IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Robust Technique of Adaptive Retinal Mechanisms Used For Underwater Image Enhancement

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Abstract: Image enhancement is a common method of improving the look and feel of a photograph. This idea for underwater picture enhancement was inspired by the shape and function of a teleost fish retina. The blurring and non-uniform colour biases in underwater photos are causing problems. Using red channel compensation and feedback from color-sensitive horizontal cells helps to correct the eye's unbalanced perception of colours. To improve the output image's edges and contrasts, the bipolar cell has a center-surround opponent mechanism and feedback from amacrine cells to inter-plexiform cells. It is possible to use the color-opponent ganglion cells to enhance and correct colour. Finally, we're using a fusion technique based on brightness to reconstruct the improved image from fish retina outputs that are both on and off. To construct each low-level filter automatically, our approach employs global data (such as picture contrast), which allows the major parameters to self-adapt. Extensive qualitative and quantitative examinations of our technology in diverse underwater settings demonstrate its competitive performance. Our technique also improves the transmission map estimate and local feature point matching accuracy when using an underwater image. Our methodology is based on a single image and does not require any prior knowledge of the undersea scene's condition or structure. For greater colour contrast and colour correction, used technique is Laplacian multiscale fusion reconstruction method. Results and parameter computations will reveal the disparity between the proposed work and actual performance data.

***Index Terms* – Fish Retinal Mechanism, Laplacian Multi-scale fusion Reconstruction, Dehazing, UnderWater Image Processing.**

I. INTRODUCTION

Underwater digital photographs have become increasingly important in the exploration of marine resources in the modern era. The upkeep of undersea faculties and submarine tourism necessitate a considerable volume of underwater visual data. Because of the low visibility, the camera's underwater images are degraded. Low-quality underwater photos are also due to the light's absorption and scattering properties. This causes blurriness and color biasing in underwater photos. As a result, in computer vision applications, consistent color biasing and reducing blurriness from underwater images are highly suggested. The difficult process of uniform color biasing, haze identification, and haze reduction is required to improve the image's quality. Algorithms to remove haze and fix colour were developed to enhance the image's quality. Based on the finding that a dehazed image with consistent colour bias is more informative and devoid of haze than one with non-uniform colour bias. Image processing programs heavily rely on dehazed colour correcting images.[1]

1.1 What is DIP?

It's possible to think of an image as having a two-dimensional characteristic called the depth or grey stage, which is defined as the amplitude of that characteristic at any given pair of coordinates (x, y). A virtual image is one in which x, y, and the amplitude values of f are all discrete, limited components. DIP stands for digital image processing and refers to the use of a virtual laptop for this purpose. A digital photograph is made up of a limited number of components, each with a specific location and cost. Pixels are the technical terms for these parts.

1.2 Aim and Objective of the paper

With the use of the Laplacian multiscale fusion reconstruction method, the research aspires to detect and remove haze from an image while maintaining uniform colour biassing. Haze and uneven colour biassing decrease the image quality, so they must be removed. For the most part, many applications call for color-corrected photos that have been dehazed, such as those used in underwater resource research to collect priceless antiquities.

1.3 Methodology

The procedures involved in putting this system in place to identify a single true colour image while submerged. Making the dehaze image have a homogeneous colour bias by using Laplacian multiscale fusion reconstruction. Pyramid rebuilding using Laplacian filters and gaussian filters is referred to as Laplacian reconstruction. The Laplacian filter function is used to compute the overall winner. The gaussian filter's noise-canceling capability comes in handy here. Using the multiscale fusion principle as the basis, the algorithm was developed.

1.4 Significance of the work

There are numerous dehazing filters available. Uniform colour biassing and haze reduction are achieved via adaptive retinal mechanisms, but these techniques failed to correct the fine artefacts. In these situations, a technique known as Laplacian multiscale fusion reconstruction is employed. Using Laplacian pyramid reconstruction and multiscale fusion, a straightforward single-image haze removal approach is shown for the first time. Filters like the Laplacian and Gaussian filters are commonly utilised. Images to be color-balanced and sharpened are the filters' inputs. The gaussian filter is designed to isolate the most important parts of an image. Multiple picture weights are combined using the normalised weights extracted from saliency identified regions. Afterwards, using Laplacian multiscale fusion reconstruction, the output picture must be recreated.

