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Super Under Water Image Enhancement for Real Time Applications

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Abstract- Ocean exploration is a major challenge that we are facing today. With advancements to fields of marine engineering and aquatic robotics, we are capable of performing autonomous and complex decision making deep underwater. Significance of online Underwater Computer Vision Algorithms is ever increasing. Underwater images, however, suffer from inaccurate colors, hazing, colour cast and degradations because of unequal absorption of light by water. Algorithms designed for detection/enhancement in the air are of no use underwater. Although a lot of underwater image enhancement algorithms have come up in recent times, most of them are not suitable for real-time applications like AUV, due to their high computational times. These algorithms are more suitable for offline analysis. In this paper, we propose an algorithm which is fast enough for real-time systems such as AUVs/ROVs and is comparable to the offline state of the art image enhancement algorithms. We will be exploring histogram equalization techniques for dehazing and automatic white balancing algorithms for color correction. UIEB (Underwater Image Enhancement Benchmark) is used for evaluation of our algorithm. The codes and results are available at https://github.com/opgp/underwater-imageprocessing.

Keywords-underwater image enhancement, real-time, color-cast, CLAHE, white balancing.

I. INTRODUCTION

In the last two decades an exponentially growing interest has been observed in ocean exploration and marine robotics. This has led to significant advancements in the field of aquatic robotics enabling them to perform increasingly challenging tasks autonomously underwater. Underwater image processing thus becomes an essential area of research, such algorithms are deployed in AUVs (Autonomous underwater vehicles). At present, underwater image processing algorithms are used in underwater mine detection [1], submerged robots [2], underwater imaging[3], underwater archaeology [4], ocean basement mapping [5], some of the commercial devices such as cameras, video cameras are also integrated with such application. Even though a lot of exceptional methods for underwater imaging have been proposed. Most of the methods are suitable to be performed on the recordings for research purposes rather than online applications due to the computational power and time required.

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Fig. 1. Proposed method for underwater image enhancement

Transportation characteristics of light in underwater environment makes image enhancement challenging problem. Water is hundreds of times denser compared to the air. As the light passes through water a lot of energy gets attenuated which results in low colour and contrast of underwater images thus resulting in distortion of information about the image.To tackle this problem, the use of artificial lighting was proposed but that produced another problem. Artificial lighting produces a bright spot at the centre of the image and the intensity reduces as we move away from the centre which results in non-uniform illumination[5]. Apart from non-uniform lighting conditions, light's unique absorption and scattering characteristics cause the degradation of underwater images. Absorption: Specific wavelengths are absorbed at different depths. The red colour is absorbed much more than green and blue colours at a much lesser depth. Resulting in a blue or green colour cast, in most underwater photos.

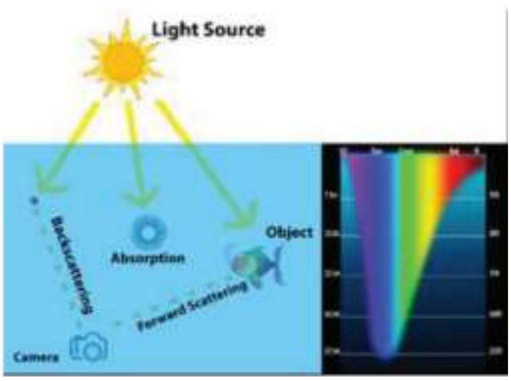

Fig. 2. Degradation of image underwater through scattering and absorption.

Scattering: Suspended particles underwater are much larger than particles found in the air. Leading to incident light reflected from objects to be scattered from particles and resulting in dull images. Contrast and edges are lost due to this phenomenon [6].

Backscattering: Artificial light might illuminate those suspended particles as well, resulting in a lot of noise in underwater images making tasks such as segmentation challenging.

Marine Snow: Macroscopic remains of organic matter from living organisms or inorganic matter present in underwater images from oceans. This results in added noise.The main contributions of the paper are summarized as follows: a) One of the fastest underwater image enhancement method for real-time applications and computationally light and suitable to be run on CPU (Central Processing Unit) only. b) An online enhancement algorithm comparable to state-of-the-art methods that are used for offline analysis. Comparison based on UIEB (underwater image enhancement benchmark).c) Method capable of removing colour casts, enhance colours, boost contrast and dehazing, with minimal parameters to be manually trained.

