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Underwater Image Refinement: Color Distance and Image Formation Model (DIMFM)

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Abstract: Underwater photography is frequently used for research purpose in various domains. Domains caters to archaeology, surveillance of aquatic life movements, oceanic changes leading to alterations in weather and many more. Scientists are eager to investigate the mysterious undersea environment. For underwater surveys, archaeology departments and weather forecasting scientists obtain undersea photos. The underwater imagery however has low vision and contrast due to haze. The elimination of haze could be difficult because it depends on depth information that is unclear. Moreover, it's challenging and complicated to clear the haze so as to enhance the underwater image. According to the investigation, fog removal algorithms currently in use do not take noise reduction approaches into account. Dehazing techniques have a hard time dealing with areas that are unevenly and excessively light. Therefore, it is vital to alter current techniques in order to make them more efficient. This work presents an innovative integrated underwater picture restoration technique. The proposed technique is in line to a pre-determined technique namely Underwater Image Formation Model. The new approach combines Bilateral Filtering, Contrast Limited Adaptive Histogram Equalization and Dark Channel Prior for better results. First, the underwater image undergoes bilateral filtering to eliminate color discrepancies. The improved image is output of the differentiation between forward and background channel. Further, the Contrast Limited Adaptive Histogram Equalizations methodology is used to produce contrast-enhanced images. Experimental results signpost that the proposed novel technique generates superior visual effects compared to other widely used undersea color image quality evaluation techniques.

Index Terms: Image Processing, Dehazing, Light Intensity, Visibility Restoration.

1. Introduction

The topic of underwater photo improvement and restoration has drawn the attention of research scholars in recent years. Submarine images usually have low resolution, blur and color distortion because of dispersion and absorption. The fields of underwater photo enhancement and repair have proven to be difficult. Researchers have presented a variety of methods that might be divided into two groups to produce high-quality photographs. The two options are Picture Enhancement and Image Restoration [4]. The technology for enhancing photographs does not consider the physics model but instead improves the images by using simple image processing methods. The physics concept of how images are formed is the foundation of image restoration technology. Contrast distortion is a problem that this technology struggles to handle well. In this research, the two techniques are integrated and got satisfactory results combining the advantages of each. In this work, a special way to enhance underwater photos via dehazing is described. The important challenges for undersea imaging are scattering and color alteration. Scattering is produced due to substantially thick and suspended particles in murky water. When light travelling through water at different wavelength experiences varying degrees of attenuation, It causes color alteration or color distortion which causes close underwater surroundings to be dominated by a chromatic tone [2]. Haze removal can be harsh and excessive recoil is mostly decided by anonymous depth information. Haze weakens color representation because it makes it difficult to distinguish between different parts of a scene. Therefore, removing haze is a difficult and forward-looking process.

Approaches to deal with photo processing are as:

1. Image preservation deals with restoring the original images that were originally made well before deterioration and salvage damaged photographs. The table for these methods does not contain many well-known parameters and those that are there can have a wide range of values.
2. In the picture-sweetening process, newly visible images are produced using a special image formation technology and qualitative, subjective standards.

Our main contributions are the speedy joint pure mathematics filter based dehazing rule and a brand-new underwater model that is expected to make up for the attenuation difference on the propagation path. Outdoor images show atmospheric particles that contribute to smoke, fog, dust and other sorts of region degradations. An image produced with a different finish has less color visibility and reduced color distinction. The result could be fascinating in a creative setting, so the degradation removal process is required. Weather leads to changes in types and sizes of the particles in the atmosphere [1]. As an illustration, majority of laptop vision algorithms nurtured the idea of considering only contains the scene light in input data, thereby excluding haze from the outcome. A very harmful algorithmic rule will malfunction if this idea doesn't work. Therefore, creating effective techniques for haze removal is a promising field. The applications of this work are advantageous in various fields of underwater image refinement process.

2. Literature Survey

The polarization of light may have a major degrading effect. This paper presents a new picture recovery algorithm with various orientations. A distance map was also created from the scene. It improved the scene's contrast and color correction while roughly tripling the undersea visibility range [1]. The authors claim that integrating color-changing devices improves the quality of underwater images. To equalize color distinction among the photos in support of slide stretching, the authors initially employed distinction pushing in RGB formulas. In a subsequent phase, HSI intensity and saturation stretching are used to further the color verification and fix the lighting problem. The value of quantitative connections can be changed to influence them [2].

Dark channels were suggested as an effective and simple way for improving undersea image quality in this paper. The author suggested a different method for estimating the depth map of an image median filter than the soft matting trick. Color-correcting techniques were implied to improve color contrast for undersea photographs. The suggested method not only decreased computation time but also significantly enhanced underwater images. It allowed for underwater navigation and real-time observation [3].