II. LITERATURE SURVEY

Underwater photographs are increasingly important in a wide range of applications these days. Images must be free of haze and have uniformly good colour bias. It's difficult to improve the image's quality while maintaining a uniform colour bias and removing haze. A wide range of colour correction techniques are already available on the market. However, there are certain downsides to using them. The following section provides a quick summary of some popular colour correcting and dehazing models.

2.1 Various methods of Underwater Image dehazing

The following sections provide a quick overview of the various dehazing and colour basing processes used to create an underwater image.

The state-of-the-art in underwater image processing; approaches for picture restoration and augmentation.

The field of underwater image processing has gotten a lot of attention in the previous few decades and has made significant progress. In this paper, we take a look at some of the most cutting-edge underwater imaging systems currently available. These methods have the potential to improve underwater imaging's contrast and resolution while also broadening the use of underwater imaging. After examining the fundamental physics of light propagation through water, we turn our attention to the many methods that have been proposed. Every one of them is emphasized together with the quality assessment methodologies used to assess their performance, initially devised for specific conditions.

III. WORK IMPLEMENTATION

3.1 The fish retina inspired model

As can be seen in Fig. 3.1, our model is based on the teleost fish retina's basic visual signal processing systems.

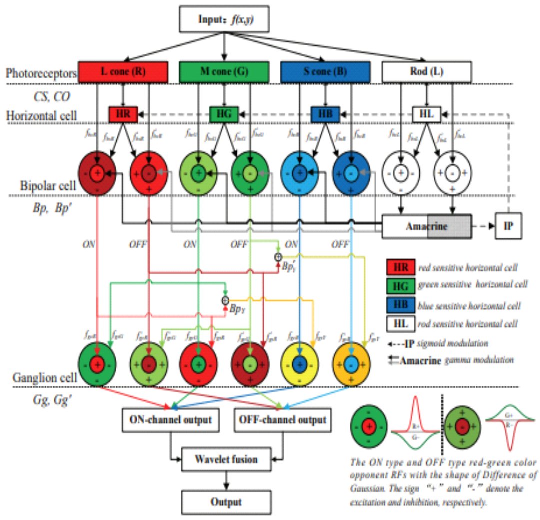

Fig.3.1. The suggested model's block diagram, which makes use of fish retinal mechanics.

3.1.1 Photoreceptors

The rod and cone photoreceptors are found in the retina's initial layer and are responsible for transmitting the received light signal to the brain. Cone cells can be further classified into long (R), intermediate (G), and short (B) kinds based on their sensitivity to spectral wavelengths [1]. We use the R, G, and B channels of the underwater image f(x, y) as the inputs to cone cells. The brightness signal received by rod cells is easily defined as

$$L(x,y) = (f_R(x,y) + f_G(x,y) + f_B(x,y))/3$$

3.1.2 Horizontal Cells

Photoreceptor signals can be integrated over relatively large areas because horizontal cells (HCs) have the retina's largest RF size. One of the most important feedback paths for CC realization is the bidirectional arrow between photoreceptors and HCs, which is represented in Figure 1.

Fig.3.2. CC with various values of θ. (a) original images, (b) θ = 0.15, (c) θ = 0.3, (d) θ = 0.45, (e) images with the global contrast improvement.

It is clear that the non-uniform color fluctuation of the underwater environment is ignored in existing CC models influenced by retina mechanisms [2] because they employ the global mean of the R, G, and B channels as input from HCs to each cone type. Most retina-based models ignore the inhibitory regulation of horizontal cells found in interplexiform cells. The RF of HCs is modelled using a local mean filter, which estimates the colour of the local light source from the input and then returns the estimated local signal as feedback to correct the signal encoded by the cone cells.. In order to eliminate the red artefact following CC processing, such HC feedbacks in the red channel are calculated globally utilising the bright sections of the scene, taking into account that fish eyes are more sensitive to longer wavelength photons [3], [4], [5], [6]. The three channels' HC feedback is calculated as follows:

$$HCF_R(x,y) = \underset{f_R > \theta}{mean}\{\{f_R(x,y)\}mean_{N\times N}\}$$

$$HCF_G(x,y) = \{f_G(x,y)\}mean_{N\times N}$$

$$(HCF_B(x,y) = \{f_B(x,y)\}mean_{N\times N}$$

Where the red channel's brightest sections are selected using a parameter called. The selection is controlled by HCF R(x, y) = max (fR NN) when no pixel value higher than in the local window centred at fR is found (x, y). According to Fig.3.2, there is a substantial discrepancy between the estimated light source colour map produced by HC feedbacks (i.e. HCF (x,y), R, G, B) and two methods generally employed for CC processing of an underwater image [7], Because the colour attenuation inside an underwater image is not often uniform over the spectral range, our suggested HC feedbacks assess an image's spatially changing light source colour map. The conventional methods, on the other hand, always return a homogeneous colour map of the light source. Because of the HC feedback, the cone signals transform into

$$CS_\lambda(x,y) = \frac{f_\lambda(x,y)}{HCF_\lambda(x,y)}\ , \lambda \in \{R,G,B\}$$

Next, dopamine is released from interplexiform cells to limit horizontal cell activity, which improves visual contrast with intermediate brightness by inhibiting horizontal cell activity in the dark As a result, we use the sigmoid function to reduce the intensity of the low-level cone signals after they have been modulated by HC feedbacks.

$$CO_\lambda(x,y) = \frac{1}{1+e^{-10(CS_\lambda(x,y)-0.5)}}\ \ , \lambda \in \{R,G,B\}$$

Since rod cells only have one channel (i.e., L), we can simply get their output COrod (x, y) using Esq. (3) (5) and the input L(x, y). Once this has been accomplished, the modulated signals are sent to the layer of bipolar cells with the spatial centre surround radio frequency in order to enhance the local contrasts and edges.

Laplacian multiscale fusion reconstruction

In comparison to the red and blue channels, the green channel has been retained relatively well underwater. As a result of the larger attenuation caused by the red light's longer wavelength, it is especially vital to adjust for the red light's weaker attenuation than the green light when passing over clear water. 2. As a result, a small amount of the green channel is added to the red channel to make up for the red attenuation. Adding a bit of green and a bit of blue to the red in this study was a first attempt, but using only the green channel's information allowed a better recovery of the complete colour spectrum while keeping the background (water regions) looking realistic.

VI RESULT

Images with non-uniform colour bias are used as input. There is a comparison between retinal mechanism and Laplacian multiscale fusion reconstruction. Images with consistent colour bias and no haze are produced using the Laplacian multiscale fusion reconstruction approach.

4.1 MATLAB Simulation Results

4.1.1 Execution of input image 1

We took the database of specific photographs in order to improve the underwater images. The input for the execution is a true colour image with a pixel size of 600x450 of the undersea scene.

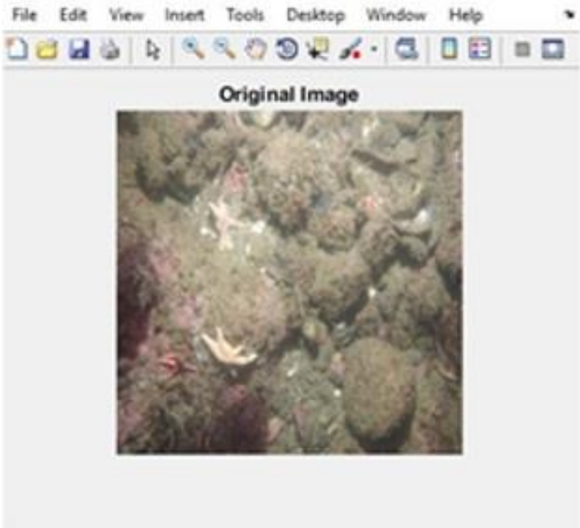

Fig. 4.1(a). Original Image

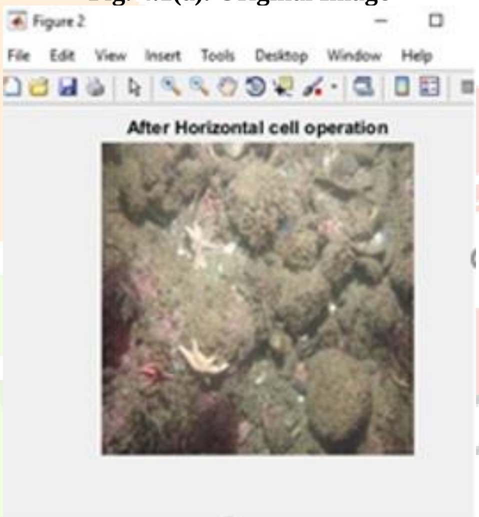

Fig. 4.1(b). After Horizontal cell operation

The image's non-uniform colour biassing was reduced, but the contrast and edge information remained unclear after the transformation.

