there has been various hardware and software-based methods have been adopted by researchers to enhance underwater images. A superior-grade camera equipped with a topnotch resolution lens is an exemplary hardware-based, highly expensive solution. So, the researchers show interest in software-based solutions that include various feature extraction and enhancement methods such as scale-invariant feature transform, polarization effect, dehazing, contrast enhancement, the fusion of images, etc. [2, 7‐10].

Iqbal et al. [2] used an Integrated color model to improve underwater images' low illumination and contrast. Hitam et al. [8] employed Adaptive Histogram Equalization to enhance underwater images by Enhancing contrast and removing noise and artifacts. By employing the compensation and image dehazing (WCID) technique, Chiang et al. [9] could eliminate haze from underwater images and increase their quality. A fusionbased method was proposed by Ancuti et al. [10] to enhance the underwater images. The original underwater image undergoes color correction and contrast enhancement, along with applying four weight maps that enhance the visibility of objects far from capturing devices.

Petit et al. [11] used geometric quaternions transformation and principal component analysis to adjust pixel colors and improve contrast. Andono et al. [12] applied Contrast Limited Adaptive Histogram image Equalization (CLAHE) preprocessing to improve image registration success. Ghani et al. [13] modified the image histogram in both RGB and HSV color models to increase contrast and reduce noise. Singh et al. [14] proposed a fusion-based technique that uses contrast stretching and Auto White Balance to enhance contrast and color without producing a greenish or bluish effect.

3. METHODOLOGY

The proposed algorithm endeavors to rehabilitate the chromaticity and perceptibility of a deteriorated image by utilizing two inputs derived from the same image. The primary input concerns color equilibrium to eradicate any chromatic casts, while the second input amplifies low-contrast areas through contrast-based limited histogram equalization. To compute these inputs, weight maps such as Laplacian, Luminance, Saliency, and exposedness are utilized and normalized to prevent any artifacts. The resulting images from both inputs are then amalgamated to form a solitary, fused image.

The fundamental characteristics of these derived inputs are calculated utilizing diverse weight maps. The weight maps obtained in the proposed model include Laplacian, Luminance, Saliency, and Exposedness. To prevent any distortions, the weight maps are normalized. Once the weight maps have been normalized, the resulting images are fused to create a solitary image.

3.1. Color Balance

Color balance is the global adjustment of the intensities of the colors. It removes additional and unrealistic color casts, a tint of a particular color produced by the underwater environment due to scattering and wavelength selective absorption. To remove these effects, a Simple color balance method is adopted.

The simplest Color Balance algorithm works to saturate a specific percentage of bright pixels to white and dark pixels to the black of the input image. Changing the saturation level will improve the output quality. 0.01 and lower values are considered to be typical [15].

1. For each RGB channel, create a histogram and find the quantiles that correlate to the required saturation level.

2. Remove the outlying values by saturating a particular percentage of the pixels to black and white.

3. Scale the saturated histogram to cover the entire 0 – 255 range.

3.2. Contrast Enhancement

CLAHE, or contrast-limited adaptive histogram equalization [16], is an adaptive histogram equalization enhancement method that limits contrast amplification to reduce noise amplification. It is preferable to redistribute the histogram component that exceeds the clip limit evenly among all histogram bins rather than discarding it. The contrast transform function of each tile is calculated independently by CLAHE. The contrast of each tile is increased until the histogram of the output region resembles. The nearby tiles are then blended to remove and bounries produced artificially. The contrast might be limited to avoid exaggerating any noise in the image, especially in homogeneous areas.

3.3. Weight Maps

To re-create the original image, we’ re looking into weight maps. Final fused results are greatly influenced by weight maps. The generated weight maps must have a positive value. The weight maps serve as quantifiable indicators of the input image and epitomize the proposed multi-scale fusion technique that encapsulates the minutest intricacies of the image [17].

Weight maps based on the laplacian Contrast, luminance, saliency, and exposedness are used to measure and extract information from the input image. We can then get more accurate results by integrating the images together.

