© May 2023| IJIRT | Volume 9 Issue 12 | ISSN: 2349-6002

Python Based Subaqueous Image Advancement

Dr.Rohini Chavan[1], Sumedh S. Pande[2], Sahil Dutta[3] ,Vaishnavi Jagdale[4]

[1] *Assistant Professor, Department of Electronics and Telecommunication, Vishwakarma Institute of Information Technology (Pune), Maharashtra, India*

[2,3,4] *UG Student, Department of Electronics and Telecommunication, Vishwakarma Institute of Information Technology (Pune), Maharashtra, India*

***Abstract*—The image processing has always been a very difficult and challenging problem specially under water. The article is all about advancement of subaqueous images using python. Underwater images have many problems like cast colors, blurriness, low visibility, and low brightness mainly caused by absorption of light. The objective is to enhance the image and evaluate the images quantitively and graphically. The paper discusses the overview of implementation, development and operations performed for advancement of subaqueous images**

***Index Terms*— Advancement, subaqueous, Python, absorption, enhance, implementation**

I. INTRODUCTION

Underwater exploration has become very popular in last decades with increasing application demands. Also, the waterproof cameras are specially designed to easily capture and record underwater images and videos respectively. This can be very helpful in underwater analysis of scenes, search and rescue operations, study of marine species [1]. However, assuming a perfect transmission medium, the features of camera lenses and target objects can occasionally be modified by the light that is received; this is pertinent in the case of underwater photos. Due to these numerous issues, the scattering and absorption of light results in very low intensity images, fog, and blurriness. The requirement for subaqueous image progression is much needed [2]. Various degrees of color change result from light attenuation underwater, depending on the wavelength, dissolved organic components, water salinity, and level of phytoplankton concentration. In comparison to green and blue light, red light with a longer wavelength is absorbed more readily in water [3]. The physical paradigm of picture production serves as the foundation for image restoration technologies. However, this technique struggles to correct the color distortion. It is possible to get pleasing outcomes by merging two technologies.[4]

To estimate scene depth, we use a new method that gets around the issue. We suggest measuring scene depth by picture blurriness since greater scene depth results in higher object blurriness for underwater photographs. In single image defocusing, the measurement of picture blurriness is frequently debated. The edge-aware interpolation method is used to create the defocus map, in which blurriness at non-edge pixels is interpolated and propagated by close-by edge pixels based on brightness similarities. In order to calculate the pixel blurriness, a multiscale edge detector is used.[5] Images seem mostly bluish-green as depth increases because longer wavelengths are absorbed by water, while red is absorbed owing to its greater wavelength. Images are significantly degraded as a result of these phenomena, resulting in low contrast, color asymmetry, and poor visibility. Therefore, it is necessary to enhance underwater photographs to raise their quality so that they may be utilized for a variety of purposes while still protecting the important data they contain.[6]

II. LITERATURE SURVEY

The Flourishing movement has been underway for the past few years with the goal of using image processing to enhance underwater photographs [1].

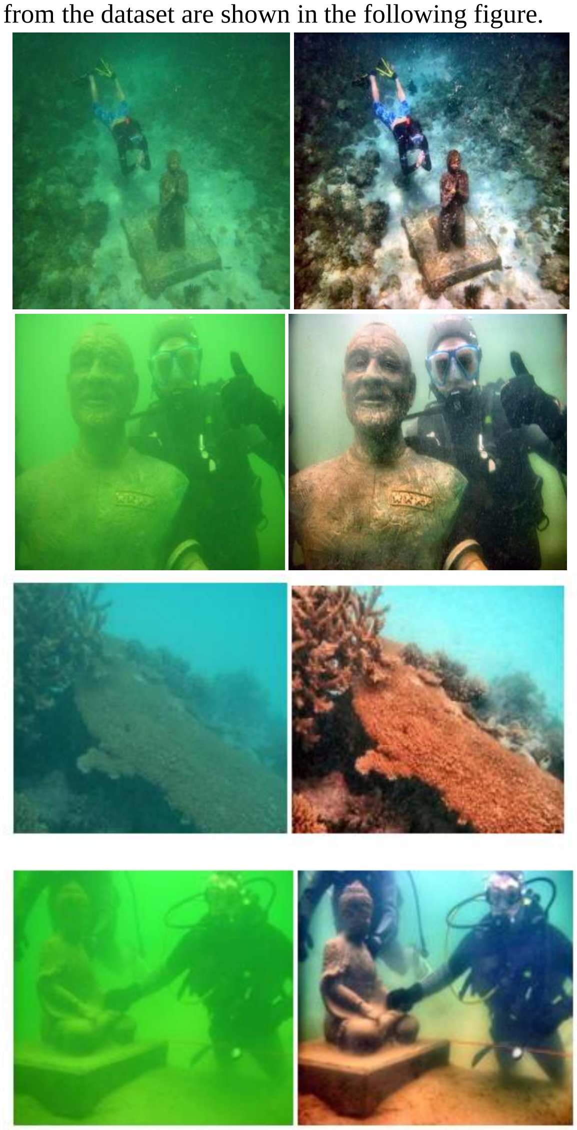
A method for restoring images using picture blurriness and light absorption based on depth estimate was published by Yan-Tsung Peng Pamela [3].

