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ENHANCING THE QUALITY OF UNDER WATER IMAGES USING DEPTH ESTIMATION AND FUZYY CONTRAST ENHANCEMENT METHOD

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Abstract

Clarity of images are degraded by light absorption and scattering in underwater. Due to which one color is dominating in the image. The proposed approach is capable in increasing clarity of such images in respect to their color, contrast and sharpness. In this paper, we propose to use image blurriness to estimate the depth map for underwater image enhancement. It is based on the observation that objects farther from the camera are more blurry for underwater images. Then color estimation is done by removing the effect of atmospheric light and finally, fuzzy based contrast enhancement system is prepared for fine tuning of contrast of image. At the last Performances of different filters, and different algorithm are analyzed on quality analysis parameters PSNR and MSE. Experiments shows better PSNR and less MSE than the previously applied algorithms.

Keywords: Fuzzy Contrast Enhancement, Depth Estimation, Color Estimation, MSE, PSNR.

I INTRODUCTION

Getting a clear image in Underwater environment is a problem for the ocean engineering. But for the last few years, a successful progress has been started towards the direction of the perfection of image processing techniques and methods. The problems faced during underwater imaging includes low contrast, diminished colours or we can say that due to the specific propagation properties of light. Another big reason includes light attenuation, the light is attenuated exponentially with the distance and depth mainly due to absorption and scattering effects. The absorption substantially reduces the light energy while the scattering causes changes in the light direction. Some underwater vehicles such as Autonomous Underwater Vehicles (AUV) and Remotely Operated Vehicles (ROV) are usually employed to capture the data such as underwater mines, shipwrecks, coral reefs, pipelines and telecommunication cables from the underwater environment. The paper is organized as follows: section 2 presents literature review and related work used for underwater image enhancements, section 3 discusses the problem identification, section 4 discusses the proposed technique and section 5 concludes this paper. The well-known problem concerning the underwater images is related to the density of the water in the sea which is considered 800 times denser than air. Therefore, when light moves from the air to the water, it is partly reflected back and at the same time partly enters the water. The amount of light that enters the water also starts reducing as we start going deeper in the sea. Similarly, the water molecules also absorb certain amount of light. As a result, the underwater images are getting darker and darker as the depth increases Not only the amount of light is reduced when we go deeper but also colors drop off one by one depending on the wavelength of the colors.

II. LITERATURE REVIEW

S. Bazeillie et.al[1] concentrates on non-uniform lighting and color correction and often require additional knowledge of the environment. It reduces underwater perturbation and improve image quality. The algorithm is automatic and requires no parameter adjustment. And the robustness of this method was analyzed using gradient magnitude histograms. Kashif iqbal et al.[2] have proposed an approach to bluish color cast and improves the low recolor. Physics based approaches are not suitable for colour correction so they proposed a UCM(Unsupervised color correction)method for underwater image enhancement. Based on color balancing, contrast correction of RGB color model and contrast correction of HSI color model. Andreas Arnold-Bos[3] presented a complete preprocessing framework for underwater images. They have proposed a model-free denoising of underwater optical images. First they apply contrast equalization to reject backscattering, attenuation and lighting inequalities caused by ray patterns. This system does not require any knowledge of medium characteristics. Back scattering is considered as a first noise addressed in the algorithm but contrast equalization also correct the effect of the exponential light attenuation with distance., Church [4] describes that the reflection of the light varies greatly depending on the formation of the sea. Another main concern is related to the water

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that bends the light either to make crinkle patterns or to diffuse. Most importantly, the quality of the water controls and influences the filtering properties of the water such as sprinkle of the dust in water [5]. Senthilkumaran N and Thimmiaraja J 2014[6] have compared different techniques such as Global Histogram Equalization (GHE), Local histogram equalization (LHE) and Adaptive Histogram Equalization (AHE) by means of diverse objective quality measures for MRI brain image improvement. Quality measures used for comparison are Weber contrast, Michelson contrast, Contrast and AMBE. Setiawan et al. 2013[7] used Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance color retinal image. In this paper, they proposed new enhancement method using CLAHE. Sowmyashree et al. 2014[8] have presented a relative study of the different image enhancement methods used for enhancing images of the bodies under the water. It also describes the various properties of water due to which the underwater images images are distorted and degraded. Image blurriness measurement is often discussed in single image defocusing [9, 10]. In [9], a multi scale edge detector is used to estimate pixel blurriness, and then the defocus map is generated by using the edge-aware interpolation method [11] in which the blurriness at non-edge pixels is interpolated and propagated by neighbouring edge pixels based on the similarities of luminance. In [10], the matting Laplacian [12] is applied to perform defocus map interpolation. However, the noise and low contrast may cause incorrect blurriness propagation, especially for underwater images. Moreover, these edge-aware interpolation methods entail high computation cost because they involve solving high dimension linear equations. Therefore, we propose to use closing by morphological reconstruction [13] (CMR), which requires less computation cost and also decreases the chance of incorrect blurriness propagation. To this end, the estimated depth map by image blurriness is adopted in the IFM to restore and enhance underwater images for better visual quality in different lighting conditions.For underwater images, one of the most significant issues is how to improve their quality in order to streamline the image processing analysis.

III. PROBLEM IDENTIFICATION

The image improvement techniques and also the image quality improvement using filers, the atmospheric light is a major difficulty to process underwater images comes from the poor visibility conditions under the water, scattering of light and light attenuation due to all the reasons the underwater images suffers a lot and affect their visibility and the contrast which they contain actually. Light attenuation limits the visible distance, at about 20 meters in clear water and 5 meters or less in turbid or less muddy water. Use Dehazing that has proposed Image Enhancement by Wavelength Compensation and Dehazing which is used to estimate the transmission of input image the atmospheric ligh-weightt is obtained by using dark channel prior and used to remove the noise like pepper noise, with this method the noise can be removed and the image which has less amount of noise and more improved image can be achieved but the actual color contrast and less sharp image is less accurate than the original image therefore in future there is a need of some methodology additionally to boost the standard of those reasonably underwater pictures.