II.LITERATURE SURVEY

Exploring the underwater world has become an active issue in recent years. Underwater image enhancement is gaining more and more attention in the research field [7]– [9]. We can classify the types of underwater image enhancement methods into four groups.

A. External Hardware-based Methods To improve the visibility of underwater images, these models use the supplementary information from multiple images, special cameras/filters, like: a) Polarization filtering [10]. b) Range-gated

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imaging[11]–[13]. c) Fluorescence imaging [14]

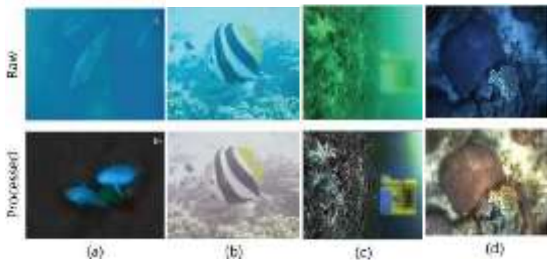

Fig. 3. Different types of Methods (a)Range Gated Underwater Imaging (b)White Balancing based enhancement (c)DCP based enhancing (d)WaterGan

These models are not suitable for challenging situations like dynamic scenes, real-time systems, etc. In these situations, more versatile underwater image enhancement is more suitable.

B. Pixel Value Manipulation Methods: In these methods, the image pixel value is modified in order to improve the underwater image quality. These are some examples where these methods showed good results: x K. Iqbal et al. in their paper enhanced the saturation and contrast of an underwater image by stretching the pixel range of HSV and RGB colour space.x Ghani and Isa in their papers modified the work discussed in the last point and reduced the over/under enhanced regions. They achieved this by reshaping the stretching process and followed the Raleigh distribution [15]. x Ancuti, C. O. Ancuti, and P. Bekaert in their paper introduced a method for underwater image enhancement in which they blended a colourcorrected image and a contrast-enhanced image in a multi-scale fusion strategy [16]. x X. Fu, Z. Fan, and M. Ling proposed a two-step method which included these algorithms: Contrast Enhancement and Colour Correction. x X. Fu, P. Zhang, Y. Huang presented a retinex model-based approach for underwater image enhancement. x Zhang et al. did research on an extended multiscale retinex-based enhancement model for underwater images.

C. Physical Modelling based Methods In the context of the physical model-based methods for underwater image enhancement, the problem is not as simple as to remove the unwanted properties from the image itself, here we use the image as the source to generate latent parameters. These methods solve the problem of underwater degradation by modelling the underwater environment and applying operations to reverse those degradations. This problem is generally solved by the same set of methods – 1) A physical model for the given degradation is built. 2) Unknown variables for the model are then estimated. 3) After the previous two methods the focus is played on the problem of generating latent parameters from the input image. The research is going on to solve this problem and we have a few methods at hand that have been well researched in order to counter these inverse problems. One such method is to tweak DCP (Dark Channel Prior). Depth map of the underwater image was obtained using median filter.Then DCP was used for dehazing of the image. Due to the greatest absorption of red colour, loss of information is a problem in underwater images, a solution UDCP(Underwater Dark Channel Prior) was formulated. It was observed that the dark channel for an image that was captured underwater tends towards a zero map Liu and Chau minimized a cost function with the aim of maximizing contrast in the image by formulating an optimal transmission map. GDCP (generalized dark channel prior) was introduced by Peng in order to restore the images by using an image formation model with the help of adaptive colour correction. D. Artificial Intelligence and Machine Learning Methods Recently there has been an increase in a shift towards Deep Learning algorithms for problems related to low-level computer vision. For training of a CNN (Convolutional Neural Network), original and ground truth images are needed. Since its almost impossible to obtain ground truth images of underwater objects, the only option left is to synthetically generate underwater images from ground truth images. Underwater images depend on temperature, depth and even turbidity of water, hence the deep learning algorithms based on underwater images cannot get the same success as in other low-vision problems. WaterGan, a deep learning-based algorithm was recently proposed. WaterGAN algorithm works by taking the images captured underwater and stimulates it in air image along with the depth pairing using an unsupervised pipeline. The authors for the algorithm created a two-staged network for restoration of images especially for removing the colour casts. An UWCNN (underwater CNN) that was trained using ten types of images captured underwater was proposed. The training images were synthesized using underwater scene variables using an image formation model. Water CycleGAN model was recently proposed on the basis of Cycle Consistent Adversarial networks. This model eliminates the need for paired images in training dataset cause of its network architecture. Thus, allowing the training images to be taken in remote locations. However, the results produced in some cases aren't fully authentic due to multiple possible outputs. Hence the robustness of Deep learning algorithms for underwater image enhancement is still lagging.