A technique using RGB Color Dependability Algorithm (UCDA) for enhancing underwater photos was presented by G- Somiyadevi and Dr. G. Kavitha [4]. This technique was used to improve photos using both light illumination and shadow color models.

With the use of depth estimation, Y-T Peng, X. Zhao, and P.C. Cosman proposed a technique for improving a single underwater image using blurriness. It has been shown that objects far from the camera are the most distorted and fuzzy. Determine the distance between scene points and the camera with the aid of the Image Formation Model (IFH) to recover and improve underwater photographs.[5]

III. DATASET

From [7], we have chosen seven pictures for our project. The photos and the related reference images from the dataset are shown in the following figure.



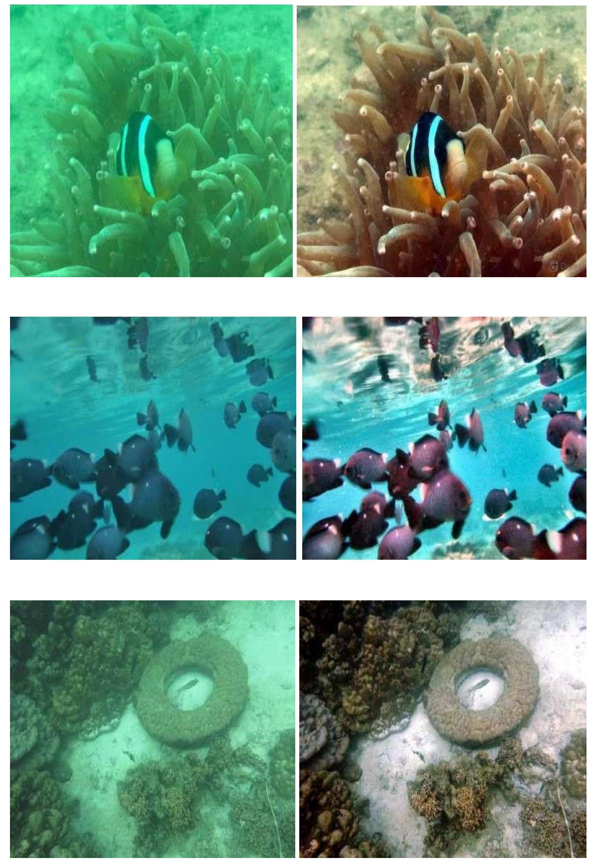


Fig 1. Images (left) and their corresponding Reference Images (right)

IV. METHODOLOGY

Plotting the histogram of RGB Channels of image
In Addition to histogram, we observed that all colors are degraded the least color degraded is green.
Then we need to restore the colors for that the color correction method is used.
For color correction, first, we need to compensate for the degradation of the R channel and in cases where images have a greenish appearance B channel also needs to be compensated. The compensation process is to add a fraction of the green channel to the Red and Blue (when required) channel as it is the least degraded channel. [1]

The formula for the compensated red channel Irc at every pixel location (x)

$$Irc(x) = Ir(x) + (g - r) * \left(1 - Ir(x)\right) * Ig\,I\,I\,(x) \quad \text{---------------(1)}$$

The formula for the compensated blue channel Ibc at every pixel location (x)

$Ibc(x) = Ib(x) + (g - b) * (1 - Ib(x)) *$
$Ig\ I\ I\ (x)Ir$ -----------------(2)

Ig represent the red and green colour channels of the image, Ir, Ig, Ib denote the mean value of Ir, Ig, and Ib respectively.[10]

After compensation the next step in color correction is to perform white balancing using the Gray World Algorithm

The output image still has low contrast and edges are not clearly visible.