The paper presents a method based on mode decomposition. It improves underwater images. The intrinsic mode functions of spatial channels combines with different weights to produce a better image. It also creates the impression of an apposite vision with pleasant aspect. The genetic set of rules was altered to automatically estimate weights. The suggested technique has a higher level of interpretability and visibility. The better images contained more obvious details as well as enjoyable and accurate contrast [4].

A novel approach called WCID (Wavelength Compensation and Dehazing) is suggested in this article. A dehazing method corrects for variations in signal attenuation along the line of propagation and the potential presence of light in the image. The calculation of the depth map came first, then the separation of the foreground and backdrop. To determine if an unnatural source of light was used when taking the image, the levels of light in the foreground and background were compared. A dehazing method corrects for variations in signal attenuation along the line of propagation and the potential presence of light in the image. The submarine propagation path was rectified for wavelength attenuation to account for artificial light [5].

An underwater image enhancement method is given in this study [6] that does not depend on ground truth underwater photos and does not require training on synthetic images. The present research is focused on developing a novel domain adaptation framework to enhance underwater images based on transfer learning; it applies the concepts of in-air image dehazing to underwater images. Experiments with different underwater scenes in real life have shown that the proposed method creates visually satisfying results. The author suggests and evaluates a brand-new technique for underwater image dehazing using an enhanced background light estimation [7]. Along with a quadtree subdivision iteration approach, a unique transmission estimation algorithm is also used. By computing a comprehensive score that considers the smoothness and color of each area of the image, the background light is assessed. An original transmission estimation algorithm is employed in addition to the quad-tree subdivision iteration strategy. A CSDRP is recommended to convert a photo from a 3D RGB to a two-dimensional UV color space. Then the transmission map is calculated and utilized for excellent dehazed photographs. It groups the pixels into mount of haze lines and establishing haze-free boundaries. This technique has competitive effects when compared to widely used underwater single-picture dehazing techniques. The [8] method for enhancing underwater photographs described in this research is based on mode decomposition. The intrinsic mode functions with different strengths of spatial channels were combined to form a better image. It gives the sense of a more suited vision with accelerated pleasantness. The genetic set of rules was altered to determine weights automatically. To create a better image, the intrinsic mode functions of spatial channels with various intensities were combined. This creates the impression of a better vision with increased pleasure. The proposed method offers more interpretability and visibility. The more appealing contrast and apparent details were present in the better photos. Deep learning has been suggested as a method for improving submarine images in earlier years [9,10,11,12,13]. Testing pairs of underwater images and the disclosure of recovered images are frequently necessary for the training of deep neural networks. Fog removal techniques are becoming more and more useful in a range of vision applications. The Depth estimation approach was described in [14], and it can be used to improve images in various lighting situations. Because of the complicated picture and the great distance between the object and the water's surface, underwater photos can accept color distortion. Previous techniques for improving images took scene depth into account by using the darkest channel prior to 21 or the preceding with the highest intensity. Due to poor results from water particles and poor lighting, these approaches have considerable limitations. The depth of the underwater picture is overly properly assessed by the proposed method. Tentative results on recovering authentic and artificial underwater images show that the methods offered have better execution than other IFM-based underwater imaging methods. A fusion model based on Adaptive Histogram Equalization (AHE) for a single blurry image was discovered in 2016 [15]. First, an image is processed using the shades-of-Gray color constancy approach and the AHE technique, which results in a white- balanced [15] and contrast image as the output.

These techniques remove color diffraction and improve an image's contrast. Applying the three weight maps to the previously calculated inputs will further eliminate the distortion of the remaining picture regions. Luminance map is employed to balance the saturation level of a picture. High level saturation value is implied to the good appearance section and a modest level saturation range to the remaining component of the image. The saliency map, which portrays a picture that is simple to study and more informative, also demonstrates the distinct characteristics of each pixel. The third one is a chromatic map that addresses the saturation gain of deteriorating images in order to deal with color distortion. Finally, multi-scale fusion is a technique used to combine two or more photos to produce an output image that is more informative [16]. The white balanced and contrast image is transformed into the Laplacian pyramid to produce this result, and the weight maps are transformed into the Gaussian pyramid. These two pyramids are then combined to create a better image. However, in AHE [15], the tendency for noise over augmentation is greater when contrast is being improved. In their 2016 study [17], used a wavelet-based fusion technique to improve the subpar image. Two variants of the image are created from the original using histogram stretching for color correction. For this image, the histogram of an image space was stretched across the entire range and converted from RGB to HSV. Further, apply CLAHE [16] to improve the contrast of the original image. In addition to an appropriate fusing procedure, the wavelet-based fusion algorithm [17] incorporates a number of low-pass and high-pass filters. They are used to remove undesired low as well as high-value frequencies present in an image.