III. PROPOSED SYSTEM

This section contains the proposed algorithm for Fast Underwater Image Enhancement. The algorithm can be divided into three major parts, the first being enhancement of the colours in the image by splitting the image into RGB channels and applying adaptive contrast correction on individual channels (to enhance colours lost due to absorption of light underwater). The second part is enhancing the contrast and dehazing the image on the luminance channel. This is achieved by converting the colour channels to YCbCr from RGB, to preserve enhanced colours and applying Adaptive Contrast Correction on the Luminance channel (Y) (to equalize brightness in the image).They used contrast stretching instead of CLAHE. The third step is related to the smoothening of the images and removal of colour cast. Smoothening is performed using denoising algorithms (to remove the noise in the image due to the backscattering and marine snow) after converting the image back to RGB colour space. The colour cast if present if removed based on automatic white balancing by histogram stretching technique (to remove blue or green tint due to the absorption of light underwater). Results generated can be further used for other real-time applications like object detection, segmentation and so on. Now the following subsections will be discussing all the steps and algorithms used in detail.

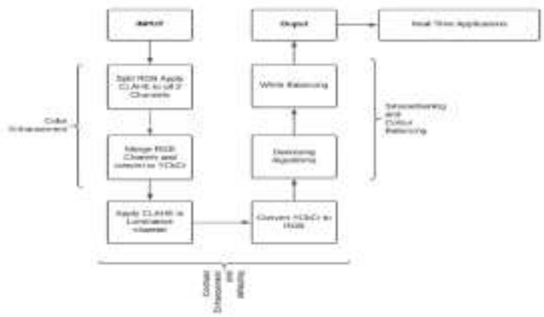

Fig. 4. Proposed Methodology

A.Colour Enhancement The colours in the images captured underwater have unnatural variations in the colour intensities due to the absorption and scattering of light underwater, these variations result in problems such as dull edges, loss of colours and colour cast. To remove these unwanted effects from the image, it will be operated on in the RGB colour space in this part. The first step will be to split the RGB components of the image into separate channels and to apply Adaptive Contrast Correction using an approach called CLAHE [36] (Contrast Limited Histogram Equalization) on the individual channels. Where window size = 8×8 and clip limit = 1. Contrast Limited

Histogram Equalization (CLAHE): Histogram equalization is a technique of distributing intensities throughout a given range. However, instead of taking input from the complete image and generating an equalization function the AHE (adaptive histogram equalization) method is a better alternative, it generates different histograms for different parts of the image and then equalizes the contrast based on those values. However, AHE is susceptible to noise Amplification in some cases where regions are relatively homogeneous. Hence variant of Adaptive Histogram Equalization called CLAHE will be used. AHE may result in overamplification, to overcome this CLAHE clips the histogram at some value before computing the CDF. Since the intensity values can lie in the range from 0 to 255, let F_k be defined as the frequency of pixel intensity k in the image, then

$$F_k = n_k ; 0 \leq k \leq 255$$

…(1)

Where n_k = number of pixels with an intensity value k Now, cdf (cumulative distribution function) of intensity value at x,y will be calculated.

$$cdf_{I(x,y)} = \sum_{k}^{I(x,y)} F_k$$

…(2)