Next step is to enhance contrast and brightness using global histogram equalization

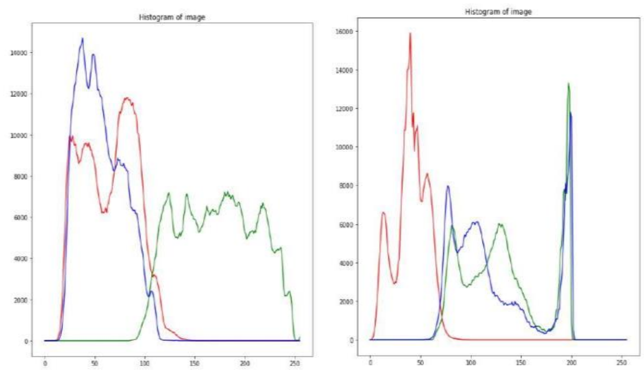


Fig 2 a) Histogram of image 1

Fig 2 b) Histogram of image 3

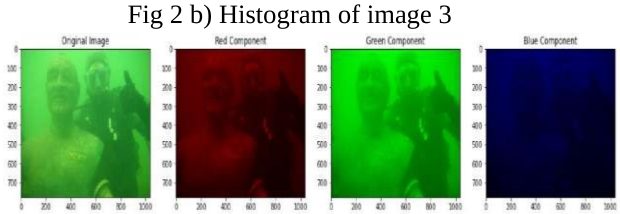


Fig 3. RGB components of image 1

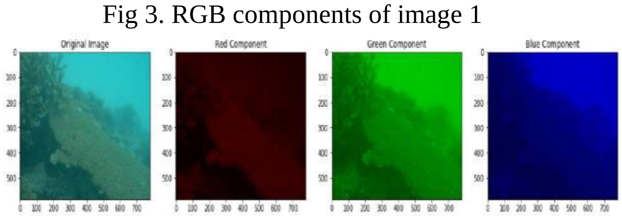


Fig 4. RGB components of image 3

The Equalization is performed by first converting the image to the HSV domain and then equalizing the Value component. The contrast-enhanced image is then obtained by concatenating the original Hue component, original Saturation component, and equalized Value component.

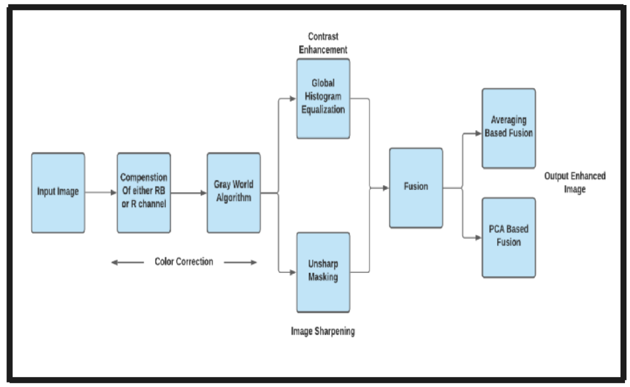


Fig 5. Block diagram

Next, we perform unsharp masking to sharpen the color-corrected image.

$gMASK\ (x, y) = f\ (x, y) - Gaussian_{Blur}(f\ (x, y))$ (3)

$g\ (x, y) = f\ (x, y) + gMASK(x, y)$-------------- (4)

$g(x, y) = 2 * f(x, y) - Gaussian_{Blur(f(x,y))}$-----(5)

The image that we want to perform unsharp masking on in this case is $f\ (x, y)$.

We currently have a contrast-enhanced image and a sharpened image; we must now execute fusion to combine these two images and get a final enhanced image.

There are two techniques that we have used for the fusion of two images.

Averaging Fusion Method.

This method uses the average intensity of matching pixels from both the input and output images to create the final fused image. When a collection of photos from the same scene or Viewfield are collected, the method calculates an average or arithmetic mean of the intensity values for each pixel point.

$$F(i, j) = \frac{A(i,j)+B(i,j)}{2} \quad \text{----------------- (6)}$$

$A(i, j)$, $B(i, j)$ are input images and $F(i, j)$ is fused image.

PCA-based Fusion.

The processes below are carried out for each channel of the image in PCA-based fusion The parts of both photos are first flattened to create a column vector.

Then, the two column vectors obtained above are concatenated to produce

$a\ 2 * N\ (N = x * y, x, y\ is\ the\ size\ of\ the\ image)$ -(7)

matrix.

Next, calculate each column's mean and deduct it from the corresponding column. Next, after removing the mean from the matrix you previously obtained, find its covariance matrix.