The image smoothness and total haze reduction are not possible with the current fusion process. For improving the image, Garg D. et al. [16] offer Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Percentile methods. The suggested method was used to convert this RGB image to HSV color by first applying the R, G, and B channel components, followed by Hue, Saturation, and Value. In a specific area, CLAHE was used to boost contrast in a picture in order to prevent excessive enhancement. Application of the percentile methodology [16] to a real undersea object. In order to divide the RGB image space into its three components—Red, Green, and Blue—Percentile [16] is used. Finally, for the purpose of enhancing image clarity, these two procedures are integrated. The issues with Adaptive Histogram Equalization (AHE) are handled by the newly presented approach [15]. The suggested technique is used to segment digital images instead of taking them as a whole, as well as eliminate the undesirable portions of the histogram. A white-balanced and multi-scale fusion technique was suggested by Ancuti et al. [6] to improve the accuracy and quality of an image. Color correction is accomplished using the white-balanced technique. Use the white balancing approach to eliminate unwanted color tones from the supplied underwater image.

The white-balanced version of the image was then sharpened and the gamma adjusted. Gamma correction is used to boost the photos' overall contrast and brightness. By using the Gaussian filter, edge sharpening used an unfocused image [16]. The white-balanced image was sharpened and gamma-corrected to create the weight maps. Multi-scale fusion, which is the combining of two or more images, is a technique used to produce output images that are more informative using weight maps that broke down into the Laplacian and Gaussian pyramids after normalization [15]. Following their fusion, the standard for underwater photographs will be visible that is independent of depth, color distortion, camera, and lighting circumstances and provides full information about the image. To improve the underwater image, Qing et al. created an adaptive dehazing system [18]. The suggested approach comprises two tasks: adaptive histogram equalization and adaptive estimation of atmospheric light [18]. Considering the features of the undersea environment, the suggested framework enhances image quality. The feature map can be changed by using the adaptive brightness estimation approach, which also uses the AHE methodology to enhance the underwater image's appearance and reveal the genuine waterscape. The dehazing technique described here enhances visual clarity in underwater photographs. However, the immoderate amplified noise in the image is an AHE restriction.

Luminance adjustment and dark channel previous approaches were used by Xiu Li et al. in 2016 to improve underwater image quality [4]. Different light wavelengths correspond to each color channel. The hue of an image is dominant depending on wavelength. The image underwater maintains a modest brightness. The application of the dark channel prior technique and estimation of the image's depth map results in a haze-free underwater image. Then, to balance the uneven brightness and minimize information loss, an author uses a luminance correction approach [4].

Improved color contrast and minimal information loss are visible in the resulting image.

3. Proposed Algorithm and Methodology

The use of haze removal techniques is increasing for a wide range of applications. Different haze reduction methods are needed for various situations. According to the survey, it was discovered that the existing approaches ignore ways to reduce the issue of noise in photos produced by current fog removal techniques. An issue also exists in relation to abrupt and excessive illumination. As a result, it is necessary to alter current practices to enhance the effectiveness of the changed strategy. As a result, new algorithms incorporate bilateral filters, Contrast Limited Adaptive Histogram Equalization (CLAHE) and dark channel priors (DCP) to enhance performance.

3.1. Architecture of Proposed System

Fig. 1 represents the design of the planned system. Three factors play a major role in this system direct transmission component, and forward and backward scattering light. While capturing the images in water, the presence of particles leads to forward scattering light. Backward scattering light is an exposure from the camera. The spacing between the subject and the camera signifies a vital role in the undersea image formation model and is also known as direct transmission. At the surface of the water natural illumination, turbid water is responsible for the deprivation of the image. Exponential decrease in light attenuation is directly proportional to depth of water. The images captured at the highest depth are more greenish or bluish. The undersea image formation model deal helps to deal with this type of degraded image.