Fig. 6. Effects of dehazing; Left column: Raw; Right Column: processed

Where x = 1 to M (number of rows), y = 1 to N (number of columns) and $I(x,y)$ = intensity value at . Now, calculating Histogram equalized Intensity value for each x,y.

$$I'(x,y) = \left\{ \frac{(cdf_{I(x,y)} - cdf_{min})}{(M \times N - cdf_{min})} \times 255 \right\}$$

…(3)

Where, cdf_{min} is the minimum cdf value for the segment. For implementing CLAHE a clip limit of 1 is put to avoid over-amplification of noise. After equalization of the intensities across all the channels they will be merged in the image. Now, as it can be seen in Fig. 6 since the red channel has low pixel intensities (darker image), CLAHE increased the intensities (made the single channel image brighter). Blue channel had a lot of high intensities, so the single-channel image got darker after CLAHE.

B.Dehazing and Contrast enchancement

Another main problem for the images obtained underwater is the variation of brightness or luminance. Due to the behaviour of light underwater, some parts appear lighter while some parts appear darker, making it impossible to detect some fine edges in the image. To overcome this issue the image is converted from RGB colour space to YCbCr colour space. The conversion from RGB to YCbCr is given below:

Fig. 6. CLAHE on RGB Channels

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Fig. 8. Top Row: Blue colour Cast; Middle Row: Green colour Cast; Bottom Row: Yellow colour Cast

$$\begin{bmatrix} Y' \\ P_B \\ P_R \end{bmatrix} = \begin{bmatrix} K_R & K_G & K_B \\ -\frac{1}{2}\cdot\frac{K_R}{1-K_B} & -\frac{1}{2}\cdot\frac{K_G}{1-K_B} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2}\cdot\frac{K_G}{1-K_R} & -\frac{1}{2}\cdot\frac{K_B}{1-K_R} \end{bmatrix} \begin{bmatrix} R' \\ G' \\ B' \end{bmatrix}$$

…(4)

Where KR + KG + KB = 1. Y here represents Luminance while Cb and Cr represent blue difference and red difference chroma component. CLAHE is applied on the Y (Luminance) channel to equalize brightness in the image, again since the variation in brightness is non-homogenous over the image, using a single Histogram Equalization function is not a good idea. Image is now converted back to RGB according to the following matrix:

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} 1 & 0 & 2-2\cdot K_R \\ 1 & -\frac{K_B}{K_G}\cdot(2-2\cdot K_B) & -\frac{K_R}{K_G}\cdot(2-2\cdot K_R) \\ 1 & 2-2\cdot K_B & 0 \end{bmatrix} \begin{bmatrix} Y' \\ P_B \\ P_R \end{bmatrix}$$

…(5)

C. Colour Balancing After applying Histogram Equalization over various channels, there is a need for colour cast removal. White balancing is the process of ensuring white colour is actually white in a picture. Due to the scattering of light underwater the blue and green intensities are usually higher than red intensities resulting in blue/green colour casts. Tint in the images makes it impossible to apply thresholding, segmentation using colour ranges. To overcome this issue, we will be White Balancing our images. White balancing in the images is performed by Histogram.The very first step will be to compute the R G B channel colour histograms. The second step will be to compute two thresholds Higher and Lower proceeded by processing every individual pixel of the R, G, B channel. Let H be the colour threshold higher than 98% of all the pixels and L be the colour threshold lower than 98% of all the pixels. 2%i s left here to maintain robustness.

$$I_{out} = \left\{\frac{(I_{in} - L)}{(H - L)} \times 255\right\} + I\_min$$

…(6)

Where I_{out} = Output tonal value, I_{in} = Input tonal value and I_min = minimum tonal value possible; 0 for range [0,255]. Image obtained after white balancing as shown in Fig. 8 can be observed to be free of unnatural green and blue tint because of scattering of light underwater.

D.Smoothening(Optional) Underwater images contain a large amount of noise due to effects such as backscattering and marine snow. It depends on the application, if image smoothening is required or not. Algorithms performing segmentation or thresholding tasks perform better in the absence of noise. On the other hand, for human perception or manual analysis, denoising is not necessary. The Primal-dual algorithm was used for denoising. The images will be first converted to CIELAB. Then L and AB channels are denoised. All the results calculated below will be done without this step.