Find the covariance matrix's eigenvalues and eigenvectors. The following is how the coefficient is determined: Choose the column vector of dimensions $1 * 2$ that corresponds to the highest eigen value.

$Coefficient\ 1: V\ [0, V\ [0, and\ V\ [1]$ ----------- (8)

$Coefficient\ 2: V[1], V[0], and\ V[1]$ ----------- (9)

A fused image is created by multiplying the coefficient for each channel by the corresponding images for each pixel value after obtaining the coefficient for both images for each channel

After the fusion process, the final image obtained is an enhanced image.[6]

Next, we used MSE and PSNR to compare the quality of the images obtained from the above method and the reference image provided in the dataset.

V. RESULT AND DISCUSSION

We can infer from Fig. that the image obtained through the fusion process has improved contrast and visibility, and the R, G, and B components are less degraded, as shown in Figs. and. The tables below, Tables and, show the MSE and PSNR values of both the PCA-based fusion method and the averaging-based fusion method.

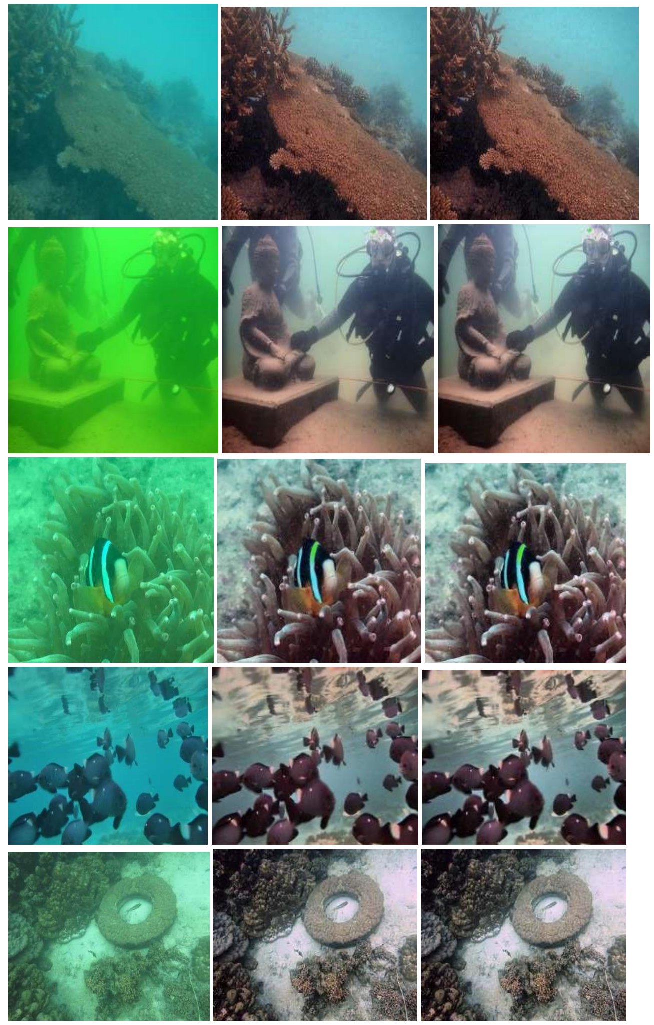


Fig 6. (Left to right) Original Image, averaging based Fusion Enhanced Image, PCA Based fusion Enhanced Image

Image compression quality is compared using the peak signal-to-noise ratio (PSNR) and mean-square error (MSE). The PSNR gives a measure of the peak error, whereas the MSE represents the cumulative squared error between the original and compressed picture. The error decreases as the MSE value decreases.

The block initially computes the mean-squared error using the following equation before computing the PSNR.

$$MSE = \sum_{M,N} \frac{[I_1(m,n)-I_2(m,n)]^2}{M*N} \quad \text{-------------- (10)}$$

M and N in the above equation stand for the input pictures' respective rows and columns. The block then uses the following calculation to get the PSNR.:

$$PSNR = 10\log10\left(\frac{R^2}{MSE}\right) \quad \text{--------------- (11)}$$

R represents the largest variation in the input picture data type in the preceding equation. For instance, R is

1 if the input picture is of the double-precision floating-point data type. R is 255, for example, if the data type is an 8-bit unsigned integer.