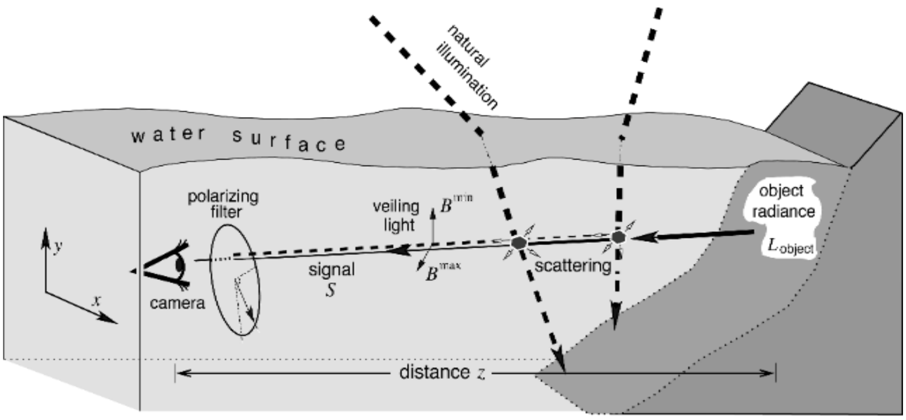


Fig. 1. Architecture

3.2. Steps-wise flow diagram of implementation

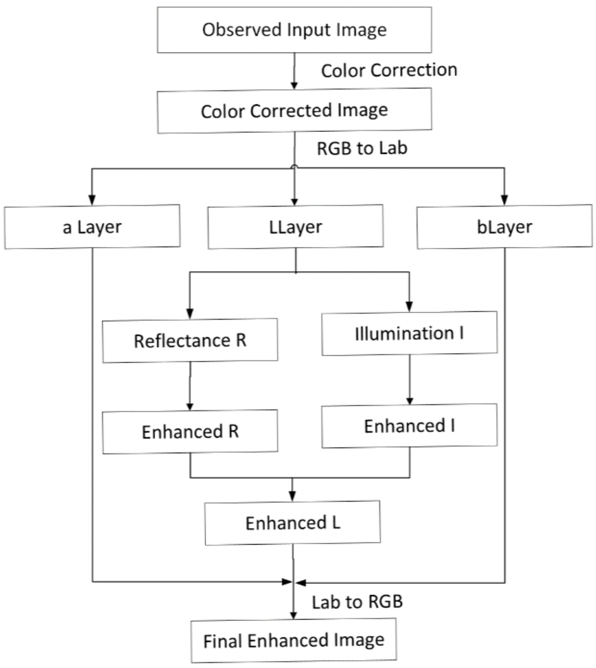


Fig. 2. Steps-wise flow diagram of implementation

Fig. 2 illustrates the implementation steps of the projected system. At first the input image is converted into RGB. As this model work to get clearer undersea images RGB images need to convert into the LAB. After this step techniques like dark channel prior, CLAHE and the bilateral filter will be applied to LAB images to get a restored image. Restored images are again converted into an RGB color model and finally enhanced image will be displayed.

3.3 Underpinning Methods

The estimation of transmission map for given image is carried out by Under Water Image Formation Model. It considers color distance from the background light. The context of scattering of the image (forward and background) is alienated in terms of equation.

3.3.1 Mathematical Formulation

$$P_c(Z) = Q_c(Z)\, s_c(Z) + Q_c(Z) s_c(Z) * R_c(Z) + A_c\big(1 - s_c(Z)\big) \tag{1}$$

The mathematical formulation for Image Formation Model is depicted in Equation 1. Based on input of underwater image and the scene radiance image, $P_c(Z)$ helps to indicate the severity of RGB channels at pixel location Z.

$$PSNR = 10 \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{2}$$

Peak Signal Noise Relation (PSNR) in equation 2 measures how much noise can degrade an image's quality in relation to its greatest attainable power.

$$MSE = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \big(Y_i - \hat{Y}_i\big)^2 \tag{3}$$

The mean square error (MSE) depicted in equation 3 is used to calculate the frequent errors squares or the average square difference between calculable worth and actual value (MSD). The operation is risky because of the initial occurrence of the square error loss.

3.3.2 Estimating White Balance

White balancing is the technique of removing the color cast from photographs. The presence of a specific color in the scene at the time the photograph was taken causes color casts or color distortion in images. Underwater, the influence of color perception and identification is related to depth. The underwater photos' major flaw, which needs to be fixed is their greenish-bluish tint. The white balancing process aids in color casting of selected colors for the input results from depth-selective absorption process. In the proposed research, the Grey World method is chosed because it does a better job of removing the bluish tone found in underwater photographs. The light reflection from the image is thought to be either colorless or achromatic [18]. The Grey World algorithm has a flaw in that it has severe red artifacts. These artifacts result from the red channel's overcompensation in areas where red is present due to its extremely low mean value. Each channel is divided by its mean value in the Gray world. Following the recommendations from earlier underwater research, making up the loss of the red channel is only the primary goal. The grey world algorithm is then employed in a subsequent phase to determine the white-balanced image so as to accomplish red channel compensation:

The equation 4 symbolizes the compensated red channel (I_{rc}) at every pixel location (x):

$$I_{rc}(x) = I_r(x) + \propto (\overline{I_r} - \bar{I}r) * \big(1 - I_r(x)\big). I_g x \tag{4}$$

I_r (red color channels) and I_g(green color channels) of the image (also denoted as the mean value), after being normalized by the maximum bound of their frequency response, with each channel falling within the range [0, 1]. There is a need to mute blue channel in locations with high plankton density or murky waters as it leads to amalgamate by organic materials. In such cases, adjustment of red channel is mostly found to be inadequate. It necessitates minimizing blue channel attenuation through its compensation. Grey World algorithm is used in the following phase of white balancing process.

3.3.3 Sharpening

Sharpening of white-balanced image is proposed in this section which is accomplished through unmasked masking [11]. Unsharp masking subtracts the low-pass image version from the original one which produces a more sharper image with accurate corners and boundaries. These results in the image being high pass filtered. S = I + (I - (G I)) serves as the formula for doing so. where I stands for the image that has to be sharpened, G I stands for the image that has been filtered via a Gaussian filter, and is a parameter whose low value insufficiently sharpens the photo and maximize value results in an oversaturated region. Thus, the following is how unsharp masking is carried out:

$$S = (K + M\{K - N * K\})/3 \tag{5}$$

Where K stands for the picture that needs to be sharpened, M for normalization, N for the Gaussian-filtered version of K and lastly, the 3 for the unsharp masking.

4. Experimental Analysis

4.1. Input Image

For the restoration process, Fig. 3 (a) and Fig. 3 (b) is employed [19]. These pictures shows a hazy image with extra white color. Therefore, the restoration process involved the use of the aforementioned techniques. The procedure is described in the steps that follow.

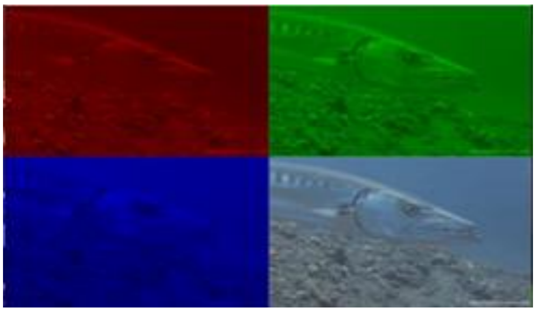
(a)

(b)

Fig. 3. (a) Input Image [19], (b) Input Image [19]

4.2. RGB Channel color model:

A square measure is used to represent the RGB, BGR, HSV, CMYK, etc. saturation areas in a photo (Fig. 4). These channels are used to create images. The RGB colors model is an additive colors mode. Red, green, and blue, the three colors of light are blended in numerous combinations to produce diversified colors. The initials of the three additive fundamental colors—red, green, and blue—were used to create the models name. Traditional photography has utilised the RGB colour paradigm, although it is mostly used to perceive, represent, and display images on electronic devices like computers and televisions. Before the invention of electronics, the RGB color model already had a strong foundation based on how people see color.



(a)

(b)

Fig. 4. (a) Result of converted RGB Images of Fig. 3 (a), (b) Result of converted RGB Images of Fig. 3 (b)

4.3. RGB to LAB

As stated in Fig. 5, Lab* is a potent tool because it has its own unique color space. It serves as the focal point for color conversions and administration. By giving colors numerical values, Lab* enables us to quantify color data and make it clear. Utilizing a separate color space, you may quantify the color using the Lab* color space. In other words, the values provide you with a separate value that represents that hue. The simplest explanation is that if your lab* values are the same, your color will be the same, and if they are different, your color will be different. The three samples exhibit identical Lab* readings when you look at them. However, the CMYK values for each printer have been adjusted to account for the inherent difference in the printing process (dependent color space).

(a)

(b)

Fig. 5. (a) depicts the converted LAB Image of Fig. 3 (a), (b) depicts the converted LAB Image of Fig. 3 (b)

4.4. Median Filter Image (MFI)

The nonlinear technique of median filtering removes noise from an image (Fig. 6). It is broadly used in over all techniques as it is exceptional to eliminate noise and retaining edges. This solution does a particularly good job of eliminating noises with a salt and pepper flavors. It functions by gradually converting each pixel to the median value of its neighbors. The pixel value is changed in line with the median value after the pixel intensities are numerically sorted to determine the median. Its easy and effective to use this non-linear clear-out. It is used to lessen the depth version between a pixel and the pixel to the opposite. In this clear-out, the pixel fee is updated using the median fee. Sorting of pixel values in ascending order aids in determining the median. The center pixel value is updated accordingly.