IV.RESULTS

Dataset and Benchmark We used the UIEB for benchmarking and evaluation of our method. Dataset consists of 950 underwater images. Out of which 890 images have a corresponding reference image. Remaining 60 images are classified as challenging and no reference image is present. Reference images are generated using 12 models in total out which 9 image enhancement methods ((i.e., fusion-based, two-stepbased, retinex-based, UDCP,

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regressionbased, GDCP,Red Channel, histogram prior,and blurriness-based), 2 image dehazing methods (i.e., DCP and MSCNN), and 1 commercial application for enhancing underwater images (i.e. dive+). After all the images are generated, 50 volunteers voted for each algorithm, pairwise and the best image was chosen for each raw image. Thus, UIEB provides a method to evaluate our method against the best results in a wide range of underwater image enhancement methods.

Fig. 8. Results; Top Row: Raw Image;Bottom Row: Final Result;

It is evident that the method is capable of colour correction, colour cast removal, dehazing on a variety of images taken in different kinds of water at different depths.

TABLE I. NON-REFERENCE IMAGE QUALITY EVALUATION

Method	Metrics	
	UCIQE ↑	UIQM ↑
Fusion-based[24]	0.6414	1.5310
Two-step-based[25]	0.5776	1.4002
Retinex-based[26]	0.6062	1.4338
UDCP[29]	0.5852	1.6297
Regression Based[38]	0.5971	1.2996
GDCP[30]	0.5993	1.4301
Red Channel[39]	0.5421	1.2147
Histogram Prior[40]	0.6778	1.5440
Blurriness Based[41]	0.6001	1.3757
dive+	0.6227	1.3410
Proposed Method	**0.6471**	**1.7702**

*Best in red, Second best in blue

Along with reference images,non-reference metrics i.e., UCIQE(Underwater Colour Image Quality Evaluation Metric) and UIQM(Universal Image Quality Metric). Reference Metrics, i.e., PSNR (Peak signal-to-noise ratio), SSIM (Structural Similarity Index Metric), MSE (Mean Square Error) is also available for comparison with reference images.

Non-reference metrics In most of the cases, the ground truth images are not available for the test images, we can always encounter unidentified objects in the ocean. Especially, for underwater images, it can be extremely hard or even impossible to get ground truth images. For evaluating the quality of those kinds of images, we can use metrics like dynamic range independent image quality assessment, visible edges in an image and image entropy, we can also make use of applications like edge detection, feature point matching, etc. for evaluation. Here we specifically use two metrics (i.e., UIQM and UICQE) which are commonly used for evaluating underwater image quality.

1) UICQE UICQE measures the contrast, saturation and chroma component of an image and then combines them in a linear manner to give results. Images having a better balance between these attributes are likely to get a better UICQE score. As it can be seen in Table I, our algorithm performs second best after histogram prior.

2) UIQM UIQM focuses on the attributes like contrast, colourfulness and sharpness of an image for evaluation, inspired by the human visual perception. A higher UIQM score implies that the image is more perceivable to the human eye. Again, as seen in Table I, our method outperforms all the other methods. Even though a good score of UICQE and UIQM should correspond to a more visually perceivable image for humans but it is not always the case. Their results are not always consistent as we are not yet evolved to see properly underwater so it might be possible that after enhancing an image, we get good scores of UIQM and UICQE even though the image isn't visually pleasing for humans. It is because our way of perceiving underwater image is not accurate, we focus on the flashing details of images like colours, familiar objects, etc. Below we will be discussing the full reference metrics used.