IV. METHODOLOGY

Proposed System Flowchart

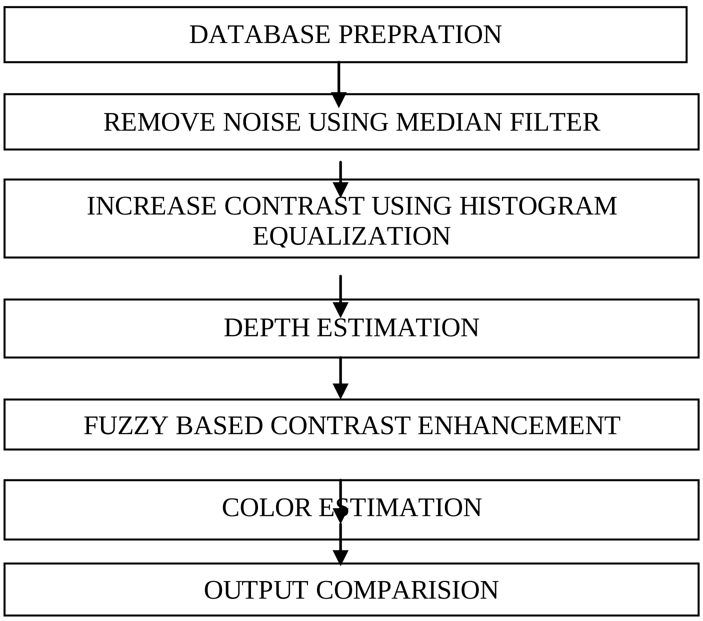

Figure1: Flowchart of methodology

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A. Image Database

Image database used in this study is taken from various sources and categorized in 3 categories.

1. Image from reference research papers

2. Images taken from own HD Camera for analysis of our system.

3. Images taken from internet and goggle.

In each category we have approximately 100 images to test our system
Finally, converted into same size, same data type by applying following steps:
The database preparation steps are as follows:

- Input Images from various sources.
- Resize all the images into 512*512 sizes
- Convert all the Images into same Format (.JPG)
- Store into Database

B. Noise Removal

Here, for Noise removal we are applying median filter. The median filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.
Median flter can be applied by following equation

F(x,y)=median(g(s,t) ……………………………………………………………………………………..(1)

Here, f(x,y) is output gray value ,were as g(s,t) is input gray value.

C. Histogram Equalization:

In the process of contrast enhancement, pixels with lower pixel value than a specific value are displayed as black, whereas the pixels having higher pixel value are displayed as white, and pixels having pixel value in between these two values are displayed as tint of gray. For best output different upper and lower limits are analyzed.
The contrast stretching algorithm is used by stretching the range of the color values to use all possible values to enhance the contrast. For preserving the accurate color proportion when the contrast stretching algorithm is used, similar scaling is applied for stretching all channels
.

D. Depth and Color Estimation:

(i) Algorithm for Parameters estimation:

Input: the training brightness vector v, the training saturation vector s, the training depth vector d, and the number of iterations t

Output: linear coefficients ,θ_0,θ_1,*and* θ_2, the variable σ^2

Auxiliary functions:

Function for obtaining the size of the vector: n =size(in)

Function for calculating the square: out = square(in)

Begin

1. n = size(v);
2. θ_0= 0; θ_1= 1 and θ_2 = -1;
3. sum = 0; wSum = 0; vSum = 0; sSum = 0;
4. **for** iteration from 1to t **do**
5. **for** index from 1 to n **do**
6. temp = d[i] - θ_0- θ_1 * v[i] -θ_2 * s[i];
7. wSum = wSum + temp;
8. vSum = vSum + v[i] * temp;
9. sSum = sSum + s[i] * temp;
10. Sum = sum + square(temp);

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11. **End for**
12. σ^2 = sum/n;
13. $\theta_0 = \theta_0$ + wSum; $\theta_1 = \theta_1$ + vSum; $\theta_2 = \theta_2$ + sSum;
14. **end for**

End

(ii) Estimation of the Depth Information:

As the relationship among the scene depth *d*, the brightness *v* and the saturation *s* has been established and the coefficients have been estimated, we can restore the depth map of a given input unclear image according to Equation (4.6). However, this model may fail to work in some particular situations. For instance, the white objects in an image are usually with high values of the brightness and low values of the saturation. Therefore, the proposed model tends to consider the scene objects with white colour as being distant. Unfortunately, this misclassification will result in inaccurate estimation of the depth in some cases. As shown in Figure 8, the white geese in the first image are the regions for which the model can hardly handle, and these regions are wrongly estimated with high depth values in the depth map. To overcome this problem, we need to consider each pixel in the neighbourhood. Based on the assumption that the scene depth is locally constant, we process the raw depth map by:

$$d_r(x) = \min d(y), \quad y \in \Omega_r(x) \quad \text{(2)}$$

where $r(x)$ is an $r \times r$ neighbourhood centred at *x*, and *dr* is the depth map with scale *r*. However, it is also obvious that the blocking artefacts appear in the image. To refine the depth map, we use the guided image filtering to smooth the image. As can be seen, the blocking artefacts are suppressed effectively.

In order to check the validity of the assumption, we collected a large database of outdoor underwater images from several well-known photo websites (e.g., Google Images) also taken lots of pictures with own camera and computed the scene depth map of each input image with its brightness and saturation components.