(a)

(b)

Fig. 6. (a). Outcome of MFI of Fig. 3 (a), (b). Outcome of MFI of Fig. 3 (b)

4.5. Dark Channel Prior

Despite the fact that air particle size when it is foggy is bigger than visual light wavelengths and changes experienced on apparent lights with different frequencies are equivalent, the dark channel has previously failed to rapidly fix the degraded undersea image. In this paper, straightforward but efficient dark channel employing data collected outside in blinding glare conditions is discussed. Most of the areas that are not the sky contain a few pixels that are really dark. Additionally, achieving low values in the current patch (K) should be easily possible for a picture.

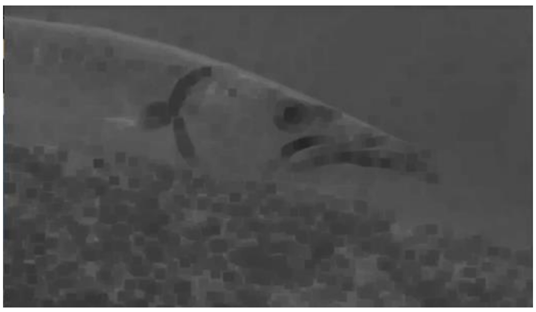
$$K^{dark}(y) = \min(\min(K^c(z))), \quad c \in \{r, g, b\}\ z \in \Omega(y) \tag{6}$$

K^c represents the color channel of 'K', 'y' denotes a native patching. If K^{dark} is an image taken outside without any haze, the intensity is weak and typically zero, with the exception of the sky region. K^{dark} is frequently regarded as K's dark channel,

$$K^{dark} \rightarrow 0$$

Before, this finding was referred to as a "dark channel."

Three things primarily contribute to the dark channel's dimness: A) Completely black objects or textures, like dark tree branches and rocks; B) Colorful objects or surfaces, like those with little or no refractive index in any color channel (like lush greenery, tree branches, and succulents, blue water surfaces and red/yellow flower petals); and C) Shadows like those made by buildings, moving objects, insides of openings in metropolis images or shadows by tress, leaves and rocks in landscape images. The black channels (Fig. 7) of these photographs are incredibly dark because the outside nature images are frequently vibrant and rich in shadows.



(a)

(b)

Fig. 7. (a) Result of DCP technique on Fig. 3 (a), (b) Result of DCP technique on Fig. 3 (b)

4.6. Transmission Refine

The work as depicted in Fig. 8 utilises the graph-cut based expansion approach to estimate the map after getting the segmentation result since it can deal with regularization and optimization issues and has a solid track record with vision-specific energy function [20]. In more detail, each transmission map component has a label assigned to it, and the collection of labels stands in for the transmission values. Initially the incoming RGB image is transformed into a gray-level image before tagging. Since the labelling unit of the pixel value is set to 8, there are 32 labels total. The corresponding energy function is minimised by the most likely labelling.

(a)

(b)

Fig. 8. (a) Result of Transmission Refine technique on Fig. 3(a), (b) Result of Transmission Refine technique on Fig. 3(b)

4.7. UDCP transmission by UIFM

Fig. 9 (a) and Fig. 9 (b) display the findings of the UDCP with the help of Underwater Image Formation Model (UWIFM), respectively. As the green and blue channels have comparable intensities (the red channel has low intensities), the min and median values are similar. As illustrated in Fig. 9, the red channel intensities account the difference between UDCP and MDCP.

(a)

(b)

Fig. 9. (a) Result of UDCP transmission by UIFM technique on Fig. 3 (a), (b) Result of UDCP transmission by UIFM technique on Fig. 3(b)

4.8. ULAP Depth Map Transmission by UIFM

Fig. 10 (a) and Fig.10 (b) shows ULAP Depth Map Transmission by UWIFM. Three factors affecting dimness of the dark channel: A) Shadows cast by objects like buildings, cars, and the inside of windows. The background light is determined by the largest intensity difference between R,G,B light based on the frequency in which the radiation of green and blue light is less absorbed compared to red light. The rule encourages us to run tests on various underwater photos to identify a useful prior for restoring a single underwater image.

