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A Novel Appraoch for Underwater Image Enhancement using MultiWavelet and Fusion Technique

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Abstract—*Image enhancement recovers the visibility of one aspect or component of an image. Current camera systems often fail as a result of deprived visibility underwater rising from light scattering, light refraction, absorption, and uncontrolled particles in underwater. As well the correct conception of components and their arrangement, henceforth it is vital to create a sophisticated image enhancement and processing, for the uses of camera systems in the underwater area. Subsequently concluded that de-noising is required for under water image enhancement which will significantly enhance the quality of underwater image. In this research we have proposed the use of Multi-Wavelet for de-noising of image. Further for image enhancement we will apply multiscale fusion approach, in which gaussian pyramid, laplacian pyramid weighted, exposedness weight calculated and fusion applied, eventually output image quality validated by calculating pcqi, ssim, niqe, brisque parameters. Achieved significant improvement in output image quality.*

Keywords—*PCQI, MSE, SSIM, NIQE, PIQE*

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I. INTRODUCTION

Image enhancement uses qualitative subjective approach to process a more visually pleasing image. They do not depend on any physical or visible model for the image formation. These approaches are usually effortless and faster than deconvolution methods. The existing research has shown that underwater images raise new challenges and impose significant problems due to light absorption and scattering effects of the light and inherent structureless environment. Exploring, understanding and investigating underwater activities of images are gaining more importance for the last few years. Scientists are keen to search the mysterious underwater world. Even so, this area is still lacking in image processing analysis techniques and methods that could be used. Researchers have tried to employ several different enhancement techniques.

There are various techniques of underwater image enhancement some of them are as follows:

- Contrast-limited adaptive histogram equalization (CLAHE)
- Image enhancement by correcting image intensity value or color space
- Image Enhance by enhancing contrast using histogram equalization
- Gamma Correction

We did experimental analysis for some image enhancement techniques, implementation done on Matlab 2019a.

CLAHE

pcqi =

0.8417

Adjust image intensity values

pcqi =

0.7768

Enhance contrast using histogram equalization

pcqi =

0.7835

Adjust image colormap (Gamma Correction)

pcqi =

0.9105

Adjust image colormap (Gamma Correction)

pcqi =

0.8003

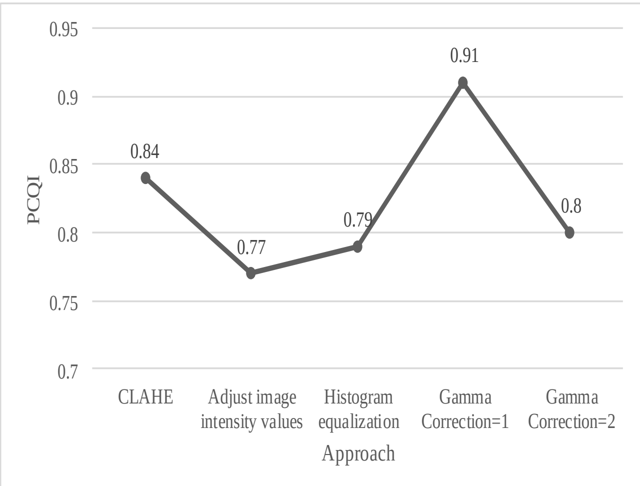


Figure -1 Comparison of Image Enhancement Techniques based on PCQI value

Further in section II of this paper we will give a tabular comparison among earlier study in this field, in section III we will discuss some bottle necks towards research, in section-IV we will discuss proposed method, in section V we will detail about experimental evaluation at last we will conclude our research.