(ii) Estimation of the Atmospheric Light:

We have explained the main idea of estimating the atmospheric light in Section II. In this section, we describe the method in more detail. As the depth map of the input image has been recovered, the distribution of the scene depth is known. Bright regions in the map stand for distant places. we pick the top 0.1 percent brightest pixels in the depth map, and select the pixel with highest intensity in the corresponding degrated image **I** among these brightest pixels as the atmospheric light **A**.

Now that the depth of the scene *d* and the atmospheric light **A** are known, we can estimate the medium transmission *t* easily according to Equation (3) and recover the scene radiance **J** .

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{t(x)} + \mathrm{A} = \frac{\mathbf{I}(x) - \mathbf{A}}{e{-}\beta d(x)} + \mathrm{A} \quad (3)$$

For avoiding producing too much noise, we restrict the value of the transmission *t (x)* between 0.1 and 0.9. So the final function used for restoring the scene radiance **J** in the proposed method
can be expressed by:

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{\min\{\max\{e{-}\beta d(x), 0.1\}, 0.9\}} + \mathbf{A}, \quad (4)$$

where **J** is the output image we want. Note that the scattering coefficient β, which can be regarded as a constant in homogeneous regions, represents the ability of a unit volume of atmosphere to scatter light in all directions. In other words, β determines the intensity of enhancing indirectly. on the one hand, a small β leads to small transmission, and the corresponding result remains still unclear in the distant regions. On the other hand, a too large β may result in overestimation of the transmission. Therefore, A moderate β is required when dealing with the images with dense regions. In most cases, β = 1.0 is more than enough.

E. Fuzzy Based Contrast Enhancement:

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Gray scale transformations, with the image contrast enhancement as a main application, are among the most frequent areas in which fuzzy techniques for image processing are applied. This rule based approach includes the following steps.
Step 1: Specifying the input membership functions.
Step2: Specifying the output membership functions.
Step3: Obtaining the fuzzy system response function F using following rules.
IF a pixel is dark, THEN make it darker
IF a pixel is gray, THEN make it gray
IF a pixel is bright, THEN make it brighter
Step 4: Construct the intensity transformation function T using fuzzy system response function F. Step 5: Transform the intensities of input image using T.

Fuzzy Inference System Tools for Imag Enhancement: We can use five GUI tools for building, editing and observing fuzzy inference systems, which are as follows:
1 .Fuzzy inference system editor
2 .Membership function editor
3. Rule editor
4 .Rule viewer
5. Surface viewer

(i)Input Membership Function:

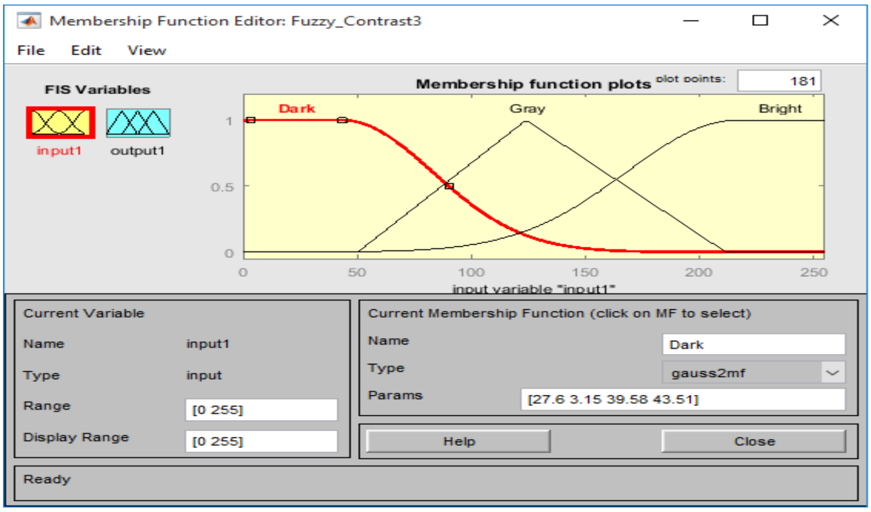

Figure.2. Input Membership function for contrast Enhancement

Figure2. shows FIS editor, which displays the general information about a fuzzy inference system. The names of each input variable are on the left, and those of each output variable are on the right. Input variable is Gray Level Image and output variable is Enhanced Image.

(ii) **Output membership function**

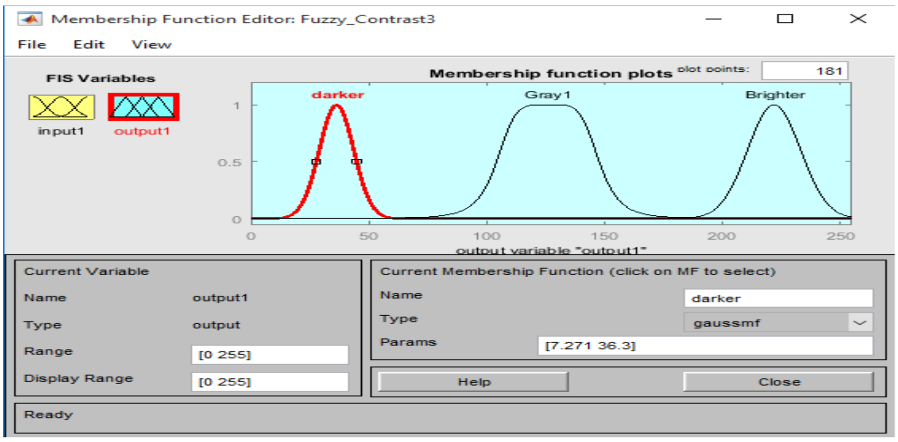

Figure.3. Output membership function

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Figure.3 shows the Surface Viewer. Surface Viewer presents a two dimensional curve that represent the mapping from gray level image to enhanced image.