3.3.1. Luminance Weight

Typically, the deteriorated input image appears dull, and the luminance weight map regulates the luminance amplification of the eventual result. The luminance weight value is determined by the variance between each R, G, and B color channel and the input luminance channel (L). It generates elevated values corresponding to the extent of conservation in each input area. Multiscale blending enables a smooth and uninterrupted transition between the inputs, despite the possibility of this map amplifying the deteriorated input [18]. Nevertheless, this map diminishes the overall contrast.

3.3.2. Laplacian Contrast Weight

The Laplacian contrast weight method calculates the absolute magnitude of a Laplacian filter applied to every input luminance channel to evaluate the overall contrast. This simple metric assigns significant values to edges and texture, making it useful in various applications such as tone mapping and enhancing the depth of field [19].

3.3.3. Saliency Weight

The saliency weight approach accentuates the distinguishing objects that become indistinct in underwater scenes, and this quality is measured by Achanta et al. [20]. The algorithm is characterized by computational efficiency and simplicity, grounded on the biological principle of center-surround contrast. Meanwhile, it prioritizes the most conspicuous regions. To enhance the accuracy of the output, the exposedness weight map is employed as an additional weight map.

3.3.4. Exposedness Weight

Exposedness weight determines the degree to which a pixel has been properly exposed. This evaluated quality allows an estimator to maintain a uniform appearance of the local contrast, which should be neither overstated nor undervalued. Usually, it is considered that if a pixel' s normalized value is closer to the average value of 0.5, it appears more exposed. Distance to the average normalized range value (0.5) is expressed as a Gaussian modeled distance:

$$W_E = exp(-\frac{(I^K(x,y) - 0.5)^2}{2\sigma^2}) \qquad (1)$$

Pixel coordinates (x, y) of the image' s input I^K is represented by IK(x, y), and the standard deviation is $\sigma = 0.25$. Here, the tones with a distance close to zero will be assigned greater values by the exposedness weight map, whereas pixels with bigger distances will be associated with over-and underexposed locations, respectively. As a result, this weight tempers the saliency map' s outcome and preserves the fused image' s appearance. To ensure that our results are consistent, we use W values that are normalized (Normalized weight for an input K is computed in the following way: $W^K = W^K / \sum_{K=1}^{K} W^K$) by restricting that the sum of the weight maps W at each pixel location equals one.

3.4. Image Fusion

The amalgamation of pertinent data from a group of pictures into one image, resulting in a more informative and comprehensive fused image than any of the input images, is known as image fusion [3]. This study combines the average weight map value of four weight maps, namely W_{LC},W_L,W_S,&W_E, and the Laplacian pyramid fusion technique is employed to fuse them.

In our study, we executed the Laplacian operator on various scales, disintegrating each input into a pyramid. We have computed a Gaussian pyramid for every normalized weight map (W). We have ensured that the number of levels in the Gaussian and Laplacian pyramids is identical. Fusing the Laplacian inputs and Gaussian normalized weights leads to forming a fused pyramid at each level.

$$R^l(x,y) = \sum_{K=1}^{K} G^l\{\overline{W}^K(x,y)\} L^l\{\overline{I}^K(x,y)\} \qquad (2)$$

Where l = No. of the pyramid levels (l = 5). Gl{W} = Gaussian version of the normalized weight map W. L{I} = Laplacian version of the input I. This step is performed successively in a bottom-up manner for each pyramid layer. Summing the fused contribution of all inputs yields the restored output.

Algorithm 1: Fusion Algorithm

Input: *Raw Underwater image*
Output: *Enhanced underwater image*

1 Select an Input an Underwater Image
2 Color balance the input image using Simplest Color Balance Algorithm to remove the color cast (First Input)
3 Apply CLAHE on the output of Step 2 for Contrast Enhancement (Second Input)
4 Convert both inputs from RGB Colorspace to L*a*b Colorspace, designed to approximate human vision.
5 Calculate the Luminance weight map of the first and second inputs, which evaluates the pixel visibility by assigning low values to low visibility and high values to high-visible regions.
6 Calculate the Laplacian Contrast weight map of the First and second inputs to estimate global contrast.
7 Calculate the Saliency weight map of the First and Second inputs. It emphasizes silent objects that fade away.
8 Calculate the Exposedness weight map of the First and Second inputs to reduce or gain Under- or over-exposed pixels' weight.
9 Calculate the Normalized weight of the First and Second inputs.
10 Find the Gaussian pyramid of normalized weight for Laplacian pyramid fusion.
11 Find the Laplacian pyramid of the Input Images for Laplacian pyramid fusion.
12 Perform fusion.
13 **return** *Enhanced image*