Sr. No	Averaging based Fusion			
	Reference Image & Original Image		Reference Image & Our result	
	MSE	PSNR	MSE	PSNR
1	307.7587848574467	23.248699023168	255.3803710029	24.0589284731
2	301.2079594930013	23.342139168511	282.0235875447	23.6279492803
3	330.55965811965	22.9383051019	298.34620644	23.383598408
4	314.2733835242555	23.157727596086	288.2103903637	23.5337072722
5	321.1966878858025	23.063093025935	269.4710988940	23.8256816746
6	320.0508887043189	23.078613234031	322.2196137873	23.0492838809
7	324.693584	23.01606653889	161.9284266666	26.0375726467

Table 1.MSE & PSNR for Averaging based fusion method

Sr. No	PCA based Fusion			
	Reference Image & Original Image		Reference Image & Our result	
	MSE	PSNR	MSE	PSNR
1	307.7587848574467	23.2486990231683	260.463545475	260.463545475
2	301.2079594930013	23.3421391685114	272.826347351	23.7719405222
3	330.5596581196581	22.9383051019592	301.161023449	23.3428159651
4	314.2733835242555	23.1577275960860	284.919585862	23.5835805645
5	321.1966878858025	23.0630930259357	265.895315715	23.8836967444
6	320.0508887043189	23.0786132340313	323.386128529	23.0335897372
7	324.693584	23.0160665388935	156.233872	26.1930516469

Table 2. MSE & PSNR for PCA based fusion method

We can conclude from looking at the MSE and PSNR values that, except for picture 6, the images created after fusion have low MSE when compared to the MSE of the original image and reference image. Additionally, except for picture 6, the final photos had greater PSNRs than the original and reference images.

VI. CONCLUSION

The proposed processes performs better than conventional underwater image enhancement techniques after testing. The method is used for degraded underwater images [1]. Here a system for enhancing underwater images to remove blurriness fogginess and excessive color degradation [2]. Marine snow can be considered to improve this idea since it may also contribute to distortion in underwater camera photos. It is demonstrated that the depth estimate method based on blurriness performs effectively for a range of photos. The underwater images are very useful resource for learning variety of topics [3]. To reduce blurriness and noise from underwater photos, we perform some pre-processing. A comparison of picture performance metrics is also run, demonstrating how much superior our suggested approach is [4]. The experimental findings demonstrate that, in comparison to existing IFM-based enhancement techniques, the suggested method may create superior improved underwater photos under a variety of illumination circumstances [5].

We were able to successfully improve the underwater photographs using the technique. We also used measures, specifically MSE and PSNR, to assess the effectiveness of the approach in producing high-quality pictures. The approach described above has the drawback of occasionally producing blue artefacts on white portions of photographs, especially in underwater images when there are water bubbles. Therefore, it is not reliable for all kinds of photos. Additionally, if the image is noisy, the noise should first be eliminated by performing Gaussian smoothing. Then, as demonstrated in, our approach may be used.[6]

VII. FUTURE SCOPE

Currently, the enhancement process is not automated; instead, we must choose the type of compensation we require. For example, we must include a variable flag in the algorithm that accepts the values 0 and 1, where 0 indicates that the image is greenish and that R and B channels must be compensated, and 1 indicates that the image is bluish and that only R channel must be compensated because B is not significantly degraded. We can use a deep learning-based model to automate this procedure, but for effective results, it needs a sizable dataset. Increase the process' overall robustness to get rid of the problem with bluish artefacts that was described earlier. that it functions for all conceivable photos. In our upcoming effort, we will concentrate on adding the dehazed frame to the underwater image input for better underwater image quality.

REFERENCE

1] A Review on Underwater Image Scene Enhancement and Restoration using Image Processing Ms. Tejal R. Haware1, Prof. P. R. Gumble2.

[2] Underwater image enhancement using white balance and fusion- Sophia Philip, Gisha GS
[3] Yan-Tsung Peng and Pamela C. Cosman, "Underwater Image Restoration Based on Image Blurriness and Light Absorption" in IEEE Trans. Img. Proc. Vol. 26, No. 4, April 2017.
[4] G. Sowmiyadevi and Dr. G. Kavitha, "UCDA: An Underwater Image Restoration using RGB Color Dependability Algorithm" in National Conference on Innovations in Computing and Communication (NCICC- 2016).
[5] Y.-T. Peng, X. Zhao, and P. C. Cosman, "Single underwater image enhancement using depth estimation based on blurriness," in Proc. IEEE Int. Conf. Imag. Process. (ICIP), Sep. 2015, pp. 4952–4956
[6] Implementation of Underwater Image Enhancement- Pranjali Bajpai, Yogesh Vaidhya.
[7] https://li-chongyi.github.io/proj_benchmark.html