II. LITERATURE SURVEY

S. No.	Author/Publication Year	Title	Approach Used	Description
1.	Md Jahidul Islam et. al. / 2019	Fast Underwater Image Enhancement for Improved Visual Perception/ arXiv	Conditional generative adversarial network-based model	Proposed model can be used as an image processing pipeline by visually-guided underwater robots in real-time applications
2.	Codruta O. Ancuti et. al./ /2018 IEEE	Color Balance and Fusion for Underwater Image Enhancement	Combining white balancing and image fusion	Blending of two images that are directly derived from a colorcompensated and white-balanced version of the original degraded image.
3.	László Neumann et. al./ 2017	Fast Underwater Color Correction Using Integral IMAGES / arXiv	Ruderman-opponent color space	Presents a fast enhancement method for color correction of underwater images. The method is based on the gray-world assumption applied in the Ruderman-opponent color space
4.	M. D. Kodak F.R.Dalgleish, M.F.Caimi and Y.Y. Schechner. / 2008	A focus on recent developments and trends in underwater imaging.	Image formation and Image processing methods and Extended range imaging techniques.	This proposed approach focuses on the recent advancements in hardware, software and algorithmic methods to overcome the absorpt and scattered nature of sea water.
5.	G.L.Foresti/ 2001	Visual inspection of sea bottom structures by an autonomous underwater vehicle.	It uses three-dimensional model of the environment and of an extended kalman filter allows the guidance and the control of the vehicle in real time.	This paper describes a vision-based system for inspection of underwater structures by an autonomous vehicle.
6.	A.Olmos and E.Trucco/ 2002	Detecting man-made objects in unconstrained subsea videos.	Quality Metric and Bayesian Classifier	This model describes an automatic vision system capable of detecting a variety of man-made objects in underwater imaging conditions.
7.	B.A.Levedahl and L.Silverberg/ 2009	Control of underwater vehicles in full unsteady flow.	Reduced-order model, Coupled Fluid Vehicle Model and Fluid compensation control.	This model describes the full unsteady flow and measures the hydro-dynamic loads directly and also shows how a rational balance between canceling the hydrodynamic load.
8.	J.P.Tarel, N.Hautiere, L.Caraffa, A.Cord, H.Halmaoui and B.Gruyer/2012	Vision enhancement in homogeneous and heterogeneous fog.	Colour and contrast enhancement and Enhancement based on Koschmieder's law.	This model proposes the rating visibility enhancement algorithms which is based on the addition of various generated fog on synthetic and camera images.
9.	D.-M.He and G.G.L.Seet/2004	Divergent-beam LiDAR imaging in turbid water.	Under Water LiDAR Imaging (UWLI) principle and system.	Describes the divergent-beam UWLI system to range-gate on the targets which are required to capture and to range-gate out the targets which are not required.
10.	Y.Y.Schechner and Y.Averbuch/2007	Regularized image recovery in scattering media.	Restoration using adaptive regularization.	This study demonstrates the approach in atmospheric and underwater experiments based on an automatic method for determining the medium transmittance.
11.	J.Y.Chiang and Y.-C.Chen/ 2012	Underwater image enhancement by wavelength compensation and dehazing.	Wavelength Compensation and Image Dehazing (WCID) Algorithm	The propound WCID algorithm handles light scattering and colour change distortions caused by underwater images concurrently.
12.	P.Drews-Jr., E.Nascimento, F.Moraes, S.Botelho, M.Campos and R.Grande-Brazil/ 2013	Transmission estimation in underwater single images.	Underwater Dark Channel Prior (UDCP).	UDCP examines that blue and green colour channels are the underwater visual information source which allow a remarkable improvement over DCP.
13.	A.Galdran, D.Pardo, A.Picon and A.Alvarez-	Automatic red-channel underwater image	Red Channel Underwater Image Restoration	This method is an extension of Dark Channel Method which adapts the

	Gila/ 2015	restoration.		way images are degraded and it handles visibility loss and colour corruption.
14.	S.Emberton, L.Chittka and A.Cavallaro/ 2015	Hierarchical rank-based veiling light estimation for underwater dehazing.	Region-based approach, Superpixel segmentation and clustering and Transmission estimation	This method considers scene features thus it avoids estimation of veiling lights from regions that contain objects also it includes transmission estimation which handles over saturations and the production artefacts.

III. PROBLEM STATEMENT & METHDOLOGY

Image enhancement recovers the visibility of one aspect or component of an image. Current camera systems often fail as a result of deprived visibility underwater rising from light scattering, light refraction, absorption, and uncontrolled particles in underwater. As well the correct conception of components and their arrangement, henceforth vital to create a sophisticated image enhancement and processing.

For demising of image we have proposed the use of Multi-wavelet. In Multi-wavelet based denoising the first step is preprocessing for the input image, we are using Row preprocessing method. After preprocessing we will change the image into the multi-wavelet as domain using an orthogonal periodic multi-wavelet transform. Now the thresholds will be calculated by using the proposed method. Then we will perform the inverse multi-wavelet transform to acquire the reconstruction information then perform post-processing. the reconstruction information to get the denoised image.