F. Output Comparisons

We use different parameter for the result comparison, which shows the result improvement after each step. PSNR and MSE are the parameter we used for comparisons.

The mathematical formulae for MSE and PSNR are:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{i=1}^{N} [g(i,j) - f(i,j)]^2$$

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right)$$

where f(i,j) is the original image, g(i,j) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognise that it is a better one.

V. RESULT ANALYSIS

In this we have worked on the image enhancement and compare the performance in terms of the peak signal to noise ratio(PSNR) and mean square error(MSE) rate and shows that our enhanced image is having peak signal to noise ratio. We have made The graphical user interface for the whole image enhancement process using MATLAB.This section shows the result of Fuzzy on the set of eight test sequence. In this section, the results of various set of Images are shown ,we have used 8 color images to demonstrate the results. The experimental results are carried out on color images by using depth estimation and fuzzy contrast enhancement algorithm which gives pretty good results as shown in the below figures.

Calculation of PSNR

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often utilized as a quality estimation between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

$$PSNR = 10 * \log({(255)^2}/{MSE}) \quad \ldots\ldots \quad (1)$$

Calculation of MSE

The Mean Square Error (MSE) *and the* Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

$$MSE = sum(sum(X_o - X_r))/(M * N) \quad \ldots\ldots \quad (2)$$

Where X_o is original image and X_r is the enhanced image

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The experimental results are carried out on color images by using depth estimation and fuzzy contrast enhancement algorithm. This analyses and discuss the result obtained after performing experiment which gives pretty good results as shown in th below figures.