TABLE II. FULL REFERENCE IMAGE QUALITY EVALUATION

METHOD	METRICS		
	MSE ($\times 10^3$) ↓	PSNR (dB) ↑	SSIM ↑
Fusion-based[24]	0.8679	18.7461	0.8162
Two-step-based[25]	1.1146	17.6596	0.7199
Retinex-based[26]	1.3531	16.8757	0.6233
UDCP[29]	5.1300	11.0296	0.4999
Regression Based[38]	1.1365	17.5751	0.6543
GDCP[30]	3.6345	12.5264	0.5503
Red Channel[39]	2.1073	14.8935	0.5973
Histogram Prior[40]	1.6282	16.0137	0.5888
Blurriness Based[41]	1.5826	16.1371	0.6582
dive+	0.5358	20.8408	0.8705
Proposed Method	**1.1014**	**18.5279**	**0.7865**

Full Reference Metrics Full-reference metrics are employed when the ground truth image is available for the test image. Pair of test images and corresponding ground truth images for full-reference evaluation is usually prepared artificially by taking objects underwater or by simulating the underwater environment. We compare the features of the result images with the reference images in the full-reference evaluation method. Although, sometimes the reference images might be different from ground truth images. Here we used three commonly used metrics, PSNR, MSE, and SSIM. A higher SSIM score suggests that the texture and structure of the result image is more similar to that of the reference image. Similarly, a lower MSE score and a higher PSNR score signifies the content similarity of result and test image.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i')^2 \quad \ldots(7)$$

Where, n = number of data points, Yi = observed values, Y-I ' = predicted value.

$$PSNR = 20.log_{10}(MAX_I) - 10.log_{10}(MSE) \quad \ldots(8)$$

Where MAXI = Maximum value, MSE = Mean square error. Our algorithm achieves the third best score in SSIM, MSE, PSNR amongst all the algorithms discussed in [7].

Runtime Evaluation We implemented our method in C++. MATLAB codes are converted to C++ code using MATLAB coder and some manually so that we can compare runtimes. All the experiments are conducted on a PC with an Intel(R) i7-7700HQ, CPU, 16GB RAM, on Ubuntu 18.04 LTS. OpenCV was used for the implementation of computer vision algorithms. Average runtimes over all the 950 images available in UIEB dataset is shown in Table III. Images were resized to fit the dimensions to calculate average runtime.

TABLE III. AVERAGE RUNTIME IN SECONDS

METHOD	DIMENSIONS OF IMAGE		
	500 × 500	640 × 480	1280 × 720
Fusion-based[24]	0.065	0.072	0.170
Two-step-based[25]	0.030	0.041	0.120
Retinex-based[26]	0.075	0.080	0.230
UDCP[29]	0.210	0.290	0.840
GDCP[30]	0.312	0.422	0.942
Red Channel[39]	0.243	0.310	0.922
Histogram Prior[40]	0.509	0.563	1.76
Blurriness Based[41]	4.103	4.682	14.294
Proposed Method	**0.014**	**0.018**	**0.044**

*Best in red, second best in blue

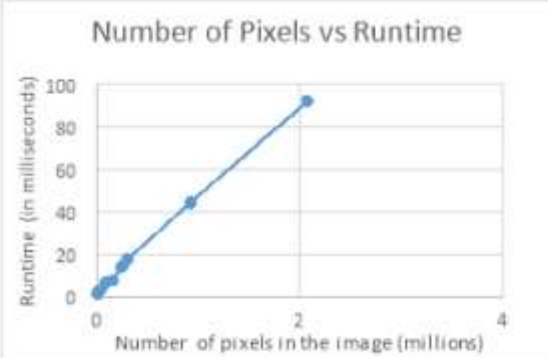

Fig. 9. Change in runtime with respect to changes in total number of pixels

The chrono library in C++ was used to calculate the runtime of the algorithms. As seen in Table III, proposed methodology is the fastest among all the evaluated algorithms. As expected from [7], two step based ranks second. Regression based method was skipped due to complexity of converting it into a C++ implementation. The entire UIEB (950 images) was processed at an average of 21 milliseconds/image. As shown in Fig. 10, the time complexity of the method is linear, i.e. with respect to changes in the size of input, the runtime will increase linearly. Thus, even a 4K (3840×2160) image will be processed in 370 milliseconds.