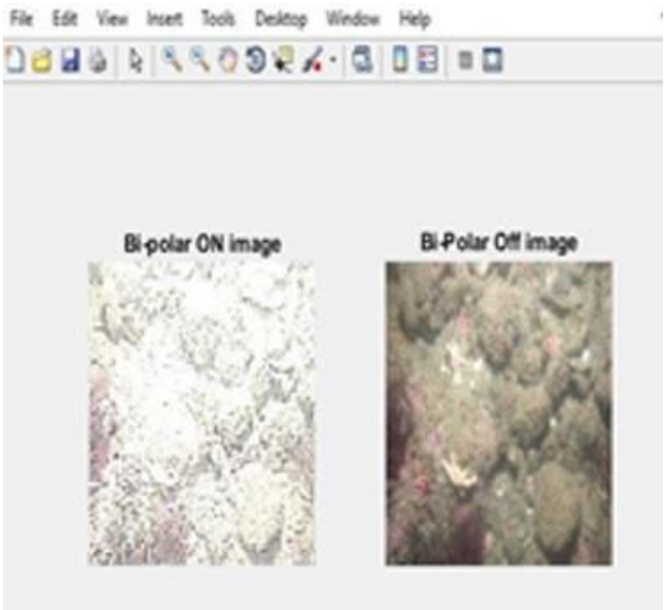

Fig.4.1(c).Bi-polar-ON image and Bi-polar-OFF image

However, while the edges and contrast have been enhanced, the colour correction and augmentation have not been done.

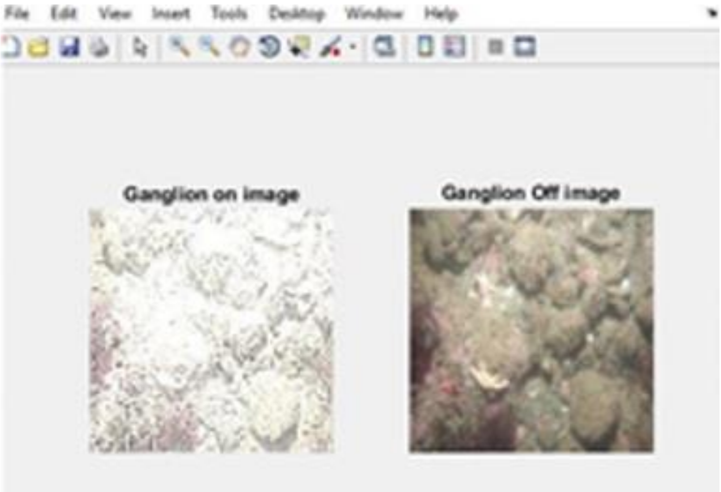

Fig.4.1(d).Ganglion ON image and Ganglion OFF image

The image has been brightened and the colors have been adjusted. The ON and OFF paths of ganglion cells must be fused to obtain the final output.

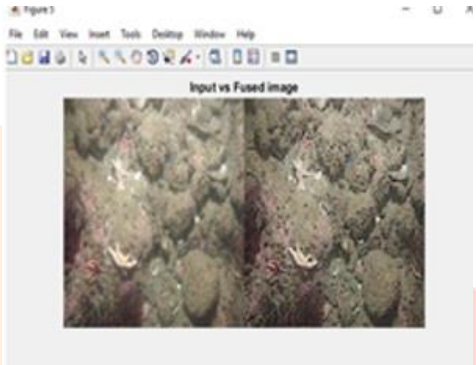

Fig. 4.1(e). Input vs Fused image

The path ways for Ganglion ON and Ganglion OFF have been combined to produce a better image.

Execution of input image2:

The same Source image is taken as input-2.