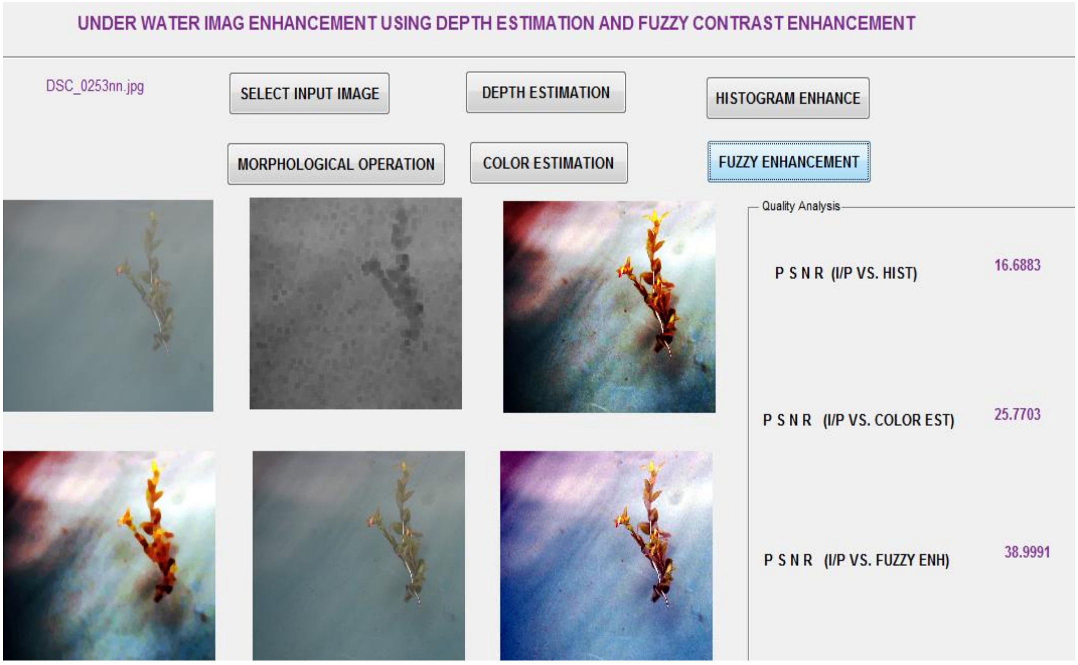

Figure 1 showing improvement in quality of image 1 after applying each step

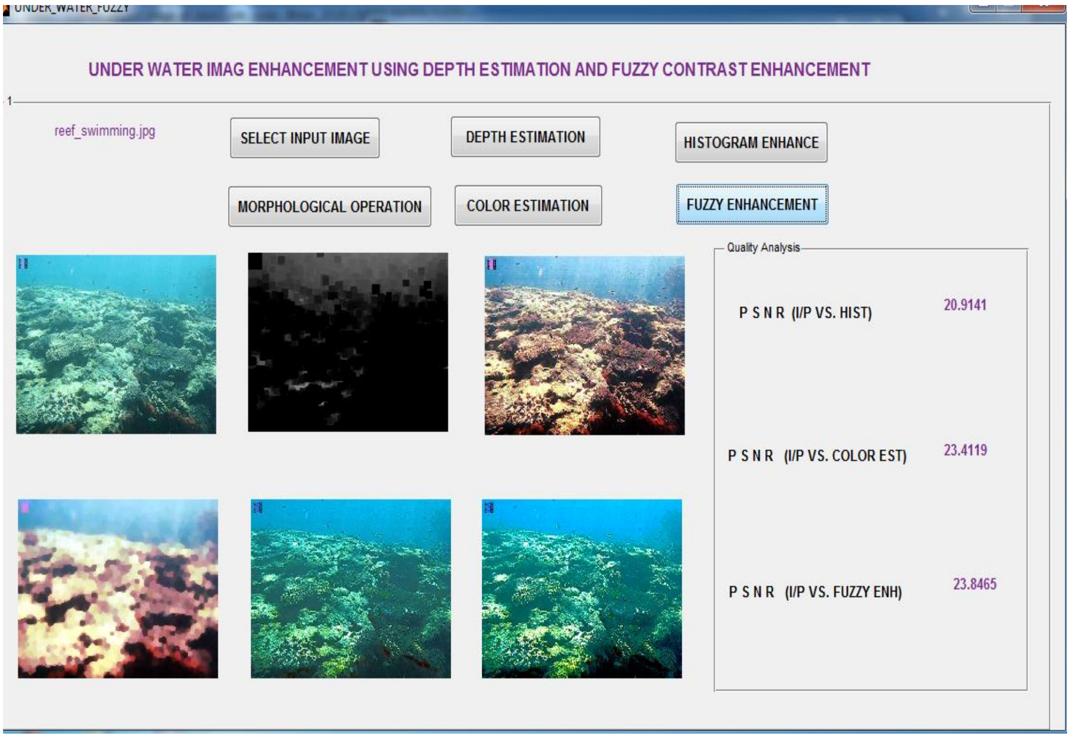

Figure 2 showing improvement in quality of image 2 after applying each step

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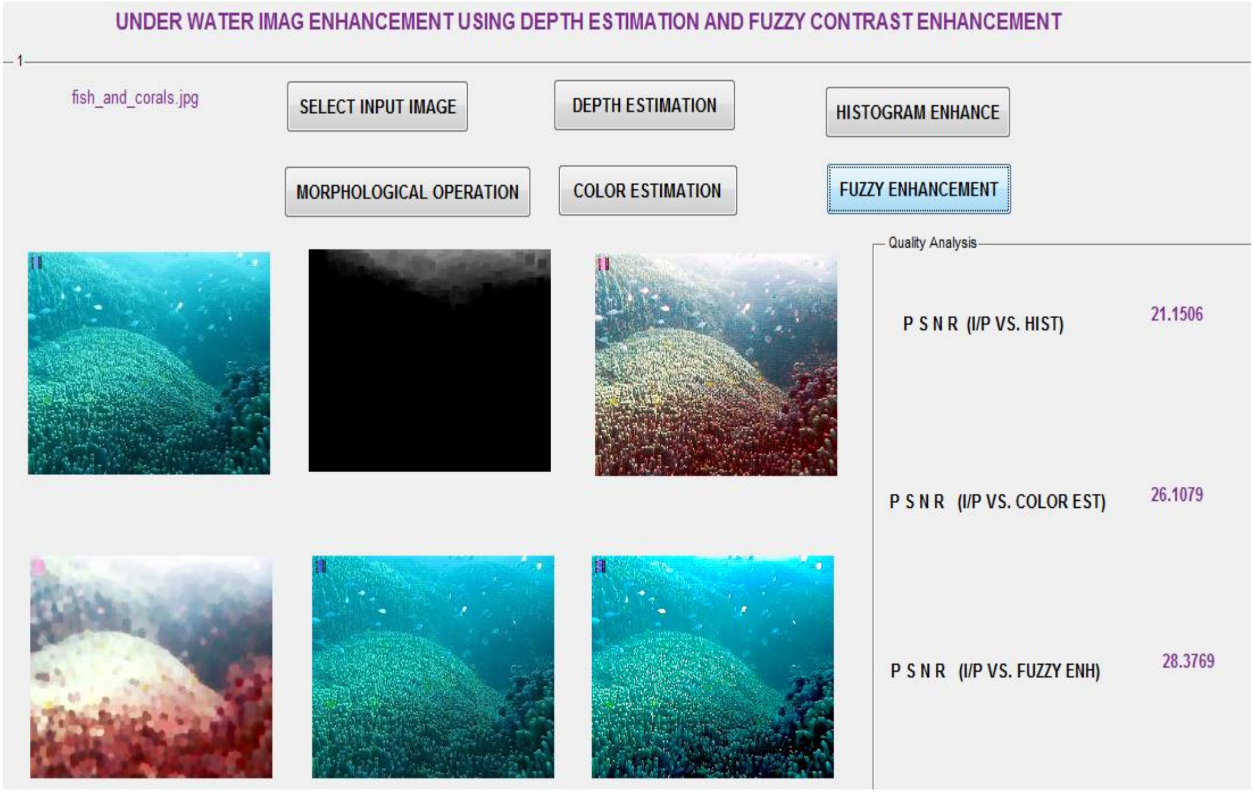