4. SIMULATIONS AND RESULTS

The experiments are carried out in Intel i3 8th gen CPU @ 2.4 GHz, 4 GB RAM with 64-bit Windows 7 Operating system using MATLAB R2016a. For the experiment, the images are taken from other studies with classic underwater pictures. For the assessment of image enhancement, performance metrics are used. Quality parameters like Entropy, underwater image colorfulness measure (UICM), and underwater image contrast measure (UIConM) [23] have been calculated to measure the performance of the proposed method. Entropy is used to evaluate the information content of an image. It represents the information carried out by an enhanced color image. The high value of entropy indicates the high information in the enhanced image. UICM and UIConM metrics are used to evaluate the performance of color correction and contrast. The high value of UICM and UIConM means improved, enhanced image color and contrast. The other works we have considered for the comparisons are the works of H.Y. Yang et al. [21], Fu et al. [22], Kumar et al. [24], and Singh et al. [14].

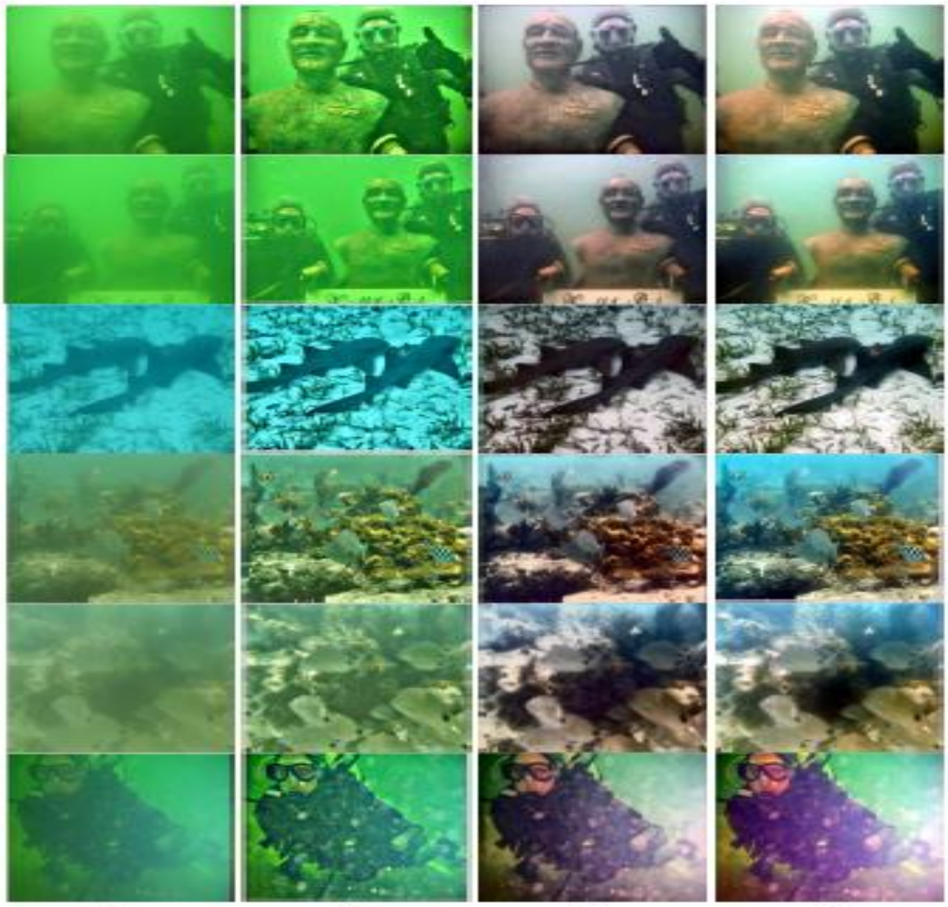

Fig. 2: Results of our fusion method. From left to right-(a) Underwater degraded images, (b) Result from Dark Channel Prior [21], (c) Result from Retinex-based method [22], (d) Proposed method