Preprocessing in Multiwavelet: - Multiwavelet necessitates that some preprocessing has to be accomplished on input image while and before doing transform, so the signal preprocessing is necessary. It is a process to enhance the image in order to make it suitable for further processing which improves the image. Techniques are used to enhance contrast of image and isolating the objects of interest. We had applied following three preprocessing on input image.

a. Repeated Row Preprocessing
b. Matrix First Order Approximation
c. Matrix Second Order Approximation

Repeated Row Preprocessing: **-** In this case the given scalar input fk of length N is mapped to a sequence of N length-2 vectors as a result of the Preprocessing operation. The most obvious way of getting two input rows from a given signal is to repeat the signal. Thus, the input to the filter-bank is produced from the original data.

Approximation: **-** The approximation preprocessing algorithm is based on the approximation properties of the continuous-time multi-wavelets, and yields a critically sampled signal representation. This kind of preprocessing produces 2 N/ length-2 vectors. Approximation preprocessing is a special case of matrix pre-filtering, such that

$$y\ 0,k = {}_{m=0}^{M} P_m \begin{matrix} f2(m+k) \\ f2(m+k)+1 \end{matrix}$$

P_m are 2 x 2 matrices. Methods of designing approximation pre-filters for various multi-wavelets.

Multi-wavelet transform:- Transform the preprocessed image into the multi-wavelet as domain using an orthogonal periodic multi-wavelet transform.

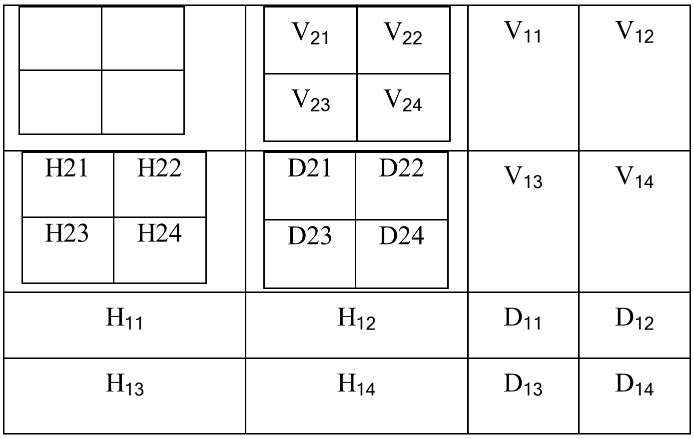


Figure 2: Multi-wavelet image decomposition upto two levels,with r=2

We had applied all three above preprocessing on input image and we got repeated row processing gives better PSNR value. In next step we had applied multi-wavelet decomposition on all three preprocessed image i.e.
a. GHM with Repeated-Row Processing
b. GHM with Matrix first order approximation
c. GHM with Matrix second order approximation

GHM with Repeated-Row Processing: **-** GHM is a single-level discrete 2-D multi-wavelet transformation. GHM applies a single-level 2-D multi-wavelet decomposition using the GHM multi-wavelet with four multi-filters Y = GHM(X) computes the approximation coefficients matrix LL and details coefficients matrices, LH, HL, HH, which are obtained by a multi-wavelet decomposition of the input matrix X and puts the result in Y=[LL,LH;HL,HH]. The size of Y is double that of X which should be a square matrix of size NxN where N is power of 2 since X is vectorized by a repeated row preprocessing. LL, LH, HL, and HH will have the size of NxN.

GHM with Matrix first order approximation: **-** Y = GHMAP(X) computes the approximation coefficients matrix LL and details coefficients matrices LH, HL, HH, obtained by a multiwavelet decomposition of the input matrix X and puts the result in Y=[LL,LH;HL,HH]. The size of Y is the same as that of X which should be a square matrix of size NxN where N is power of 2 since X is vectorized by critical sampling preprocessing. The preprocessing filter is of order 2 degree 1. LL, LH, HL, and HH will have the size N/2xN/2.

GHM with Matrix second order approximation: **-** Y = GHMAP2(X) computes the approximation coefficients matrix LL and details coefficients matrices LH, HL, HH, obtained by a multiwavelet decomposition of the input matrix X and puts the result in Y=[LL,LH;HL,HH]. The size of Y is the same as that of X which should be a square matrix of size NxN where N is power of 2 since X is vectorized by critical sampling preprocessing. The preprocessing filter is of order 2 degree 2. LL, LH, HL, and HH will have the size N/2xN/2**.**

After this step we had applied hard threshold on multiwavlet transformed image.