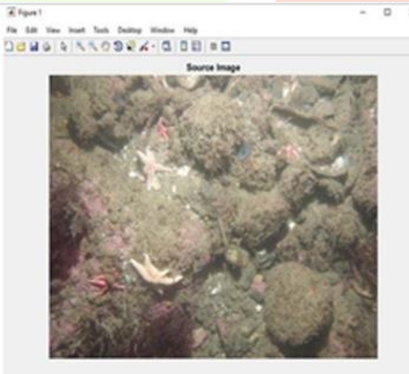

Fig. 4.2(a). Source Image

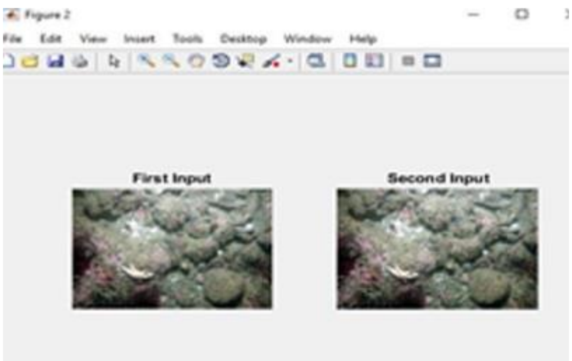

Fig. 4.2(b). First input and second input.

With the unsharp masking approach as a second input, the image's colours are balanced and sharpened.

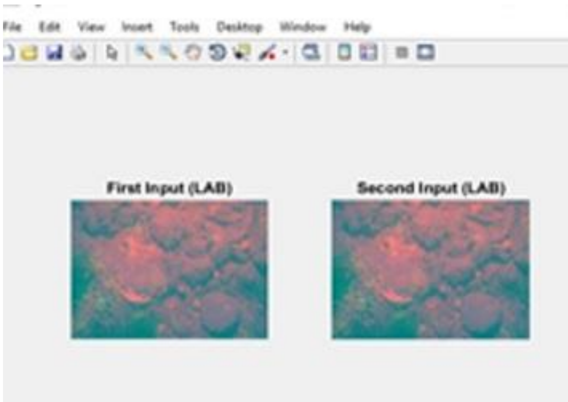

Fig. 4.2(c). First input(LAB) and second input(LAB)

It is necessary to carry out the RGB to LAB conversion. It'll make the image's background stand out more clearly.

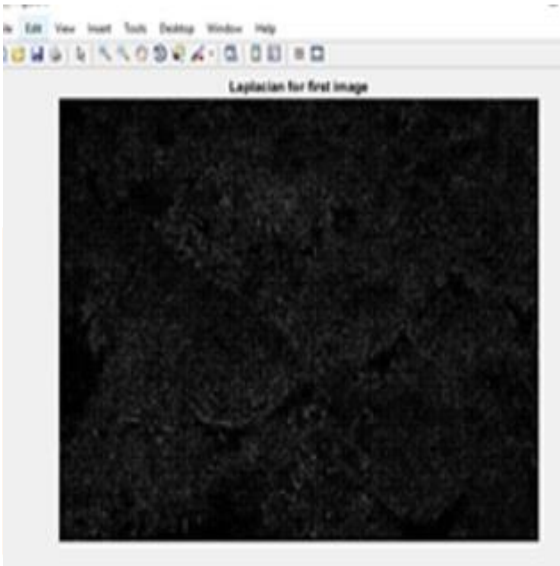

Fig. 4.2(d).Laplacian for first image.

The edges are readily detected by the Laplacian filter. Even yet, the useful data isn't readily apparent.