Figure 3 showing improvement in quality of image 3 after applying each step

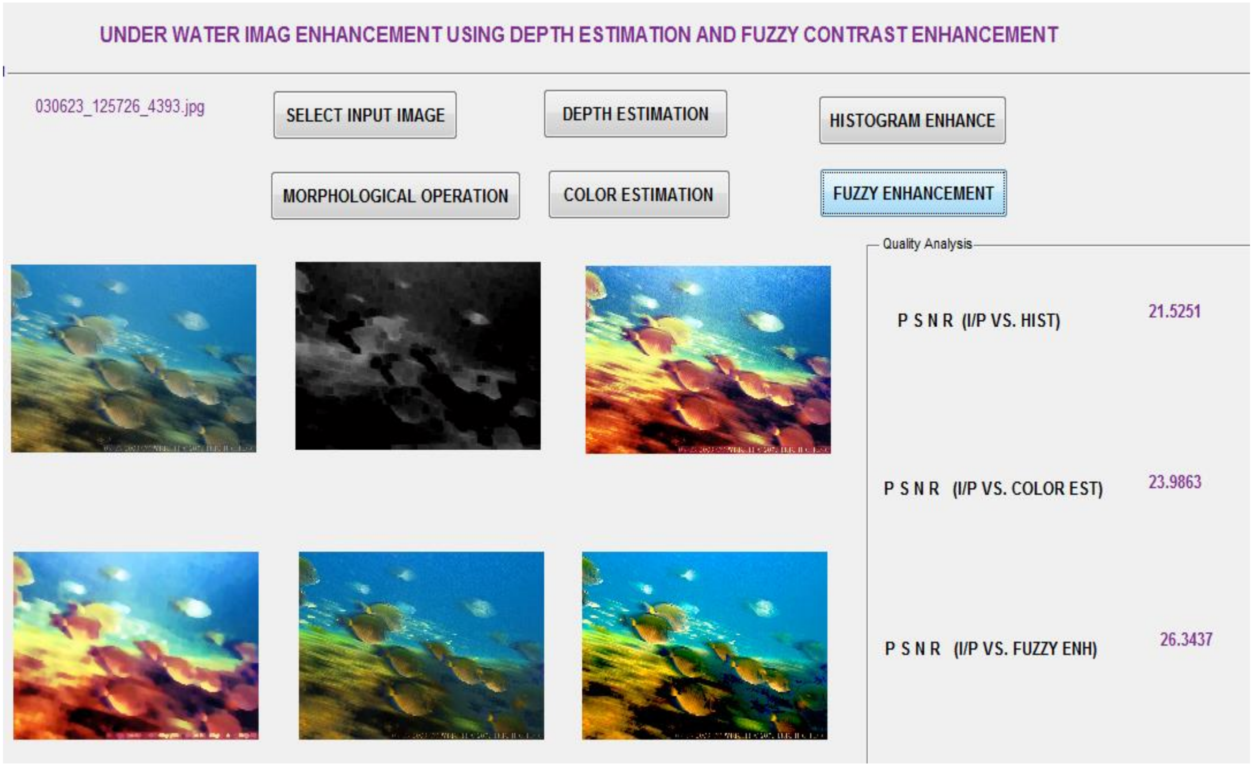

Figure 4 showing improvement in quality of image 4 after applying each step

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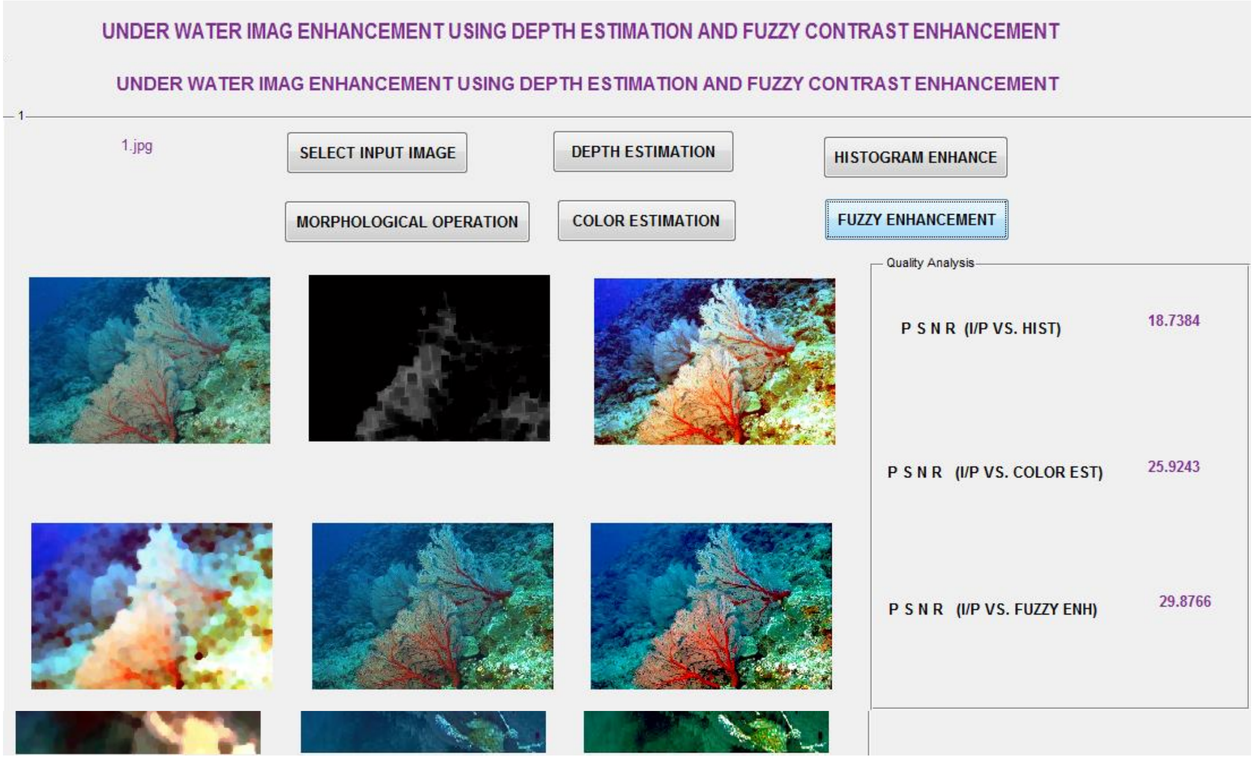