Hard Thresholding: **-** To reduce the noise we apply the following nonlinear transformation to the empirical wavelet coefficients:

$$f(x) = x.((x) > t)$$

Where t is a certain threshold. The choice of the threshold is a very delicate and crucial statistical problem. On one hand, a big threshold leads to a huge bias of the estimator. But on the other hand, a small threshold gives rise to the variance of the smoother. Theoretical considerations posses the following value of the threshold:

$$t = \sqrt{2v^2 \log(n)\,/n}$$

Where n is the length of the input vector and σ2 is the variance of the noise. The variance of the noise is estimated and based on the data. We do this by averaging the squares of the empirical wavelet coefficients at the highest resolution scale. We provide two possibilities for choosing a threshold. First of all you can do it by ``eye'' using the Hard threshold item and entering the desired value of the threshold. The threshold offered is the one which is described in the paragraph before. Note that this threshold value is conservative in most cases and hence we should choose a threshold value below the offered one. The item Automatic means that the threshold will be selected as

$$t = \sqrt{2v^2 \log(n)\,/n}$$

with a suitably estimated variance.

After this step we had applied inverse multiwavelet and postprocessing performed on output image of above step.

Inverse GHM Repeated-Row Processing: - IGHM Single-level inverse discrete 2-D multi-wavelet transform. IGHM executes a single-level 2-D multi-wavelet reconstruction using GHM multi-wavelet with four multi-filters Y = IGHM(X) which computes the original matrix from the approximation coefficients matrix LL and details coefficients matrices LH, HL, HH, which is obtained by a multi-wavelet decomposition of the original input matrix and puts the result in Y. The size of Y is half that of X which should be a square matrix of size NxN where N is power of 2 since X is de-vectorized by a repeated row post-processing. X should be arranged as [LL, LH; HL, HH].

Inverse GHM Matrix First order approximation: - IGHMAP executes a single-level 2-D multi-wavelet reconstruction using GHM multi-wavelet with four multi-filters Y = IGHMAP(X) computes the original matrix from the approximation coefficient matrix LL and details coefficients matrices LH, HL, HH, which is obtained by a multi-wavelet decomposition of the original input matrix and puts the result in Y. The size of Y is the same as that of X which should be a square matrix of size NxN where N is power of 2 since X is de-vectorized by critical sampling preprocessing. The post-processing filter is of order 2 degree 1. LL, LH, HL, and HH should have the size of N/2xN/2. X should be arranged as [LL,LH;HL,HH].

<table>
<tr><td>L1L1</td><td>L1L2</td><td rowspan="2">H1L1 H2L1
H1L2 H2L2</td></tr>
<tr><td>L2L1</td><td>L2L2</td></tr>
<tr><td colspan="2">L1H1 L2H1
L1H2 L2H2</td><td>H1H1 H2H1
H1H2 H2H2</td></tr>
</table>

Inverse GHM Matrix Second order approximation:- Y = IGHMAP2(X) computes the original matrix from the approximation coefficient matrix LL and details coefficients matrices LH, HL, HH, obtained by a multi-wavelet decomposition of the original input matrix and puts the result in Y. The size of Y is the same as that of X which should be a square matrix of size NxN where N is power of 2 since X is de-vectorized by critical sampling preprocessing. The post-processing filter is of order 2 degree 2. LL, LH, HL, and HH should have the size N/2xN/2. X should be arranged as [LL,LH;HL,HH].

Proposed Algorithm

1. Input Under water Image.
2. Apply Multiwavelet based De-noising.
3. White balance
4. Create color transformation structure
5. Apply device-independent color space transformation
6. Apply Contrast-limited adaptive histogram equalization
7. Create color transformation structure
8. Apply device-independent color space transformation
9.Calculate laplacian contrast weight
10. Calculate Local contrast weight
11. Calculate the saliency weight
    a. Read image and blur it with a 3x3 or 5x5 Gaussian filter
    b. Perform sRGB to CIE Lab color space conversion (using D65)
c. Compute Lab average values
d. Finally compute the saliency map and display it.
12. Calculate the exposedness weight.
13. Calculate the normalized weight
14. Calculate the gaussian pyramid with level=5
15. Calculate the laplacian pyramid with Level=5
16. Fusion of all weight calculated
17. Generate enhanced image.