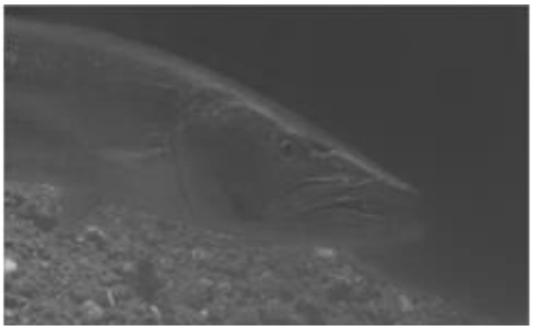
(a)

(b)

Fig. 10. (a) Result of ULAP Depth Map Transmission by UIFM technique on Fig. 3(a), (b) Result of ULAP Depth Map Transmission by UIFM technique on Fig. 3 (b)

4.9. ULAP transmission by UIFM

Any of underwater images depth maps may be made by ULAP transmission since the connection between the scene-based image dd(xx), the M V G B. Moreover, recognition of V R is done leading to learning of equations (Fig. 11). The estimated depth maps display darker color in the deeper regions and lighter colors in the closer regions, as seen in fig., which makes sense. Once the appropriate depth map has been gained, determining the background light level and producing the distribution maps for RGB luminaries becomes simple.



(a)

(b)

Fig. 11. (a) ULAP transmission by UIFM technique on Fig. 3 (a), (b) ULAP transmission by UIFM technique on Fig. 3 (b)

4.10. Light Intensity Point

In underwater photography, the sharpest pixel is typically assumed to be the background light (Fig. 12). In other cases, such as when the forefront components are more noticeable than the light coming, the assumption is incorrect. The backup brightness possibility value is at the biggest value of the enhanced depth map, which corresponds to the input undersea image. This shows that the backdrop light originates from the most remote area of the underwater image input. The valid estimation result, however, can be obstructed by certain suspended particles if the farthest point is arbitrarily chosen as the final background light.

(a)

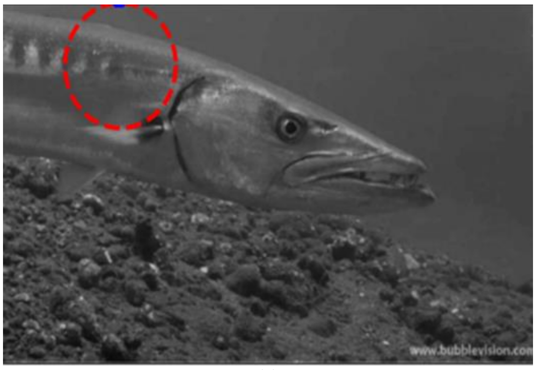
(b)

Fig. 12. (a) Result of Light Intensity technique on Fig. 3 (a), (b) Result of Light Intensity technique on Fig. 3 (b)

An example of the universal background light estimation technique. The original image, the 0.1% furthest pixels discovered in the updated depth map, and the brightness of those 0.1% furthest pixels that correspond to the original image are shown in (A), (B), and respectively.

4.11. Haze Free color

The result of image dehazing method with proposed undersea image restoration method Fig. 13 (a) and Fig. 13 (b) shows which is based on underwater RGB, LAB color model, transmission estimation, light attenuation, a DCP (UDCP), image blurriness and light absorption. This is the final output haze free image. Contrast Enhancement techniques applied later to improve its colors.



(a)

(b)

Fig. 13. (a) Haze Free Color Correction technique on Fig. 3(a), (b) Haze Free Color Correction technique on Fig. 3(b)

4.12. Contrast Enhancement

Fig. 14 (a) and Fig. 14 (b) shows final output image. Contrast improvements make objects in the scene more visible by increasing the brightness gap between them and their backgrounds. Although these might both be done in one step, contrast enhancements are commonly conducted as a contrast stretch followed by a tonal enhancement.

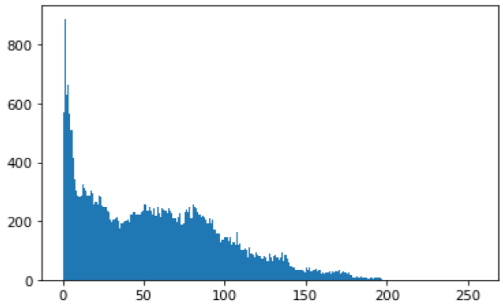
(a)

(b)

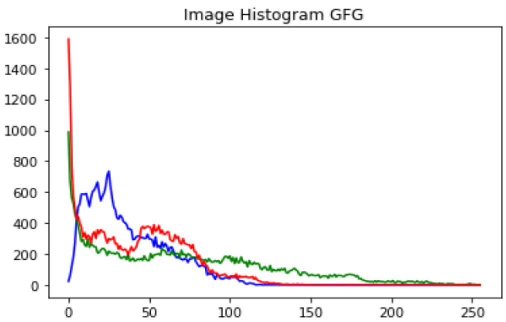
Fig. 14. (a) Contrast Enhancement technique on Fig. 3(a), (b) Contrast Enhancement technique on Fig. 3(b)

5. Results and Discussion

Fig. 15 shows histogram plots of Fresnel equations, the transmittance of the polarisation components is determined. These elements are parallel to and perpendicular to the plane formed by the principal ray and the windows normal, and they are in a local coordinate system. These aren’t always the veiling lights parallel and perpendicular parts.