Figure 5 showing improvement in quality of image 5 after applying each step

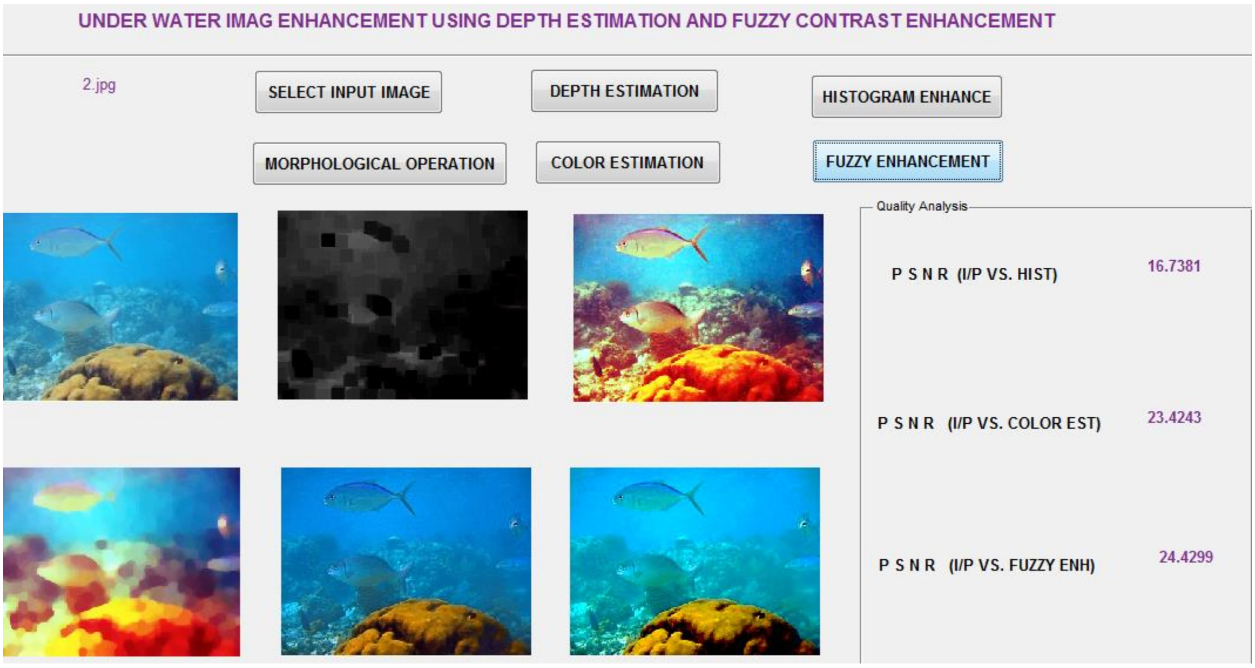

Figure 6 showing improvement in quality of image 6 after applying each step

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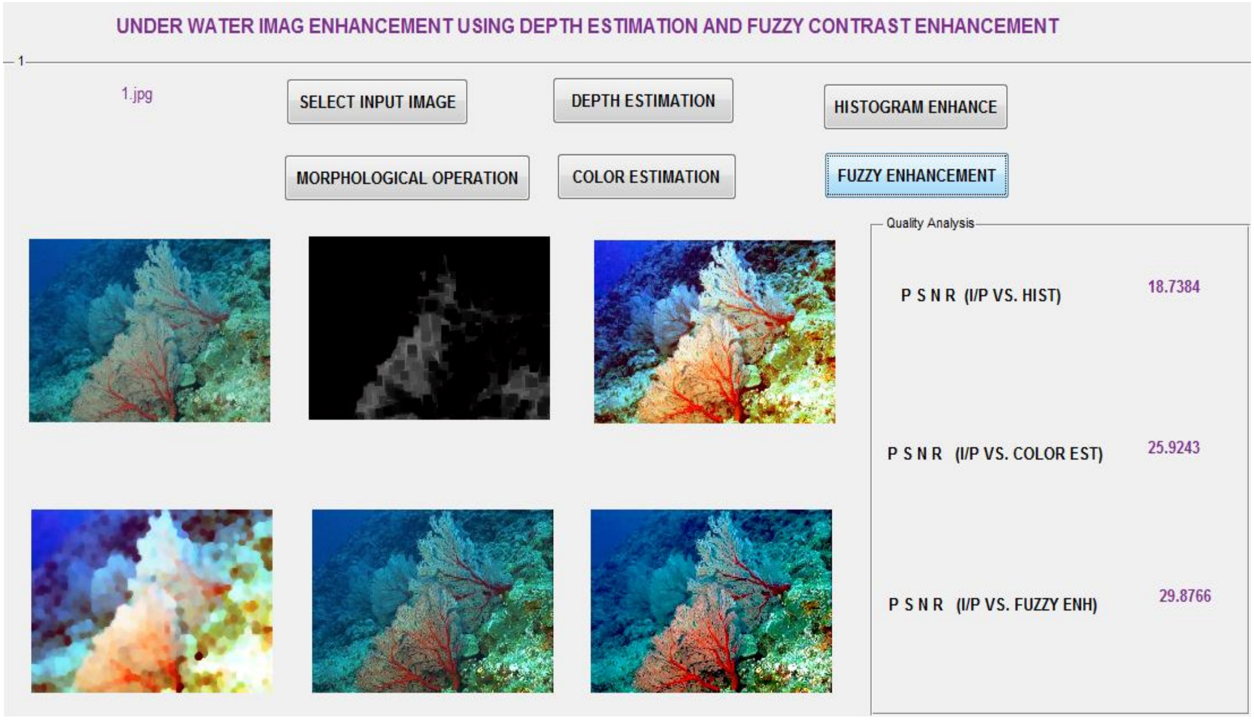