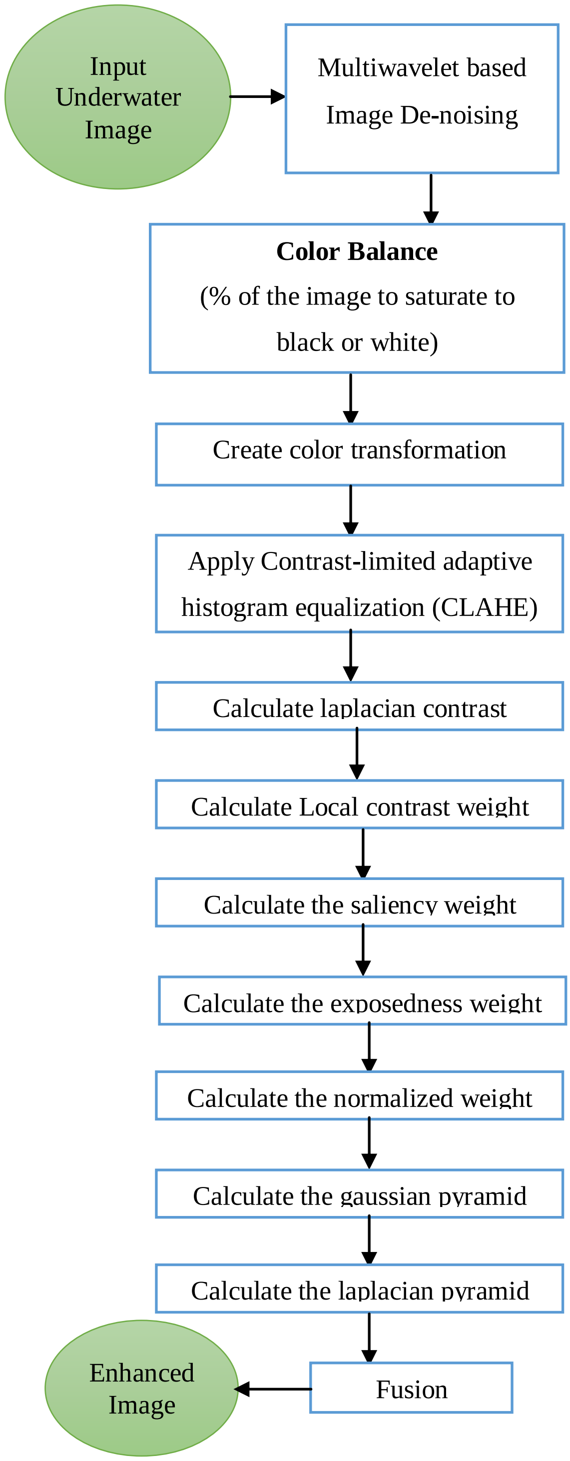


Figure 3 - Proposed Flow

IV. RESULT AND DISCUSSION

For implementation of proposed system we have used Matlab 2019a, taken different underwater images as input.