V. CONCLUSION

An underwater image enhancement algorithm is essential for computer vision tasks. In this paper, we proposed an algorithm suitable for real-time and online applications. The proposed method is fast enough to provide 20 FPS (Frames per second) on an HD (High Definition, 720×1280) video. Along with speed, the quality of images generated is comparable to reference images selected manually by volunteers. When it comes to non-reference metrics (UICQE and UIMQM), quality is evaluated as per contrast and colours present, our method performs exceptionally well. The proposed method deals with unwanted colour casts, lost colours, blurriness due to absorption. For the future, performance and effect of the method needs to be evaluated for algorithms such as object detection, automatic thresholding, edge detection etc. Underwater image degradation is a challenging problem, an algorithm that gives robust results on images with different lighting conditions, different depths, different properties of water and objects is a challenging task. The Proposed algorithm might give unsatisfactory results if the image contains multiple colour casts of variable colours and brightness. Since the white balancing algorithm used is a global algorithm. Adaptive white balancing could be considered for solving the problem, more research is required on the topic.

REFERENCES

[1] D. P. Williams, “On optimal AUV track-spacing for underwater mine detection,” 2010, doi: 10.1109/ROBOT.2010.5509435.

[2] J. Henderson, O. Pizarro, M. Johnson-Roberson, and I. Mahon, “Mapping submerged archaeological sites using stereo-vision photogrammetry,” Int. J. Naut. Archaeol., 2013, doi: 10.1111/1095-9270.12016.

[3] F. M. Caimi, D. M. Kocak, F. Dalgleish, and J. Watson, “Underwater imaging and optics: Recent advances,” 2008,doi:10.1109/OCEANS.2008.5152118

[4] P. Drap, “Underwater Photogrammetry for Archaeology,” in Special Applications of Photogrammetry, 2012.

[5] Y. Cho and A. Kim, “Visibility enhancement for underwater visual SLAM based on underwater light scattering model,” 2017, doi: 10.1109/ICRA.2017.7989087.

[6] J. Y. Chiang and Y. C. Chen, “Underwater image enhancement by wavelength compensation and dehazing,” IEEE Trans. Image Process., 2012, doi: 10.1109/TIP.2011.2179666.

[7] S. Corchs and R. Schettini, “Underwater image processing: State of the art of restoration and image enhancement methods,” EURASIP J. Adv. Signal Process., 2010, doi: 10.1155/2010/746052.

[8] M. Han, Z. Lyu, T. Qiu, and M. Xu, “A Review on Intelligence Dehazing and Color Restoration for Underwater Images,” IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2020, doi: 10.1109/TSMC.2017.2788902.

[9] R. Cui, L. Chen, C. Yang, and M. Chen, “Extended State ObserverBased Integral Sliding Mode Control for an Underwater Robot With Unknown Disturbances and Uncertain Nonlinearities,” IEEE Trans. Ind. Electron., 2017, doi: 10.1109/TIE.2017.2694410.

[10] M. Calisti, G. Carbonara, and C. Laschi, “A rotating polarizing filter approach for image enhancement,” 2017, doi: 10.1109/OCEANSE.2017.8084722.

[11] G. R. Fournier, “Range-gated underwater laser imaging system,” Opt. Eng., 1993, doi: 10.1117/12.143954.

[12] C. S. Tan, A. Sluzek, G. G. L. Seet, and T. Y. Jiang, “Range gated imaging system for underwater robotic vehicle,” 2006, doi: 10.1109/OCEANSAP.2006.4393938.

[13] P. Mariani et al., “Range-gated imaging system for underwater monitoring

in ocean environment," Sustain., 2018, doi: 10.3390/su11010162.

[14] T. Treibitz et al., "Wide Field-of-View Fluorescence Imaging of Coral Reefs," Sci. Rep., 2015, doi: 10.1038/srep07694.

[15] A. S. Abdul Ghani and N. A. Mat Isa, "Enhancement of low quality underwater image through integrated global and local contrast correction," Appl. Soft Comput. J., 2015, doi: 10.1016/j.asoc.2015.08.033.

[16] C. Ancuti, C. O. Ancuti, T. Haber, and P. Bekaert, "Enhancing underwater images and videos by fusion," 2012, doi: 10.1109/CVPR.2012.6247661.