Figure 7: showing improvement in quality of image 7 after applying each step

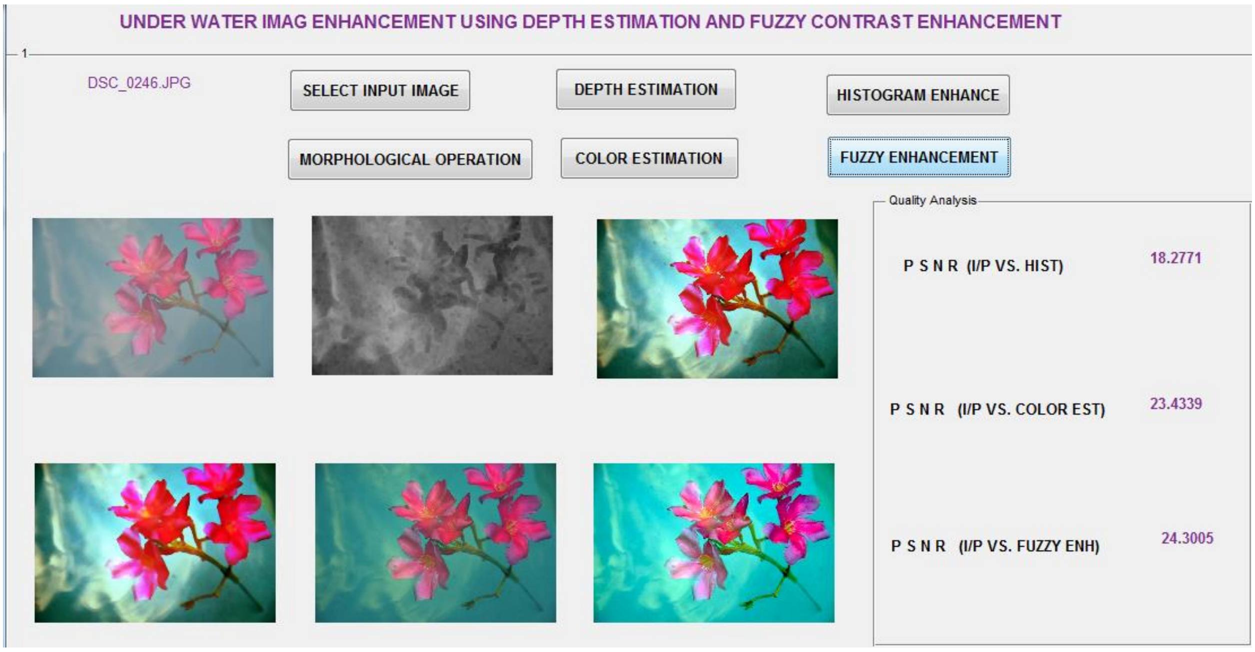

Figure 8 showing improvement in quality of image 8 after applying each step

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Table 5.1 is calculating the PSNR values of different Steps and compares the PSNR of previous methods with our method which shows a good improvement in quality after adding Fuzzy Based Contrast enhancement step.

Table 5.1 Comparison of PSNR values after each step

Image	PSNR Values		
	Input vs. Histogram	Input Vs. Color Estimation (Previous Method)	Input Vs. Color Estimation with Fuzzy Enhancement (Our Method)
1.jpg	18.74	25.93	29.87
2.jpg	16.74	23.42	24.43
3.jpg	19.45	23.57	24.11
4.jpg	21.52	24.11	26.79
5.jpg	21.15	26.15	28.44
6.jpg	20.9	23.42	23.86
7.jpg	16.68	25.68	38.49
8.jpg	16.22	23.38	24.11

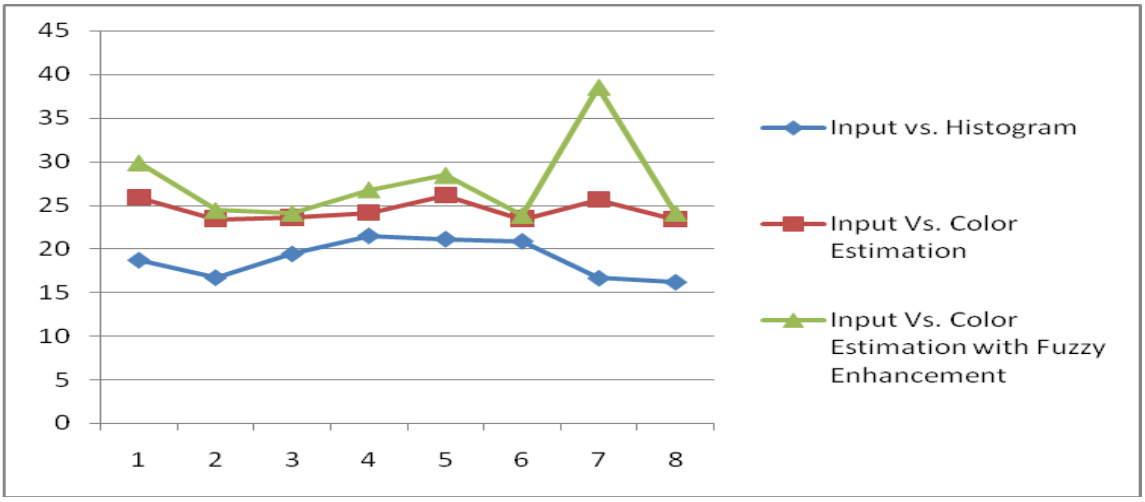

Figure 9 Comparison of PSNR values after each step

Form figure 4 we can easily observe that PSNR values are higher in all cases when comparing with previous method, the maximum PSNR value we get is 38.49 while in previous approach it was 26.15.

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VI. CONCLUSION & FUTURE SCOPE

The results shows that proposed algorithm improve low illumination and true colors of underwater images. According to our analysis, its understood that to boost underwater imaging processing, a common suitable database of test images is used. From Table 5.1 we can conclude that the PSNR values of different Steps and compares the PSNR of previous methods with our method which shows a good improvement in quality after adding Fuzzy Based Contrast enhancement step. Image enhancement techniques used in future for many areas such that Forensics, Astrophotography, Fingerprint matching and robotics etc. many researchers have applied the fuzzy logic to develop image Processing algorithms to calculate exact value and recognize.

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