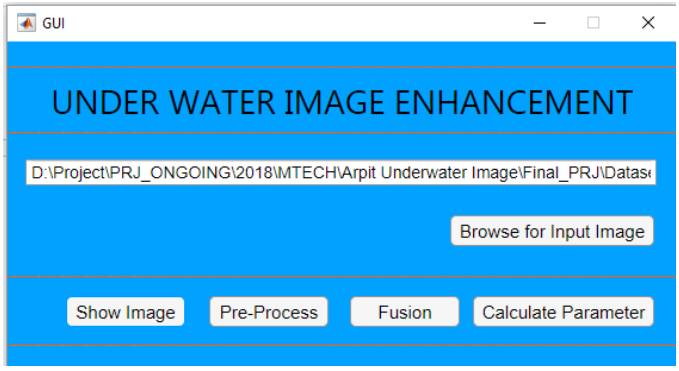


Figure 4 - First UI of Proposed System

Step-1 Input Image

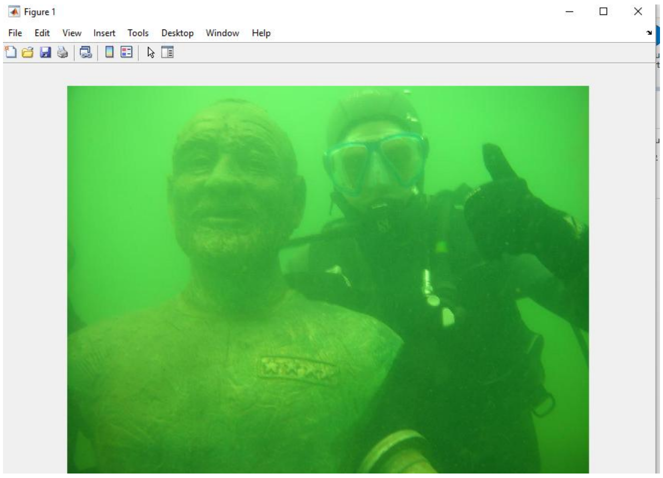


Figure 5 - Input Image

Step-2 Multiwavelet

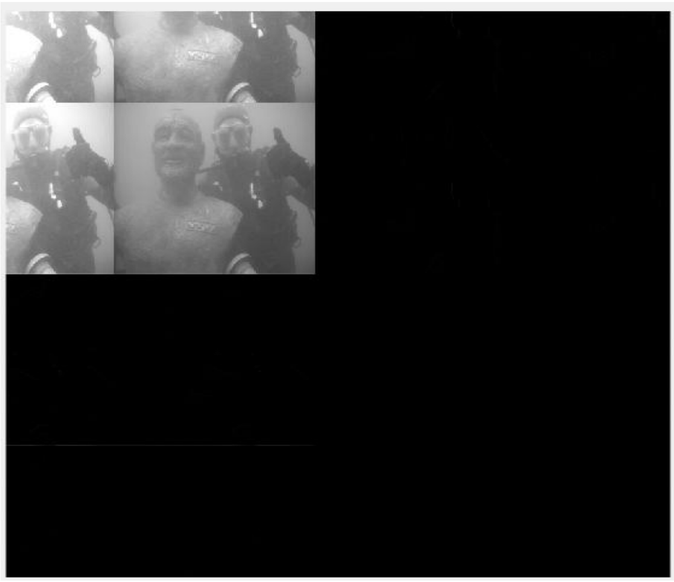


Figure 6 - GHM Processing

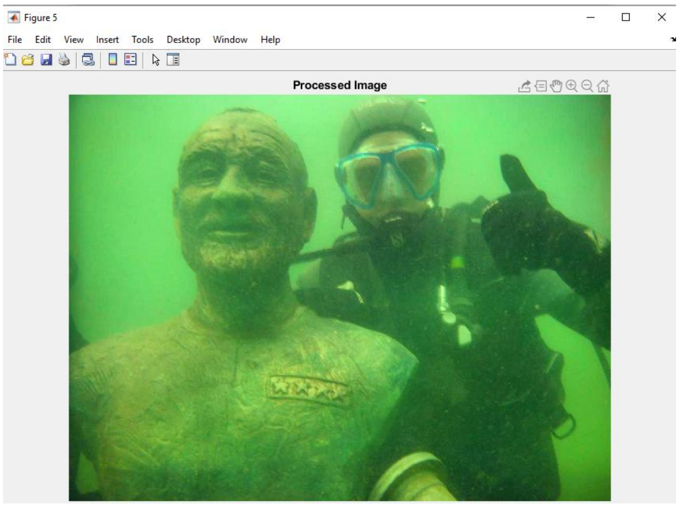


Figure 7 - De-noised Image

Step-3 Color Balance

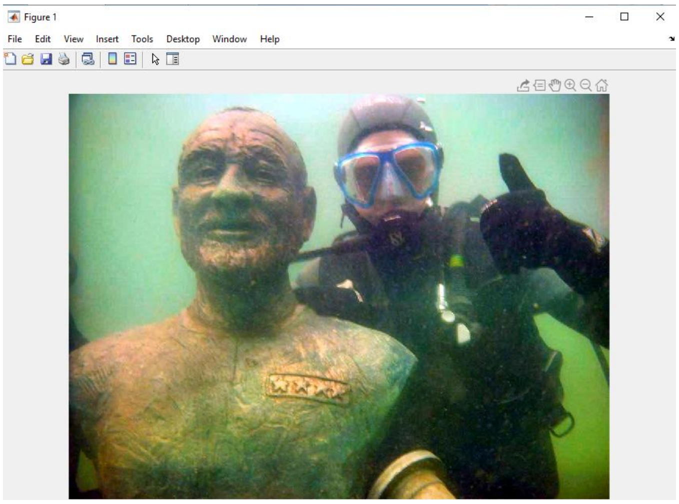


Figure 8 - White Color Balance

After calculating different weight fusion performed and fig-8 shows the enhanced image.