Table 1: UICM and UICONM Value Of Figure 2

Img No	UICM			UIConM		
	DCP	Retinex Based	Proposed Method	DCP	Retinex Based	Proposed Method
1	0.002	2.45	**3.76**	**6.07**	0.64	0.67
2	-0.003	2.52	**4.27**	**0.71**	0.64	0.66
3	-0.006	1.51	**2.50**	**10.14**	0.89	0.90
4	0.010	5.28	**7.03**	0.74	0.77	**0.79**
5	0.002	3.80	**5.35**	0.77	**0.80**	0.76
6	0.008	3.59	**6.25**	**0.94**	0.66	0.67

Table 2: Quantitative Evaluation In Terms of Entropy

Img No	DCP	Retinex Based	Kumar et.al.	Singh et.al.	Proposed Method
2	7.53	7.74	6.47	7.66	**7.93**
4	7.59	7.84	7.11	7.75	**7.86**
5	7.24	7.79	6.72	7.57	**7.80**
6	7.61	7.94	6.31	7.71	**7.92**

Through visual comparison shown in Figure 2, our work is compared with the abovementioned techniques. In Fu et al.'s [22] work, the authors restored the clarity of the dehazed image, but some darkness is observed, and some details are faded in specific raw images. The visual aspects of the raw image are increased using the DCP method, but when one color channel becomes dominant, it fails. A significant problem with this method is that it cannot remove the color cast. Regarding the results of the proposed method, one can observe that this method can enhance contrast and improve edge details together with natural visibility. Comparatively, the proposed method has ac ieved a higher UICM value than Yang et al. [21] and Fu et al. [22] Through the above analysis, it comes to an end that the color cast has been successfully removed, and the image gets better color than the state of art methods. According to the above, among six images, four images have high UIConM values using the DCP method of Yang et al. [21] In the DCP method, the UICM values are low but high UIConM value. This method couldn't remove the greenish appearance successfully and has high contrast, which shows that it doesn't work for bluish or greenish underwater images. But in the other two images, it removes haziness and has a low UIConM value compared to the retinex-based method of Fu et al. [22] and the proposed multiscale fusion method. The proposed multiscale fusion method has a higher UIConM value than the Retinex-based method. So the output image of the proposed method has high contrast. Here the proposed method overcomes the issue of contrast degradation of underwater images.

Following Singh et al. [14], we take 2,4,5,6 no. Images and compare the Entropy value provided in her paper with the calculated Entropy value of the proposed fusion method and other methods. From the above analysis, the method has a high Entropy value compared to Yang et al. [21], Fu et al. [22], Kumar et al. [24], and Singh et al. [14] The proposed method yields output images with increased information and details compared to other methods, as evidenced by a high entropy value.

5. CONCLUSION

In this paper, we have proposed an innovative image enhancement method, specifically for underwater images, that targets the issues caused by the absorption and scattering of light effects that persist in the aquatic environment. It rectifies the distorted color cast in the case of degraded input images. This algorithm has two components: a general color balance algorithm and an effective multiscale fusion algorithm specially designed for underwater images. Firstly, considering the color balance data, this algorithm adjusts the color distribution of the underwater image to make it look more natural. Second, we can effectively remove the haziness of the underwater image by adopting the multiscale fusion method. The weight maps are aimed at extracting the features of the image. These extracted features are normalized to the input range and combined using a fusion-based strategy. For evaluation purposes, we tried to bring in various underwater images by using available images with haze-like effects and a bluish and greenish appearance. The quantitative analysis used metrics such as UICM, UIConM, and entropy. The results demonstrate that the proposed method provides better details, a natural impression, increased contrast, and improved visibility. Besides, the suggested way is effective against various underwater image datasets.

6. FUTUTEWORKS

Our method's enhanced result can be extended to other vision-related applications like object recognition, identification, and classification for future work. The manual classification is expensive and time-consuming. So automated object recognition tools based on image processing techniques can be developed.

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