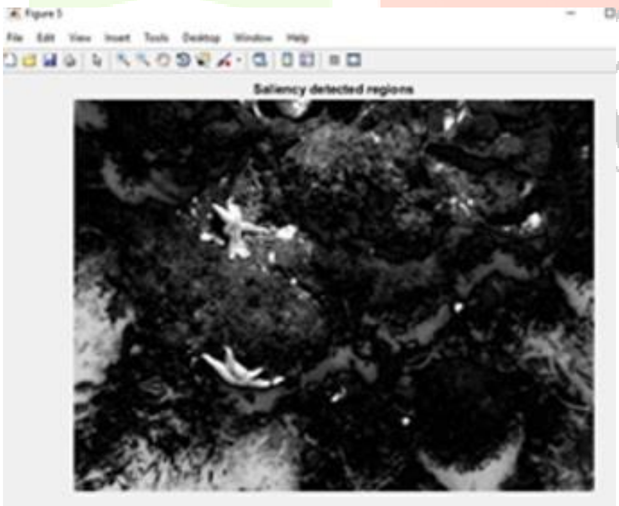

Fig. 4.2(e). Saliency detected regions

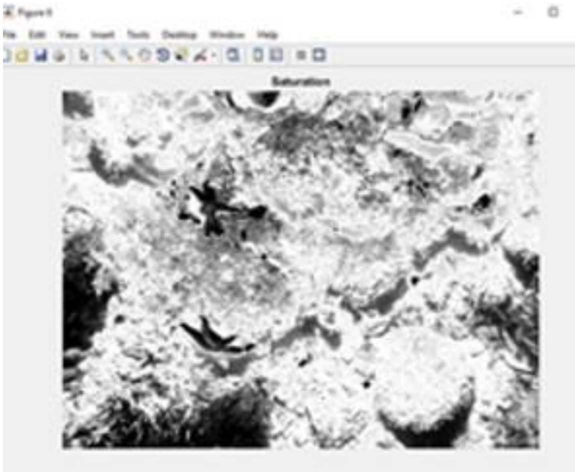

Fig. 4.2(f). Saturation

The image's colour purity will be enhanced with saturation. The method used to create the first image is repeated for the second.