(a)



(b)

Fig. 15. (a). Histogram plots of input image Fig. 3 (a), (b): Histogram plots of input image Fig. 3 (a)

The outcomes of retrieving a submerged image under non-uniform lighting (Fig. 15). Display the T M and B L generated using the MIP methodology as well as the UDCP method. It also incorporates Li's, IBLA and ULAP method including the proposed aspect. The corresponding distribution histograms in the last row depict the R, G, and B channels of the restored images. The x-axis and y-axis present the signal levels and normalised frequency respectively.

Table 1. Canny edge-point quantity

Image Description	Main Image	[5]	[9]	[15]	[10]	[11]	Proposed Technique
Fish	2087	2494	4342	4965	2551	3370	5090
Diver	4014	7195	6451	9354	5819	3740	9188
Coral	157	804	1921	2649	238	1102	1938
Wreck	87	170	378	699	99	229	476

The results of the clever edge point amount of several algorithms are displayed in the Table 1. Additionally, the same procedure is repeated. The table below displays the number of sifting feature points used by several conventional algorithms, and the model then works quickly and accurately. This is the point at which the model is most accurate.

Table 2. Sift feature point quantity

Image Description	Main Image	[5]	[9]	[15]	[10]	[11]	Proposed Technique
Fish	32543	28052	36890	32226	34695	34138	40982
Diver	66831	63768	63502	56838	64977	70382	72841
Coral	19628	18626	21268	19801	20161	20236	20152
Wreck	9492	9593	10686	11782	9717	8700	9676

The Table 2. shows the number of sift feature points used by several conventional algorithms, and the model then works quickly and accurately. This is the point at which the model is most accurate.

Table 3. Comparison of results for various methods used in existing and proposed methods

Metric	UDCP	ULAP	UIFM	Proposed
P	0.1754	0. 5481	0.9545	0.9371
P	0.1563	0.4154	0.9561	0.8012
P	0.0154	0.3415	0.6152	0.7412
P	0.1245	0.4140	0.9148	0.8410

To compare the outcomes of various existing and planned strategies, P metric is employed as stated in Table 3. After being processed, the photos are compared to the original and many alternative methods to determine the quality of improvement. First of all, it is planned to evaluate the photos in relation to UDCP, ULAP, and UIFM. For two photographs, fish and coral, these techniques were most effective. These techniques have little impact on the other two photos. The improved results are those displayed in green. This approach produced a result for the fish image of 0.9371.

Table 4. Comparison of results for various methods used in existing and proposed methods

Metric	UDCP	IBLA	NLP	UIFM	Proposed
P	0.1363	0.4154	0.5854	0.5854	0.9475
P	0.1754	0.5481	0.9561	0.9561	0.9048
P	0.0154	0.3415	0.4152	0.4152	0.7012
P	0.1245	0.4140	0.9148	0.9148	0.8410

NLP is a further evaluation technique that is taken into account in Table 4. For evaluation, NLP is combined with UDCP and IBLA. It offers three photographs of fish, divers, and wrecks that are excellent. Results in the color green are better. One outcome is highlighted in red. The coral image's quality has been diminished using NLP. However, it produces two photos with better results.

6. Conclusion

An active area of image processing is underwater imaging. Innovative product development frequently incorporates new methods and software to improve underwater images and movies. This research suggests an improved technique for restoring underwater photographs while removing artificial lighting and maintaining quality. The suggested technique intends the dazed frames to enhance the quality of the input underwater photos. Several methods including UDCP, ULAP, IBLA, and NLP utilize the Dark Channel Prior algorithm. These methods significantly enhanced the outcomes of underwater photos. Combining these techniques impacted the image of fish, divers and wrecks the most. A enhanced result of 0.9475 and 0.9048 over metric P for the Fish and Diver images was obtained by combining UDCP, IBLA, and NLP. The result for the wreck is not significantly improved by this combination, but it is still appealing at 0.8410 when compared to previous approaches. The experimental results showed that when compared to the current state-of-the-art methods, the suggested algorithm predicted the transmission map more precisely. Additionally, the results obtained noticeably depict enriched scene-radiance restoration performance.

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