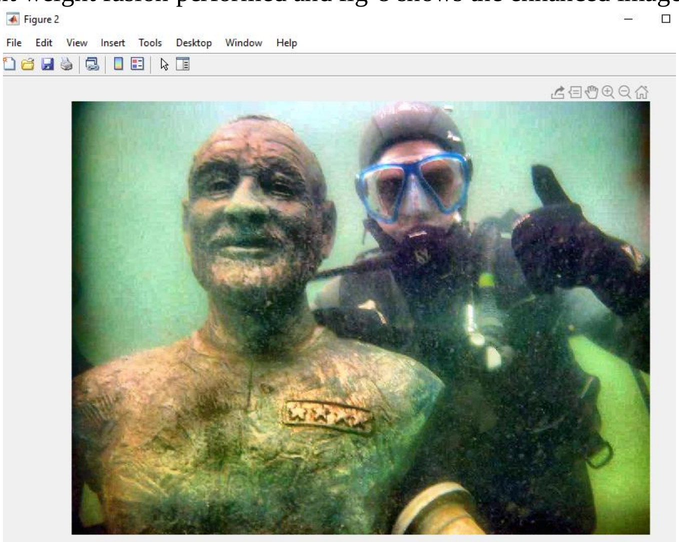
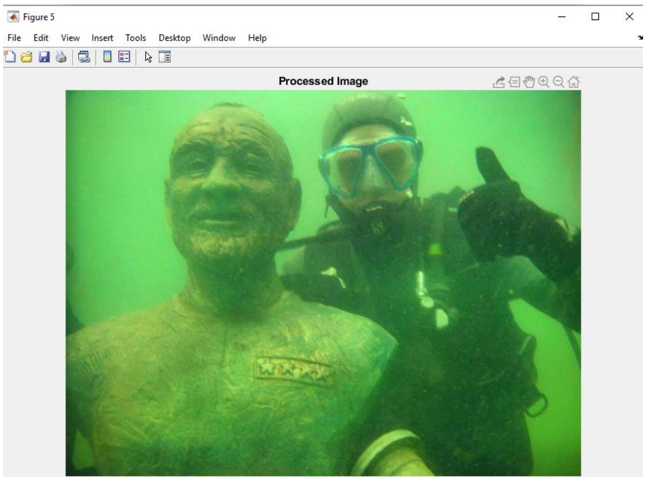


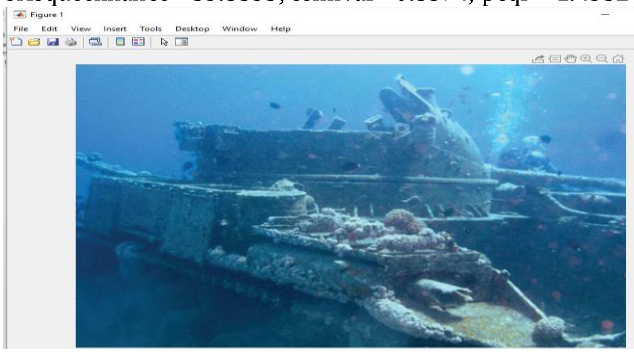
Figure 9 - Enhanced Image

We have performed same steps to different images and validated by calculating different image quality parameters as:

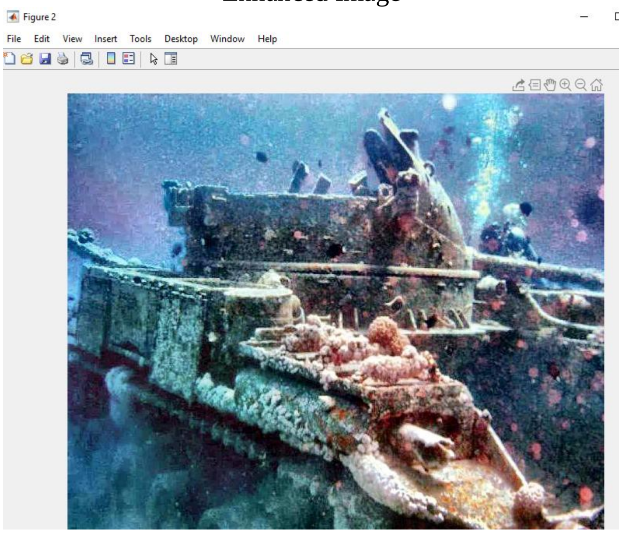
1. PIQE: Perception based Image Quality Evaluator
2. NIQE: Naturalness Image Quality Evaluator
3.BRISQUE: Blind/Referenceless Image Spatial Quality Evaluator
4. SSIM: Structural Similarity Index
5. PCQI: A Patch-Structure Representation Method for Quality Assessment of Contrast Changed Images.



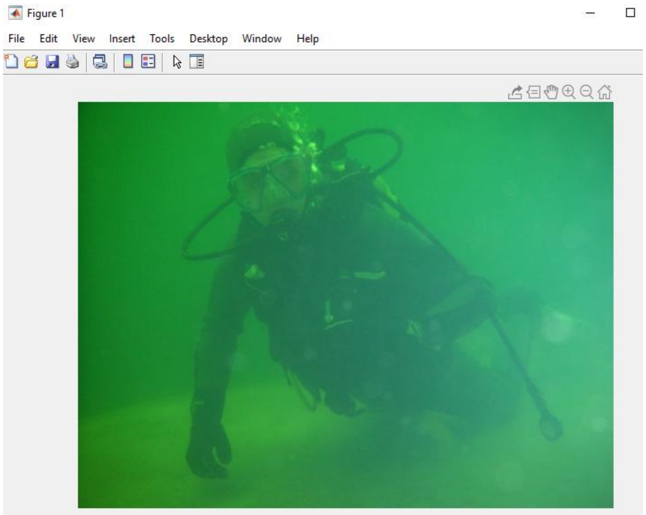
Enhanced Image- Figure - 9
piqeenhances =56.2569, niqeenhance =4.2242
brisqueenhance =39.5395, ssimval =0.3574, pcqi = 1.4932



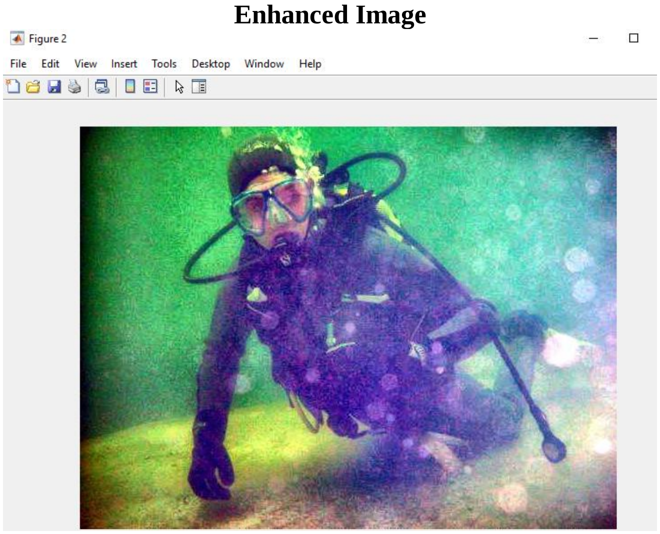
Enhanced Image



piqeenhances =18.8029, niqeenhance =2.8878
brisqueenhance =22.4082, ssimval =0.5529, pcqi =1.6177



Enhanced Image



piqeenhances =19.7602, niqeenhance =4.0921,
brisqueenhance =29.3847,ssimval =0.3692,pcqi =1.5479

Codruta O. Ancuti et. al. (IEEE 2018) has performed image enhancement in diffirent images and achieved average PCQI value= 1.3. In our proposed approach we have achieved average PCQI = 1.5.

V. Conclusion

As we have seen that the underwater images got degraded and contains noise because of the various factors like light scattering, light absorption, light refraction etc. So to create a sophisticated image this noise must be removed. For demising of image we performed Multi-wavelet based de-noising, which will significantly enhances the quality of the image. We have observed in the result secction that the average PCQI value has been increased by our proposed method.

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