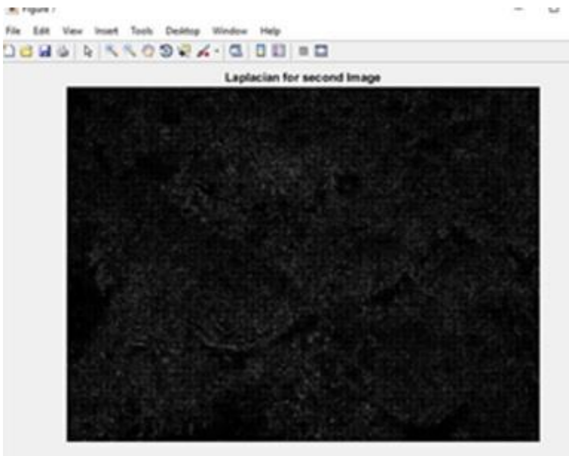

Fig. 4.2(g). Laplacian for second image

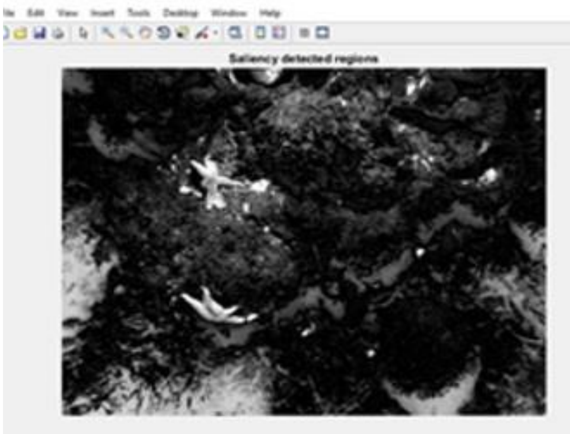

Fig. 4.2(h).Saliency detected regions

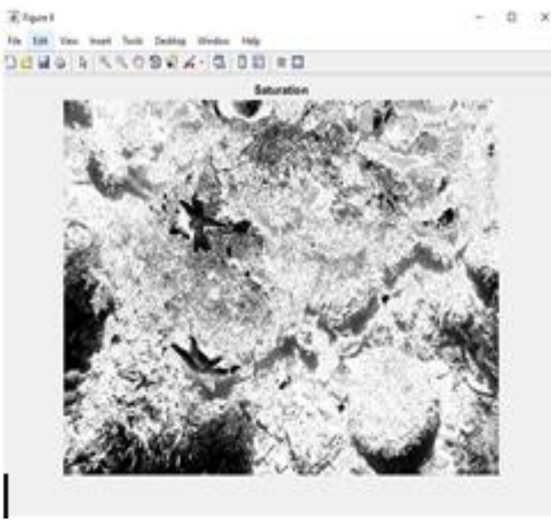

Fig. 4.2(i). saturation for second image

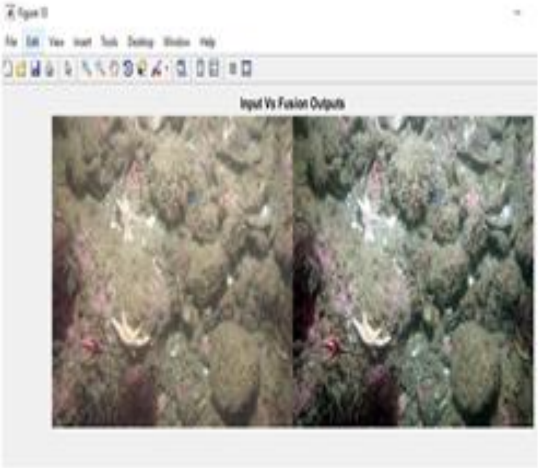

Fig. 4.2(j). Input vs Fusion outputs

Comparisons between two methods:

As a means of comparison, we've employed uc,uq, and mpcqi as three different underwater picture improvement parameters.

A)Image Contrast Measurement under Water (UIConM):

Underwater visual performance, such as stereoscopic acuity, has been demonstrated to be correlated with contrast. Backward scattering is the most common source of contrast reduction in underwater photographs. The image's intensity is analysed using the logAMEE contrast measure, as illustrated in

$$UIConM = \log\ AMEE(intensity)$$

The log AMEE in

$$\log\ AMEE = \frac{1}{k1k2} \otimes \sum_{l=1}^{k1} \sum_{k=1}^{k=2} \frac{I_{max,k,l} \Theta I_{mn,k,l}}{I_{max,k,l} \oplus I_{mn,k,l}} \times$$

$$\log\left(\frac{I_{max,k,l} \Theta I_{mn,k,l}}{I_{max,k,l} \oplus I_{mn,k,l}}\right)$$

B) Underwater image quality measure(UIQM):

UIQM includes three components and can be described as follows:

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIConM$$

C) Patch-based contrast image quality index (PCQI):

PCQI creates a spatially variable quality map of the image when applied to local patches throughout it, providing useful information about the local quality differences throughout space. image quality metric based on contrast patches, abbreviated as PCQI

$$PCQI(x,y) = q_i(x,y).\, q_c(x,y).\, q_s(x,y).$$

Where

$$q_s(x,y) = \frac{c_2^y + r^T v_2}{\| c_2^y .\, v_2 + r \|}$$

$$q_c(x,y) = \frac{4}{\pi}.\ \arctan\left(\left|\frac{c_2^y}{c_2^x}\right|\right)$$

$$q_i(x,y) = e^{\left(-\frac{|c_1^x - c_1^Y|}{\sqrt{N}L}\right.}$$

N-dimensional vector

Lis the dynamic range of the pixel values (255 for 8-bit images).

r is the residual signal perpendicular to both $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$.

Table 1: Comparision table

S.No	Methods	Image Enhancement Parameters		
		uc=Absolute value of UIConM	Uq=Absolute value of UIQM	mpcqi=Absolute value of PCQI
1	Retinal Mechanism	0.5975	1.6921	0.9832
2	Laplacian MultiScale Fusion Reconstruction	0.9404	1.0625	1.1112

V.CONCLUSION

For consistently colour biased dehazing on a single image, a simple laplacian multiscale fusion reconstruction is presented. This method is superior to the present retinal mechanism in terms of obtaining crisper images and preserving comprehensive features in regions with fine structures. For non-uniform colour base analysis and haze removal, it's used. According to the findings of the experiments, the suggested haze removal algorithm enhances the visual quality of dehazed photographs while also preserving all of the fine features in the images. Develop an approach for improving the robustness and computing efficiency of underwater circumstances that may be applied to various types of underwater applications.

VI. FUTURE SCOPE

The proposed approach will be evaluated further in future studies. In the future, in addition to using a single image as an input, we can also use movies as input. By adjusting the picture enhancement parameters, the underwater image's efficiency can be increased by taking into account the image's blocks.

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